# How Restricting Migrants' Job Options Affects Both Migrants and Existing Residents[*]

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Governments often restrict international migrants' job options. This paper shows that these restrictions can hurt not only migrants but also the existing residents whom they aim to protect. We study New Zealand's 'Essential Skills' work visa, which was New Zealand's main work visa between 2008 and 2022. Essential Skills migrants could only work for firms which could not find New Zealanders. Loosening restrictions for a single individual has no impact on their wages: migrants who win an unrestricted resident visa through a lottery switch jobs more frequently, but receive no gain in wages. However, when the Essential Skills job restrictions were loosened for *all* migrants in an occupation, both job-switching and wages typically grew. These results are consistent with a wage-posting model in which each firm pays migrants and residents equally; in such a model, the wage received by each worker will not depend directly on her own outside option but rather on the distribution of outside options among her colleagues. We estimate a wage-posting model, and compare equilibrium wages under the Essential Skills job restrictions to a counterfactual simulation in which migrants' job options are unrestricted. The restrictions decreased migrants' average wage by 8%. Although most residents were unaffected by the restrictions, 2.1% had their wage decreased by more than 2%. The restrictions increased profits, especially in firms which employed many migrants. The restrictions decreased annual welfare by $292m NZD — 30% of migrants' earnings — largely because migrants could not move to firms which they preferred for non-pecuniary reasons.

# 1 Introduction

Governments typically restrict the jobs in which international migrants can work. For example, a migrant's visa conditions might require that they work in a 'high-skill' occupation, that they work in a certain region, or that they work for a certain firm.[1] These restrictions aim to provide firms with migrant labor while protecting existing residents' wages.[2] However, by limiting migrants' outside job options, these restrictions may allow employers to pay migrants less. Moreover, if employers pay migrants and residents equally, these restrictions may reduce residents' wages as well.

This paper asks how restrictions on migrants' job options affect the migrants themselves, the existing residents of their new country, and employers. We study New Zealand's Essential Skills visa, which was New Zealand's primary employer-sponsored visa between 2008 and 2022. Workers holding an Essential Skills visa could only switch to a new employer if they obtained a new visa. Obtaining a new visa could be difficult. In most occupations, the visa was limited to employers who had demonstrated that they could not recruit New Zealanders. We evaluate the Essential Skills visa by using quasi-experimental analyses to discipline a structural model of the labor market.

In specifying our structural model, a critical modeling choice is how wages are set. If employers individually bargain with each worker, restricting migrants' job options could reduce migrants' wages, but residents would only be affected insofar as their productivity is affected. In contrast, if employers post wages that pay migrants and residents equally, equilibrium wages will depend on the job options of marginal employees. Restricting migrants' job options could thus reduce not only migrants' own wages but also the wages of their resident colleagues. In sum, to accurately model how restricting migrants' job options affects wages we must accurately

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[1] Examples of visas with a 'high-skill' restriction include the US H-1B visa, which is limited to occupations which require a "theoretical and practical application of a body of highly specialized knowledge", and the UK Skilled Worker visa, for which the British government maintains a list of occupations in which a migrant must work. In a similar vein, governments often require that prospective employers pass a 'labor market test' demonstrating that no existing residents are available to fill the job. An example of a regional restriction is that imposed by the Australian regional provisional visas, which require their holders live and work outside Australia's largest cities.

[2] The official intent of the US H1-B program is to "help employers who cannot otherwise obtain needed business skills and abilities from the U.S. workforce by authorizing the temporary employment of qualified individuals" while establishing "certain standards in order to protect similarly employed U.S. workers from being adversely affected by the employment of the nonimmigrant workers" https://web.archive.org/web/20240829160808/https://www.dol.gov/agencies/whd/immigration/h1b. The official objectives of New Zealand's Essential Skills visa included "helping New Zealand firms maintain capacity... while not displacing New Zealanders from employment opportunities or hindering improvements to wages" https://web.archive.org/web/20230218070502/https://www.immigration.govt.nz/opsmanual/66920.htm.

model how wages are set.

We use quasi-experimental analyses to understand how the firms that we study set wages. We study both individual-level shocks to specific migrants' job restrictions and market-level shocks that affect all migrants in an occupation. Loosening an individual migrant's job restrictions does not affect their earnings: when a migrant transitions to an unrestricted resident visa, they often switch jobs but, on average, receive no gain in earnings. In contrast, loosening the restrictions on all migrants in an occupation increases both job-switching and average earnings. These results are consistent with a wage-posting model in which each firm pays an equal wage to all of the workers in each occupation.

We thus evaluate the Essential Skills job restrictions using a wage-posting model. We compare equilibrium wages under the job restrictions to a counterfactual simulation in which migrants' job options are unrestricted. The restrictions decreased migrants' average wage by 8%, and decreased the wages of many residents as well. The restrictions increased aggregate profits, but these benefits were concentrated among a minority of firms: the median firm was actually hurt. The restrictions decreased aggregate welfare by $292m New Zealand dollars — equal to 30% of migrants' baseline earnings.

Our paper begins by formally showing that different wage-setting models make different predictions about the effects of restricting migrants' job options. We consider a framework in which firms have wage-setting power because workers have varying preferences over firms. Migrants can work at only some firms whereas residents can work at any. Within this framework, we consider three different wage-setting models, which each correspond to a different equilibrium concept. In a competitive equilibrium, firms choose employment levels taking wages as given. Each worker will be paid their marginal product, so job restrictions can only affect wages by reallocating workers to more or less productive firms. In a bargaining equilibrium, a worker's wage splits the difference between their outside job option and their marginal product. As such, restricting a migrant's job options can decrease their wages, even if their marginal product is unaffected. In a wage-posting equilibrium, each firm commits to a single wage that remunerates all its workers equally. Wage-posting firms account for the distribution of their workers' outside job options when choosing wages. As such, restricting migrants' job options can decrease all workers' wages.

To assess these models we first present descriptive wage regressions using a cross-section of full-time workers around the 2018 Population Census. On average, migrant workers who hold an Essential Skills visa earn about 20% less than residents. Most of this difference remains when we control for age, education and weekly hours of work. However, the difference disappears when we control for a worker's job: among workers who share both a firm and an occupation, those on an Essential Skills visa earn no less than others. In other words, in jobs with many

3

migrants, both migrants and residents are paid unusually little.

We next ask how migrants' earnings change when they transition from an Essential Skills visa (which restricts their job options) to a resident visa (which does not). This *individual-level* shock allows us to assess the importance of individual-level bargaining: In a bargaining equilibrium, but not in our other wage-setting models, an individual worker's wage depends on her own outside job option. When a migrant transitions from an Essential Skills visa to a resident visa, her job options expand: many new residents change firms shortly after receiving their resident visa. However, we find that receiving a resident visa has no mean effect on a worker's earnings. Using both a matched-control design and a lottery design we rule out any effects on log earnings larger than 0.01 with 95% confidence. We continue to find no effect when we focus on managerial and professional occupations in which existing research has found bargaining to be more common (Caldwell & Harmon, 2019; Lachowska, Mas, Saggio, & Woodbury, 2022; Caldwell, Haegele, & Heining, 2024).

We also study how migrants' average hours of work change when they obtain a resident visa: we find no evidence that they are affected. We do find that new migrants disproportionately move into larger firms, suggesting that they typically use their newfound freedom to move to a higher-amenity job, rather than a higher-wage job.

In a bargaining equilibrium, expanding the job options of a worker will increase the wage of that worker *provided she stays at her original firm.* Of course, many new residents decide to switch to one of their new job options. Among these job-switchers, the effect of the expanded job options is ambiguous: while the new residents will have a stronger bargaining position, they may decide to move to a low-wage, high-amenity job. If they do so, the results discussed thus far could be consistent with a bargaining equilibrium.

To assess this 'job-switching' concern, we estimate the average effect of greater job options *among those workers who do not switch firms.* For this exercise we use only our sample of workers who entered a random resident visa lottery. The probability that a worker switches firms is itself affected by the lottery, and thus simply conditioning on workers who do not switch firms would yield a biased estimate of this conditional average effect. Nonetheless, we show that this conditional average effect can be identified by exploiting the panel structure of the wage data.

The intuition is as follows. We observe the realized earnings of lottery-winning job stayers. The identification challenge is to identify counterfactual earnings for lottery-winning job-stayers: what they would have earned, on average, had they lost the lottery. To do so, we must infer how counterfactual earnings for job-stayers differ from counterfactual earnings for the full population. We infer this 'selection bias' by combining two relationships: the relationship between lottery-winners' post-lottery job-switching and their pre-lottery earnings, and the relationship between lottery-losers' pre-lottery earnings and their post-lottery earnings.

We find that winning a resident visa lottery has no effect on the wages of those who remain at their initial firm. This result is consistent with both competitive equilibrium and wage-posting equilibrium. It is inconsistent with individual bargaining playing a significant role in wage-setting.

Our analyses of individual-level shocks are consistent with both competitive equilibrium and wage-posting equilibrium. To distinguish *these* models, we next analyse a market-level shock. Wage-posting equilibrium predicts that a market-level loosening of migrants' job restrictions can increase migrants' wages — and indeed it can increase residents' wages as well. We test this prediction by studying how earnings are affected by an occupation's inclusion in an Essential Skills in Demand list: in occupations on these lists, migrants can work for any firm willing to employ them. Wage-posting equilibrium predicts that listing an occupation will increase earnings in that occupation. We confirm that prediction using a difference-in-difference research design: earnings in newly-listed occupations increase more quickly than do earnings in other occupations. These increased earnings coincide with increased worker mobility. We find no evidence that earnings effects can be explained by the reallocation of workers to more productive firms, as would need to be the case in a competitive equilibrium. Our analysis of market-level shocks is thus most consistent with wages being set in a wage-posting equilibrium.

Having corroborated a wage-posting model, we can use it to evaluate the distributional and welfare effects of migrant job restrictions. We identify the model using covariance restrictions between the amenity value of employment and the firm's productivity (Hausman & Taylor, 1983; MacKay & Miller, in press). Our structural estimates imply that an atomistic firm will face a labor supply elasticity of about 3.5. Workers are moderately willing to move between geographic locations: a firm which employed all the workers in its local labor market but which employed a trivial proportion of the national labor market would face a labor supply elasticity of about 1.7. Firms have decreasing returns to scale but can easily substitute between workers in different occupations. These structural estimates can explain the effects of the market level shock — the inclusion of an occupation in an Essential Skills in Demand list — that we discussed above.

With these estimates we can calculate the equilibrium effect of the Essential Skills visa system. We compare equilibrium wages given the observed set of firms which can employ migrants to a counterfactual equilibrium in which all firms can employ migrants. The Essential Skills visa system reduces the average wage of an Essential Skills migrant by about 8%. These effects are heterogeneous: migrants who largely work with other migrants typically have their wage reduced by over 20%. The typical resident is unaffected — migrants make up a small proportion of the overall workforce — but about 2.1% of residents have their wage reduced by more than 2%. These residents' average wage is about 20% less than the average wage in the full population.

The Essential Skills visa system also increases aggregate firm profit — although it slightly de-

5

creases the profit of most firms, it substantially increases the profit of other firms. Firms which benefit from the restrictions are on average larger, and typically employ migrants. There are, however, some firms which benefit from the restrictions despite employing no migrants — these firms benefit purely because the restrictions weaken competition between firms.

The overall annual welfare loss from the system is $292m NZD, which is equal to 30% of migrants' earnings. This welfare loss is due in part to a reduction in aggregate output, but is mostly due to the reduction in the non-pecuniary amenities which migrants receive from their firms. Recall our reduced-form result that migrants who transition to a resident visa frequently switch firms, but receive no gain in earnings. By revealed preference, this result suggests that the non-pecuniary aspects of employment are important. Our structural model can quantify non-pecuniary amenities and indeed we find that they account for most of the cost of the Essential Skills visa system.

We conclude our paper by studying how the Essential Skills job restrictions relate to other aspects of immigration policy. Specifically, we use our structural estimates to ask both how additional migration would affect residents' wages, and whether migration would affect residents more were migrants' job options unrestricted. In some occupations, restricting migrants' job options protects residents from the negative wage effects of migration. Under the restrictions, a migration shock which increased the total number of building laborers by 10% would decrease the mean wage of resident building laborers by only 0.2%. Were migrant building laborers' job options unrestricted, such a shock would decrease the mean wage of resident building laborers by 0.6%. The Essential Skills visa segregates migrant building laborers into different firms, and thus insulates residents from the wage effects of migration.

In other occupations, restricting migrants' job options accentuates the negative wage effects of migration. A migration shock which increased the total number of bus drivers by 10% would decrease the mean wage of resident bus drivers by 3.6%. Were migrant bus drivers' job options unrestricted, such a shock would decrease the mean wage of resident building laborers by only 2.6%. The Essential Skills visa increases firms' power over migrants, encouraging lower wages for both migrant bus drivers and their resident colleagues.

**Literature review.** We contribute to three literatures. First, we contribute to the literature evaluating visa policy. The existing literature on work visas has used reduced-form techniques to either study how market-level shocks to a visa system affect migrants' wages (Naidu, Nyarko, & Wang, 2016; Ahrens, Beerli, Hangartner, Kurer, & Siegenthaler, 2023), or to ask how an individual worker's wages change when she transitions away from a restrictive visa (Wang, 2021).[3] Analyses

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[3]A closely related literature studies the effects of regularizing undocumented migrants on the migrants themselves and on existing residents (Kossoudji & Cobb-Clark, 2002; Borjas & Edo, 2023; Elias, Monras, & Vazquez-Grenno, in press; Di Porto, Martino, & Naticchioni, 2018; Carrozzo, 2022).

of market-level shocks have found much larger effects than has the analysis of individual-level transitions. By studying both market-level shocks and individual-level shocks, we are able to reconcile these results: in a wage-posting equilibrium, an individual worker's visa status might matter little even though the overall visa system matters a lot. We further extend this literature by studying the effects of migrant restrictions both on residents and on firms.[4]

Second, we contribute to the literature assessing models of wage-setting.[5] The classic assumption is that wages are set in competitive equilibrium: firms take wages as given and choose employment levels accordingly. Among models that depict firms choosing wages, some depict firms bargaining with each of their workers individually (Stole & Zwiebel, 1996; Pissarides, 2000; Bagger, Fontaine, Postel-Vinay, & Robin, 2014; Caldwell & Danieli, 2024) while others depict firms posting inflexible wage policies (Burdett & Mortensen, 1998; Manning, 2005; Card, Cardoso, Heining, & Kline, 2018). The distinction between these three models of wage-setting is critical for understanding the causes of wage inequality and for assessing whether firms' labor market power results in a misallocation of workers (Berger, Herkenhoff, & Mongey, 2022; Silbert & Townsend, 2024). Different wage setting models also imply different effects of migration on residents' earnings (Amior & Manning, 2021; Amior & Stuhler, 2024; Chassamboulli & Palivos, 2013, 2014; Chassamboulli & Peri, 2015; Battisti, Felbermayr, Peri, & Poutvaara, 2018; Albert, 2021; Borjas, 1995, 2013; Monras, 2020).

In surveys, about a third of workers and firms report bargaining over their wage (Brenzel, Gartner, & Schnabel, 2014; Hall & Krueger, 2012).[6] However it remains an open question how important such bargaining is in practice. This paper joins a growing literature that assesses the empirical importance of wage bargaining by studying the effects of outside job options (Caldwell & Danieli, 2024; Caldwell & Harmon, 2019; Ahrens et al., 2023; Lachowska et al., 2022). We extend the literature on outside options in two ways. First, we study both individual-level and market-level shocks to workers' outside options to separately test wage bargaining and wage posting. Second, we distinguish bargaining effects from job-switching effects by estimating the

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[4]Amior and Manning (2021) and Amior and Stuhler (2024) argue that migrants may have less elastic labor supply, in part because their job options are restricted. As such, increasing migration may harm existing residents by inducing firms to set less generous wages. We ask how restricting migrants' job options mediates the effects of immigration in subsection 8.3. Doran, Gelber, and Isen (2022) ask how firms are affected by work visa policy by studying firm-level lotteries for the US H1-B visa.

[5]Beyond the outside options literature cited below, this literature includes analyses of rent-sharing (e.g. Carvalho, Galindo da Fonseca, and Santarrosa, 2023; Bloesch, Larsen, and Taska, 2022), analyses comparing workers' productivity to their wages (e.g. Delabastita and Rubens, 2022), and an analysis that requires productivity — estimated by inverting a labor supply system — be orthogonal to a concentration instrument (Roussille and Scuderi, 2024).

[6]Caldwell et al. (2024) report that firms often pay similarly productive workers different wages, even when explicit back-and-forth bargaining does not occur.

effect of better outside options among those workers who do not switch firms.[7]

Third, we contribute to the literature estimating labor market power. This literature consists of analyses which infer market power by estimating firm-specific labor supply elasticities (Manning, 2005; Lamadon, Mogstad, & Setzler, 2022; Azar, Berry, & Marinescu, 2022; Berger et al., 2022; Kroft, Luo, Mogstad, & Setzler, 2020; Roussille & Scuderi, 2023), and an overlapping literature which compares wages to marginal products from an estimated production function (Yeh, Macaluso, & Hershbein, 2022; Delabastita & Rubens, 2022; Lamadon et al., 2022; Kroft et al., 2020).

We extend this literature by estimating production functions in which distinct occupations are distinct inputs. Existing analyses either treat labor as homogenous, or as varying in some low-dimensional way (e.g. 'high-skill' vs. 'low-skill'). We show how to parsimoniously estimate a CES production function in which over 800 occupations can enter separately. By estimating firms' ability to substitute across occupations we can infer whether residents in one occupation (*e.g.* building laborers) are affected by job restrictions in another occupation (*e.g.* carpenters). The key insight is that we can estimate the production function using, as the dependent variable, the marginal product of a given occupation in a given firm, rather than a firm-level financial variable like revenue or value-added. We infer these marginal products by inverting firms' wage-setting equations, given estimates of the firm-occupation-specific labor supply elasticities.[8]

**Roadmap.** Section 2 provides our theoretical framework. Section 3 presents some additional details on the Essential Skills visa system and describes our data. Section 4 describes the cross-sectional relationship between a worker's visa status, the visa status of her colleagues, and her earnings. Section 5 describes how workers' earnings change when they transition from an Essential Skills visa to a resident visa. Section 6 describes how earnings in an occupation are affected by the inclusion of that occupation on an Essential Skills in Demand list. In Section 7 we estimate our structural model. Section 8 uses the structural model to describe the equilibrium effects of the Essential Skills visa system and analyse immigration policy. Section 9 concludes.

## 2  Three Models of Wage-Setting

In this section we present three models of wage-setting. The models are identical except for their solution concept: competitive equilibrium, bargaining equilibrium, or wage-posting equilibrium. We show that these solution concepts disagree as to how restricting migrants' job options

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[7]This estimator exploits the panel structure of wage data, and thus is in a similar vein to those presented by *e.g.* Card and Hyslop (2005) and Taber and Vejlin (2020).

[8]This procedure is similar to that used in studies of differentiated products — except that we estimate production functions using marginal products, rather than marginal costs (Berry, Levinsohn, & Pakes, 1995).

affects the labor market.

For simplicity, we assume in this section that workers have homogeneous productivity; they differ only in their preferences. In Appendix Section A we extend our model: we endow workers with varying (and, potentially, firm-specific) productivities, and we assign workers an occupation, which may be substitutes or complements and of which firms may make differing use. Our results continue to hold in this more general setting. Given that the model in Appendix A generalizes the model presented here, we include only proofs for the results in Appendix A.

## 2.1 The theoretical framework

We consider a static, partial-equilibrium, perfect-information labor market comprising a unit continuum of workers $\mathbf{I}$ and a finite set of firms $\mathbf{F}$. Each worker $i \in \mathbf{I}$ will be employed at a single firm $f_i \in \mathbf{F}$.

**Production.** Firms' only input is the total mass of labor they employ $L_f \equiv \int_{i:f_i=f} di$, with which they produce output using a concave and differentiable production function $y_f : \mathbb{R}^+ \to \mathbb{R}^+$. We focus only on strategic interactions in the labor market, and so assume that output is sold at unit price in a competitive market.

**Labor supply.** Each worker is either a *migrant* or a *resident*. Residents can be employed at any firm while migrants can only be employed at a subset of firms. Let $\mathbf{F}^{\mathrm{migrant}} \subset \mathbf{F}$ denote the subset of firms at which migrants can work. Let $\mathbf{I}^{\mathrm{migrant}} \subset \mathbf{I}$ denote the subset of workers who are migrants and let $\mathbf{I}^{\mathrm{resident}} = \mathbf{I} \setminus \mathbf{I}^{\mathrm{migrant}}$ denote the subset who are residents. For each worker $i$, let $\mathbf{F}_i \in \{\mathbf{F}^{\mathrm{migrant}}, \mathbf{F}\}$ denote the set of firms at which she can work.

Workers have preferences over their wage and the firm to which they are matched. We assume that the preferences of each worker $i \in \mathbf{I}$ over their wage $w$ and firm $f$ can be represented as

$$u_i(w, f) = we^{v_{i,f}},$$

where $v_{i,f} \in \mathbb{R}$ measures $i$'s taste for working at $f$. We assume that the conditional distribution of the random vector $v_i \equiv (v_{i,f})_{f \in \mathbf{F}}$, given a migrant's visa status, is absolutely continuous, with a differentiable PDF.

For each firm $f$, let $L_f(w_f; w_{-f})$ be the mass of labor supplied who would choose firm $f$, were it to pay all its workers wage $w_f$ and other firms were to pay wage $w_{-f}$:

$$L_f(w_f; w_{-f}) \equiv \mathbb{P}\left[ f \in \underset{g \in \mathbf{F}_i}{\arg\max} \{u_i(w_g, g)\} \right].$$

(By the absolute continuity of the distribution of $v_i$, measure zero workers will be indifferent between firms.) We assume that each firm $f$'s labor supply function $L_f(w_f; w_{-f})$ is concave in its own wage.

9

**Defining equilibrium.** We compare three solution concepts. In each solution concept we require that wages be strictly positive.

A *competitive equilibrium* comprises an assignment of workers to firms $(f_i)_{i \in \mathbf{I}}$ and a firm-specific wage schedule $(w_f)_{f \in \mathbf{F}}$ such that each worker's firm yields her the maximal utility from her choice set:

$$\forall i \in \mathbf{I} : f_i \in \underset{f \in \mathbf{F}_i}{\arg\max}\, u_i\left(w_f, f\right),$$

and the mass of labor assigned to each firm maximizes its profits, taking wages as fixed:

$$\forall f \in \mathbf{F} : L_f\left(w_f; w_{-f}\right) \in \underset{L \in \mathbf{R}^+}{\arg\max}\left\{y_f\left(L\right) - w_f L\right\}.$$

A *bargaining equilibrium* comprises an assignment of workers to firms $(f_i)_{i \in \mathbf{I}}$ and a worker-specific wage schedule $(w_i)_{i \in \mathbf{I}}$ such that each worker is assigned to that firm which could yield her maximal utility, were she paid her marginal product

$$\forall i \in \mathbf{I} : f_i \in \underset{f \in \mathbf{F}_i}{\arg\max}\, u_i\left(y'_f\left(L_f\right), f\right),$$

and her wage is bargained *a la* Nash (1950):

$$\forall i \in \mathbf{I} : w_i \in \underset{w \in \mathbf{R}^+}{\arg\max}\left\{\left(u_i\left(w, f_i\right) - u_i^{\text{option}}\right)^{\beta} \left(y'_{f_i}\left(L_{f_i}\right) - w\right)^{1-\beta}\right\}, \tag{1}$$

where $\beta \in (0,1)$ measures workers' bargaining power and $u_i^{\text{option}}$ is the maximal utility that $i$ could receive at an alternative firm:

$$\forall i \in \mathbf{I} : u_i^{\text{option}} \equiv \underset{f \in \mathbf{F}_i \setminus \{f_i\}}{\max}\, u_i\left(y'_f\left(L_f\right), f\right).$$

In particular, we follow existing bargaining models by assuming that a worker would counterfactually receive her marginal product, were she employed at her outside option. Cahuc, Postel-Vinay, and Robin (2006) provide an extensive-form justification for this approach using a Rubinstein (1982) alternativing-offers bargaining game.

A *wage-posting equilibrium* comprises an assignment of workers to firms $(f_i)_{i \in \mathbf{I}}$ and a firm-specific wage schedule $(w_f)_{f \in \mathbf{F}}$ such that each worker's firm yields her the maximal utility from her choice set:

$$\forall i \in \mathbf{I} : f_i \in \underset{f \in \mathbf{F}_i}{\arg\max}\, u_i\left(w_f, f\right),$$

and each firm's wage is chosen to maximize its profits, given the wages set by the other firms:

$$\forall f \in \mathbf{F} : w_f \in \underset{w \in \mathbf{R}^+}{\arg\max}\left\{y_f\left(L_f\left(w; w_{-f}\right)\right) - w L_f\left(w; w_{-f}\right)\right\}.$$

We assume that there exists a unique competitive equilibrium wage schedule, a unique bargaining equilibrium wage schedule, and a unique wage-posting equilibrium wage schedule.For restrictions on workers' preferences that yield a unique wage-posting equilibrium, see *e.g.* Caplin and Nalebuff (1991).

## 2.2 Predictions for wage-setting

We will show that our candidate wage-setting models have differing implications for how shocks to workers' outside options affect workers' wages. Before doing so, we characterize equilibrium wages.

Competitive wages equal the marginal product of labor:

**Lemma 1.** *Under a competitive equilibrium, each firm $f \in \mathbf{F}$ will pay a wage equal to its marginal product: $w_f = y'_f(L_f)$.*

Bargained wages will depend both on the worker's actual marginal product of labor and on the marginal product of labor at the worker's outside option:

**Lemma 2.** *Under a bargaining equilibrium, each worker $i \in \mathbf{I}$ will receive wage*

$$w_i = \beta y'_{f_i} + (1 - \beta) \exp\left(v_{i,f_i^{option}} - v_{i,f_i}\right) y'_{f_i^{option}},$$

*where $f_i^{option}$ is the worker's outside option:*

$$f_i^{option} \in \underset{f \in \mathbf{F}_i \setminus \{f_i\}}{\arg\max} \, u_i\left(y'_f, f\right).$$

A firm's posted wages will be marked down from its marginal product by a factor that depends on its firm-specific elasticity of labor supply:

**Lemma 3.** *Under a wage-posting equilibrium, each firm $f \in \mathbf{F}$ will pay wage*

$$w_f = \left(\frac{1}{1 + \frac{1}{\eta_f}}\right) y'_f$$

*where $\eta_f$ is the firm-specific elasticity of labor supply:*

$$\eta_f = \frac{w_f}{L_f} \frac{\partial L_f\left(w_f; w_{-f}\right)}{\partial w_f}.$$

With these characterizations, we can study shocks to workers' outside options. We first consider a comparative static with respect to the job options of an individual worker: we consider

turning a migrant into a resident. In all of our solution concepts, such a shock could either decrease or increase the worker's earnings if she decided to move firms. However, our solution concepts disagree as to how such a shock would affect a worker who decided to remain at her original firm. Neither her firm's marginal product nor its labor supply elasticity would be affected by the job options of an atomistic worker, and thus (by lemmas 1 and 3) under both a competitive equilibrium and a wage-posting equilibrium, the wage received by a worker who did not switch firms would be unchanged. In contrast, under a bargaining equilibrium, a worker's wage depends on her own outside option; when her outside option strengthens her wage will increase:

**Proposition 1.** *Consider a migrant i whose bargaining equilibrium firm $f_i$ would be unchanged, were she a resident:*

$$f_i = \underset{f \in \mathbf{F}^{migrant}}{\arg\max}\, u_i\left(y'_f\left(L_f\right), f\right) \in \underset{f \in \mathbf{F}}{\arg\max}\, u_i\left(y'_f\left(L_f\right), f\right).$$

*Making her a resident will increase her bargaining equilibrium wage provided that her new outside option is better than her old, i.e. provided that*

$$\max_{f \in \mathbf{F}\setminus\{f_i\}}\, u_i\left(y'_f\left(L_f\right), f\right) > \max_{f \in \mathbf{F}^{migrant}\setminus\{f_i\}}\, u_i\left(y'_f\left(L_f\right), f\right).$$

We also consider a market-level shock: allowing migrants to work at any firm. We will show that such a shock will have an unambiguous effect on posted wages under the following three assumptions.

First, we assume that firms' marginal products are homogeneous and constant:

**Assumption 1.** *Firms have a homogeneous production function which features constant returns to scale:*

$$\exists y : \mathbb{R}^+ \to \mathbb{R}^+ \text{ such that } \forall f \in \mathbf{F} : y_f = y \text{ and } \forall L_a, L_b \in \mathbb{R}^+ : y'\left(L_a\right) = y'\left(L_b\right).$$

Assumption 1 shuts down two potential channels through which a market-level shock might affect wages: It assumes that firms have a homogeneous production function, foreclosing workers moving to more- or less-productive firms. Is also assumes that this production function exhibits constant returns to scale, foreclosing changes to each firm's marginal product. Of course, firms do not actually share a homogeneous, constant returns to scale production function. When in Section 6 we study a market-level shock to migrants' job options, we will assess whether our estimated effects are due to an increase in workers' marginal product.

We also assume that workers' preferences over firms are independent of workers' visa status:

**Assumption 2.** *Migrants' preferences and residents' preferences over firms share the same distribution:*

$$\forall x : \mathbb{P}\left[ v_i \le x \,\middle|\, i \in \mathbf{I}^{migrant} \right] = \mathbb{P}\left[ v_i \le x \,\middle|\, i \in \mathbf{I}^{resident} \right].$$

When Assumption 2 fails, migrants might have such strong preferences for some firm that allowing migrants to work at that firm would induce the firm to reduce its wage, even though doing so would mean that the firm lost its resident workers. In Section 7 we weaken Assumption 3 by requiring only that migrants and residents have the same distribution of preferences given observable types.

Given a wage schedule $(w_g)_{g \in \mathbf{F}}$, let $\eta_f^{\text{resident}}\left((w_g)_{g \in \mathbf{F}}\right)$ denote the firm-specific elasticity of residents' labor supply:

$$\eta_f^{\text{resident}}\left((w_g)_{g \in \mathbf{F}}\right) \equiv \frac{\partial}{\partial \log w_f} \log \mathbb{P}\left[ f \in \arg\max_{f \in \mathbf{F}} u_i\left(w_f, f\right) \,\middle|\, i \in \mathbf{I}^{\text{resident}} \right].$$

(Recall our assumption that workers' preferences across firms $v_i \equiv (v_{i,f})_{f \in \mathbf{F}}$ follows an absolutely continuous distribution, with a differentiable PDF. This assumption guarantees that the elasticities $\eta_f^{\text{resident}}$ exist and are themselves differentiable.)

**Assumption 3.** *Each firm's elasticity of resident labor supply is increasing in other firms' wages:*

$$\forall (w_g)_{g \in \mathbf{F}}, \forall h \ne f \in \mathbf{F} : \frac{\partial}{\partial w_h} \eta_f^{resident}\left((w_g)_{g \in \mathbf{F}}\right) > 0.$$

Assumption 3 is a supermodularity assumption. By Lemma 3, Assumption 3 implies that wages in wage-posting equilibrium are strategic complements: if one firm increases its wage, other firms will increase theirs in response.[9] Assumption 3 holds, for example, when preferences take the logit form $v_{i,f} \sim \text{Gumbel}(\delta_f, 1)$. Assumption 3 need not hold more generally. When preferences are bimodal, for example, one firm might respond to a rival's wage increase by 'ceding the ground', reducing its own wage and retaining only its most committed workers. The structural parametric form we impose in Section 7 does not imply Assumption 3.

With these assumptions in hand, we consider a comparative static with respect to the set of firms at which migrants can work.

**Proposition 2.** *Consider expanding $\mathbf{F}^{migrant}$ such that occupation-o migrants can work at any firm: $\mathbf{F}^{migrant} = \mathbf{F}$. Under a competitive equilibrium, Assumption 1 implies that workers' wages will be unchanged. Under a wage-posting equilibrium, assumptions 1, 2 and 3 imply that wages at every firm will increase.*

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[9]We prove this claim within the proof of Proposition A.2.

Assumption 1 implies that firms' marginal product is exogenous. Under a competitive equilibrium, firms always pay their marginal product, and thus competitive equilibrium wages are unaffected by the shock.

In a wage-posting equilibrium, firms cannot specifically discriminate against migrants. Instead, firms which employ migrants will pay less generous wages to all their workers. Proposition 2 shows that expanding migrants' outside options can increase wages for both migrants and residents. This result contrasts with Proposition 1, in which we found that expanding the job options of a single worker has no effect on posted wages: in a wage-posting equilibrium, migrants' collective outside options matter in a way that their individual outside options do not.

Proposition 2 is silent as to the effect of expanding $\mathbf{F}^{\text{migrant}}$ on bargaining equilibrium wages. Surprisingly, this effect is ambiguous, even under Proposition 2's assumption that firms have a homogeneous and exogenous marginal product. Expanding a migrant's job options would allow them to work at a firm for which they have a strong (non-pecuniary) preference. Such a firm may be able to bargain a lower wage than could the migrant's initial firm. The model thus provides a theoretical rationalization for governments' claims that restricting migrants' job options can prevent migrant exploitation, further motivating the empirical analysis below.[10]

## 3   Institutional Context, Data and Summary Statistics

We study the period August 2008 to March 2022. During this period, the Essential Skills Work Visa was New Zealand's primary employer-sponsored work visa, constituting 20–40% of all temporary work visas held (working holiday visas, family visas and study-to-work visas made up the bulk of the remainder). Between 1% and 3% of all full-time workers held an Essential Skills visa over this period. Though Essential Skills migrants disproportionately worked in certain occupations, these occupations did not necessarily require a university education — as we discuss in more detail below, Essential Skills migrants often worked in the construction trades, in hospitality, and in agriculture.

An Essential Skills Work Visa tied its holder to a particular employer, and new visas were limited to jobs for which there were 'no New Zealanders available'. In most occupations, a prospective employer would have to convince an immigration official that they had made a "genuine attempt to attract and recruit" New Zealanders, for example by "advertising the vacancy in a national newspaper and/or website". This process was not merely perfunctory: about 10% of

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[10]For example, the objectives of New Zealand's Accredited Employer work visa — the successor to the Essential Skills visa that we study — includes "reducing risks around business models and practices that might enable migrant exploitation" `https://web.archive.org/web/20230217034245/https://www.immigration.govt.nz/opsmanual/77094.htm`.

Essential Skills applications were declined. In contrast, in occupations included on an 'Essential Skills in Demand' list, immigration officials were instructed to assume that no New Zealanders were available. As such, migrants in these occupations could obtain a visa for any firm willing to employ them.

Unlike workers who held an Essential Skills visa, workers who held a resident visa could generally work for any firm willing to employ them. (Some resident visas required that holders remain in skilled employment for the first 3–12 months of the visa.) Resident visa holders could also stay in New Zealand indefinitely, were eligible for government welfare (*e.g.* unemployment benefits and subsidized education), and could vote. In this paper we refer to resident visa holders and citizens collectively as 'residents'.

Essential Skills visas were granted for between 1 and 5 years, depending on when they were granted and on the skill level of the migrant's occupation. Expiring visas could be renewed. Among workers who arrived in New Zealand during 2010 on an Essential Skills visa, 37% had transitioned to a resident visa by 2015; 8% remained on a temporary work visa while 55% had left New Zealand (New Zealand Productivity Commission, 2022). Migrants who transitioned to a resident visa typically obtained a Skilled Migrant Category visa, eligibility for which was based on a lengthy (and time-varying) formula. New Zealand work experience was one component of this formula so migrants often became eligible for a resident visa after spending some time in New Zealand.

During the period we study, about 18% of New Zealand employees were union members (OECD, 2021). When setting wages for non-unionised employees, firms were constrained only by a nation-wide minimum wage.[11] Over our sample period New Zealand's minimum wage grew from 59% of the median wage in 2008 to 70% of the median wage in 2022 (OECD, 2024). In 2020, 9% of employees received the minimum wage (Maré & Hyslop, 2021).

## 3.1 Data

We use tax, immigration and survey data, linked within Statistics New Zealand's *Integrated Data Infrastructure*. Our analytic sample comprises all people aged at least 18; we restrict the sample further as appropriate (*e.g.* to those with positive earnings, or for whom we can infer an occupation).

**Earnings and employers.** New Zealand's income tax system requires that employers submit monthly wage records. We use this 'Employer Monthly Schedule' data to observe each worker's earnings and employers in each month. This data generally excludes owner-operators and the

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[11]Minimum wages were lower for some young workers and apprentices. A sectoral minimum wage schedule for care and support workers was introduced towards the end of our sample period.

self-employed.

**Visa status.** We observe visa spells using administrative immigration records. One limitation is that we only observe visas; we don't observe citizenship. We assume that any worker in New Zealand who lacks a visa is a citizen. This is a plausible assumption given that there are no known illegal entries into New Zealand and that very few temporary entrants overstay their visa.[12] We also use immigration records to observe entries into resident visa lotteries.

**Occupation.** Essential Skills migrants were required to list their occupation in their visa application; we observe these occupations directly. We also observe administrative occupation records for many other visa-holders, including holders of some resident visas. Finally, we observe the occupation of almost all workers at the 2013 and 2018 population censuses. We impute occupations at the worker-month level using any occupation record within the prior 5 years: we prioritise records lexicographically, prioritising any immigration record over any census record, and then taking the most recent record prior to the month of interest. All occupation data is coded using the ANZSCO 6-digit classification.

**Demographics and location.** We use both administrative and census records to infer workers' age, gender, country of birth and education level. We measure workers' geographic location of residence using Statistics New Zealand's internal predictions, which draw on both administrative and census records.

**Hours of work.** We measure hours of work using the population censuses and the Household Labour Force Survey.

**Confidentiality.** Statistics New Zealand requires that we randomly round all counts to base 3.[13] Means are calculated using randomly-rounded denominators, and proportions are calculated using both randomly-rounded numerators and randomly-rounded denominators. All other values are left unadjusted.

## 3.2 Summary statistics

Our sample is described in Table 1. Essential Skills migrants comprise 1.3% of the workforce during the 2018 Census and comprise 1.4% of all worker-month observations in our sample. About 70% of Essential Skills migrants are men, and they are slightly more likely to live in Auckland than are other workers. At the time of the 2018 Population Census, the most common country of origin was the the Philippines, accounting for only about 27% of migrants; India, the UK,

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[12]In 2016, 0.035% of temporary entrants overstayed their visa `https://web.archive.org/web/20231209062108/https://www.immigrationtrust.co.nz/new-zealand-immigration-news/overstayer-numbers-drop-to-new-low`.

[13]*I.e.* if $N$ mod 3 = 0, $N$ is left as is; if $N$ mod 3 = 1, $N$ is rounded up with probability $\frac{1}{3}$ and rounded down with probability $\frac{2}{3}$; if $N$ mod 3 = 2, $N$ is round up with probability $\frac{2}{3}$ and rounded down with probability $\frac{1}{3}$.

China, South Africa and Fiji are other common origin countries. Essential Skills migrants have varied educational backgrounds, with about 39% having only a high school education, 18% having a trade qualification, 24% having a bachelor's degree and 14% having a postgraduate degree. Essential Skills migrants are very likely to be paid employees (rather than *e.g.* self-employed or unpaid workers in a family business), are very likely to work full-time, and rarely hold a secondary job. Their earnings are somewhat lower than residents and citizens.[14]

Table 2 lists the 20 most common occupations for Essential Skills migrants during March 2018. These occupations are mostly semi-skilled, although the list includes both a highly skilled occupation (Resident Medical Officer, *i.e.* a junior doctor) and low-skilled occupations (*e.g.* sales assistant). In most of these occupations, Essential Skills migrants comprise a small-but-significant proportion of all workers. However, if we weight firm-by-occupation observations by the number of Essential Skills migrants therein — *i.e.,* we study the visa status of Essential Skills migrants' colleagues — we find that Essential Skills migrants very often work with other Essential Skills migrants. This segregation will play an important role in inducing firms which employ Essential Skills migrants to pay less generous wages.

# 4   The Cross-Sectional Relationship between a Worker's Visa Status, her Colleagues' Visa Status, and her Earnings

In this section we estimate cross-sectional Mincer-style regressions which examine the relationship between a worker's visa status and her earnings. Essential Skills migrants earn about 20% less than other full-time workers. However, this difference is entirely explained by the jobs in which Essential Skills migrants work: conditional on an occupation-by-firm fixed effect, Essential Skills migrants earn almost exactly the same as other workers. Consistent with this, we show that both Essential Skills migrants and other workers are paid less when more of their colleagues hold an Essential Skills visa.

**Analytic sample.** In this section we study the population of full-time employees with a consistent employer prior to either the 2013 or 2018 population census. Studying cross-sections around the censuses allows us to restrict our sample to full-time employees, and ensures that we observe the occupation of all workers. Specifically, our analytic sample comprises workers who, in the corresponding census, reported that they were working for a single employer for at least 30 hours per week. We include only workers who reported that they were paid employees,

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[14]The sample in March 2013, when the 2013 Population Census was held, looks similar — although between 2013 and 2018 the total number of Essential Skills migrants grew from 12894 to 21603. One difference is that in 2013 the share of Essential Skills migrants who were born in the Philippines was only 17.1%.

rather than *e.g.* the self-employed. We additionally restrict our sample to workers who, in the linked tax data, have non-zero earnings and a unique employer in the 12 months prior to the census. We discard workers with imputed census data. Finally, we include only workers who hold an Essential Skills visa, a resident visa, or who are citizens; we exclude workers who hold other temporary visas.

**Cross-sectional wage regressions.** The first column of Table 3 reports a simple regression in which a worker's log earnings are regressed on an indicator for the worker holding an Essential Skills visa. Across both censuses, Essential Skills migrants earn about 20% less than other full-time workers.

Column (2) of Table 3 adds controls to the regression: log hours of work, indicators for education levels, and indicators for decadal age bins. (Coefficient values for these controls are reported in Appendix Table A1.) Adding these controls attenuates the coefficient on Essential Skills status by at most 0.03.

Latter columns of Table 3 add fixed effects to the regression equation: occupation, firm, or their interaction. Doing so substantially attenuates the coefficient on Essential Skills status. In the regression reported in Column (5), which includes both controls and an occupation-by-firm fixed effect, the coefficient on Essential Skills status is a precisely estimated zero.

Panels B and D of Appendix Table A1 repeat these regressions with a larger sample: workers with a unique employer in the 6 months prior to the census, rather than only those with a unique employer in the 12 months prior. Doing so expands the sample to include those with less stable employment, though it may also increase measurement error if, for example, workers receive large annual bonuses. Estimates using this sample are similar.

**The relationship between a worker's earnings and her colleagues' visa status.** The results reported in Table 3 suggest that Essential Skills migrants earn much less than other workers, but only because of the jobs they hold. In other words, both migrants and non-migrants will earn less when more of their colleagues in the same firm-by-occupation cell are migrants. Figure 1 tests this directly. We first calculate the proportion of workers in each firm-by-occupation cell who hold an Essential Skills visa. We then group workers, both by the proportion of Essential Skills migrants in their cell (rounded to the nearest 10%), and by their own visa status.

Figure 1 depicts mean earnings for each of these groups. Both Essential Skills migrants and other workers earn less in cells containing more Essential Skills migrants. Comparing two workers on the same visa status – one who works almost exclusively with Essential Skills migrants and one who works almost exclusively with non-migrants, the former would tend to earn about $15000 less than the latter.

# 5   How Transitioning From a Migrant Visa to a Resident Visa affects a Worker's Earnings

In this section we follow workers who transition from an Essential Skills visa to a resident visa. Whereas an Essential Skills visa was restricted to a particular employer, a resident visa allowed its holder to work for any willing employer. We thus interpret a transition to a resident visa as an individual-level loosening of job restrictions.

In Subsection 5.1 we track the earnings of a large set of workers who transition from an Essential Skills visa to a resident visa. We compare these workers to those who worked in the same occupation and firm in the month before the migrant received a resident visa. New residents are very likely to switch firms, suggesting that their job restrictions had been binding. We find no evidence that a resident visa increases their earnings.

The key threat to Subsection 5.1's matched-control identification strategy are individual-level shocks: If workers apply for resident visas in anticipation of negative shocks to their earnings which leave their colleagues' earnings unaffected (*e.g.* a health shock), the matched-control estimator won't recover the causal effect of a resident visa. To assess this threat, in Subsection 5.2 we study Essential Skills migrants who enter a random lottery for a resident visa. Though this sample is somewhat unrepresentative of the general population of Essential Skills migrants, we can use it to estimate the causal effect of a resident visa under weaker conditions. Comparing lottery-winners to lottery-losers confirms that a resident visa has a substantial effect on job-switching, but no effect on earnings.

In light of Proposition 1, these results seem to be inconsistent with bargaining models of wage-setting: workers' job options are expanding but their earnings are unaffected. However, Proposition 1 only speaks to wage changes *among workers who remain at their original firm.* In practice, the key concern is that some new residents might be switching from high-wage low-amenity jobs to low-wage high-amenity jobs; our causal estimand could in principle average over a negative job-switching effect and a positive bargaining effect.

In Subsection 5.3 we isolate bargaining effects by estimating the average effect of winning a resident visa lottery *among new residents who stay at their baseline firm.* Among such job-stayers, winning the lottery need not be independent of potential outcomes. Nonetheless, we show that this 'stayers average treatment effect' can be identified by exploiting the panel structure of our data. We find no evidence that winning a resident visa lottery increases the average earnings of job-stayers. By Proposition 1, this result is inconsistent with the Nash bargaining model of wage-setting.

## 5.1 Matched-control estimates

**Analytic sample.** In this subsection, we study workers who transitioned from an Essential Skills visa to a resident visa. We limit our sample to workers who held an Essential Skills visa for at least 18 months prior to receiving a resident visa. We include only those who can be assigned both an occupation and a unique firm in the month prior to them receiving a resident visa. Moreover, we include only workers who share this baseline firm-by-occupation cell with at least one other worker; we will use these *baseline colleagues* as a matched control for the new resident.[15]

**Identifying variation.** Typically, workers who transitioned from an Essential Skills visa to a resident visa obtained a 'Skilled Migrant Category Resident Visa'. Eligibility for this visa was based on a lengthy, time-varying formula. Inputs into this formula included the worker's qualifications, their partner's qualifications, their partner's English language ability, their New Zealand family support, and their work experience.

Migrants often became eligible for a resident visa after spending some time working in New Zealand, both because they accumulated additional points and because the required number of points varied over time. Given that eligibility changed over time, often with little warning, a migrant who had become eligible for a resident visa may not remain eligible for long. As such, migrants often applied for a resident visa as soon as they were eligible. Nonetheless, migrants did have some discretion about when they applied, and thus a natural concern is that they apply for a resident visa in anticipation of a shock to their earnings. In this subsection, our estimates are unaffected by any shocks that affect the new resident and their baseline colleagues equally. In the following subsection we will study only workers who obtain their resident visa through a random lottery; those estimates are additionally robust to shocks that affect the new resident and not their baseline colleagues.

**Results.** The blue series in Figure 2 Panel A depicts the proportion of new residents working for a firm for the first time, by the number of months before or after the date they received a resident visa. In the year before they received a resident visa, roughly 1% of our sample found a new firm each month. In the months after, this rate increases dramatically, reaching a maximum 6 months later of 3.3%. The job-switching rate then begins to shrink, though it remains higher than the baseline rate.

The red series in Figure 2 Panel A depicts the job-switching rate for the worker's baseline colleagues. To construct it, we first find the average outcome among the baseline colleagues of each new resident, and then average over all new residents. The job-switching rate in the

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[15]We do not restrict the visa status of our matched control. As shown in Panel B of Appendix Figure A1, 12 months prior to the modal migrant receiving a resident visa 62% of the controls held a resident visa or were citizens. Four years later, 86% were. There is no discontinuity in the control group's visa status around the time when the modal worker becomes a resident.

baseline colleague series begins at about 2.5% — higher than the corresponding rate for new residents because most of these colleagues are already residents or citizens. There is no increase in the baseline colleague series around the time when the modal worker becomes a resident. (The dip in the baseline month is due to our requirement that both the new resident and her controls have a unique firm in that month.)

Figure 2 Panel A suggests that Essential Skills job restrictions are binding: when these restrictions are removed, many workers switch firms. Figure 2 Panel B asks whether these restrictions reduce the worker's earnings. There is no evidence that they do. Earnings for the new resident follow a stable trend around the date they receive a resident visa. Baseline earnings for their colleagues are very similar before the modal worker receives a resident visa (despite us not matching on colleagues' earnings) and continue to be similar after.

Appendix Figure A1 repeats this analysis for four other variables: employment, visa status, weekly hours of work, and log firm size. New residents are somewhat more likely to be employed both before and after they receive their resident visa. About 65% of control workers hold a resident visa or citizenship a prior to the modal migrant receiving a resident visa; this proportion increases smoothly to about 85% three years later. Conditional on working, new residents typically work no more or fewer hours than they did prior to receiving a resident visa.[16]

Panel D of Appendix Figure A1 shows that new residents disproportionately move to larger firms. In differentiated firm models (such as that in Section 2), larger firms either pay greater wages or provide better amenities. Given that obtaining a resident visa is not associated with increased earnings, it appears that new residents are disproportionately moving into high-amenity firms.

To provide causal point estimates, we calculate a matched regression of the form

$$y_{i,t} - \bar{y}_{i,t}^c = \beta + \delta \left( y_{i,-1} - \bar{y}_{i,-1}^c \right) + e_{i,t}, \tag{2}$$

where $y_{i,t}$ is migrant $i$'s outcome $t$ months since they received a resident visa, $\bar{y}_{i,t}^c$ is the average outcome among their baseline colleagues, and $\beta$ is the coefficient of interest. We estimate the equation on months 0–36 since receiving a resident visa. Standard errors are clustered at the level of the baseline firm.

Results are presented in the blue series of Figure 3. (The underlying estimates for that figure are available in Appendix Table A2.) The left-most bar aggregates across all occupations. We estimate a precise zero, and are able to rule out any effects on log earnings larger than 0.008 with 95% confidence. For comparison, recall from Table 3 that average resident earns about 20% more than the average migrant.

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[16]Recall that hours of work are measured using survey data. As such, Appendix Figure A1 Panel C is formed using only those workers who happen to be surveyed in a given month.

Whereas the first bar in Figure 3 aggregates across all occupations, later bars are estimated on subsets of occupations. Specifically, we divide workers on the basis of their baseline occupation: their occupation in the month before they received a resident visa. We first divide workers by whether their baseline occupation is included on an Essential Skills in Demand list at the time they received a resident visa. (One might expect to see larger effects for occupations *not* on an Essential Skills in Demand list — as discussed in Section 3, job restrictions on Essential Skills migrants are looser in listed occupations.) We find no effects for either occupations which are on an Essential Skills in Demand list or occupations which are not.

Existing work has found that professional occupations exhibit more bargaining than manual occupations (Hall & Krueger, 2012; Caldwell & Harmon, 2019; Caldwell et al., 2024). We calculate our estimator separately by high-level occupation. We find no evidence that a resident visa increases earnings in those occupations where we would most expect to see an effect: managers and professionals.

We do, however, find a positive and significant effect for workers in 'community and personal services'. To assess whether this effect is driven by these workers bargaining higher wages at their baseline firms, we re-estimate Equation (2), replacing the dependent variable with the worker's colleagues' log earnings:

$$\text{colleagues' log earnings}_{i,t} = \frac{1}{\left|C_{i,t}\right|} \sum_{j \in C_{i,t}} \log \text{earnings}_{j,t},$$

where $C_{i,t}$ is the set of workers who share a firm with worker $i$ in period $t$:

$$C_{i,t} \equiv \left\{j : f_{i,t} = f_{j,t}\right\} \setminus \{i\}.$$

In constructing this variable, we exclude workers (and colleagues) with multiple firms in a given month, and we exclude the first and last month of employment at a given firm. We construct this variable for both the new residents and for their baseline colleagues, and can thus reestimate Equation (2).

The resultant estimates are presented in the red series of Figure 3. The positive effect on workers in community and personal services appears to be driven by firm changes: these workers' colleagues' earnings increase by almost as much as their own. Indeed, we find that workers typically move into higher-paying firms when they obtain a resident visa, even though their own earnings do not tend to increase.

This analysis has shown that firm changes are important. However, we have not yet shown that bargaining is unimportant. Define a worker's *relative log earnings* as their own log earnings minus their colleagues' log earnings:

$$\text{relative log earnings}_{i,t} \equiv \log \text{earnings}_{i,t} - \text{colleagues' log earnings}_{i,t}.$$

Under a bargaining equilibrium, expanding a worker's job options will increase the relative log earnings *of workers who stay at their original firm.* However, even under a bargaining equilibrium, the effect on workers who move firms is ambiguous: workers might move to firms for which they have such strong preferences that their bargaining power decreases. It thus remains to be shown that expanding a worker's job options has no effect on workers who stay at their original firm — this is the task of Subsection 5.3. Before we do so, we will first respond to a distinct concern: that workers are obtaining their resident visas in anticipation of idiosyncratic shocks.

## 5.2   Lottery estimates

To construct the estimates reported in the previous subsection, we match workers to their baseline colleagues. As such, those estimates are unbiased even if workers apply for a resident visa in anticipation of a future economic shock — provided that the shock affects all workers in their occupation-by-firm cell equally. One natural concern is that workers apply for a resident visa in anticipation of an *idiosyncratic* shock. For example, it might be the case that workers apply for a resident visa when they become ill, or when they fall out of favor with their boss. If this is the case, the matched-control specification may be biased.

To address this concern, this subsection studies the subset of Essential Skills migrants who enter a random lottery for a resident visa. Specifically, we study migrants who enter a lottery for either the Samoan Quota Resident Visa or the Pacific Access Category Resident Visa. Like all New Zealand resident visas, these visas allow their holders to stay in New Zealand indefinitely. Citizens of Samoa are eligible to enter the lottery for the Samoan Quota Resident Visa while citizens of Kiribati, Tuvalu, Tonga and Fiji are eligible to enter the lotteries for the Pacific Access Category Resident Visa. Entrants from different origin countries enter different lotteries; each year, one lottery is held for each origin country. Typical lottery entrants reside in their home country. However, some are already in New Zealand when the lottery is drawn; these are the entrants we study.[17]

**Analytic sample and balance tests.** We include all lottery entrants who, at the time of the lottery, held an Essential Skills visa and were in New Zealand. We include both primary applicants and secondary applicants (*i.e.* dependants). We exclude a small number of workers who entered a given lottery more than once (*i.e.* as both a primary applicant and as a secondary applicant).

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[17]Existing work has studied how winning one of these lotteries affects those who had previously been living in their home country (Stillman, McKenzie, & Gibson, 2009; McKenzie, Stillman, & Gibson, 2010; Gibson, McKenzie, Rohorua, & Stillman, 2019).

Appendix Table A3 describes our sample. Entrants typically earn less, are more often men, and are more likely to live in Auckland compared to the general population of Essential Skills migrants. We observe 6123 entries across 3465 workers; 186 of these workers are successful. Entrants have typically been in New Zealand for between 3 and 4 years. 60% of successful entrants have obtained a resident visa within 12 months of the lottery, and 80% have within 24 months. Only 10% of unsuccessful entrants have obtained a resident visa 24 months after the lottery.

To confirm that the lottery is indeed random, we estimate the equation

$$y_{i,b} = \beta\text{success}_{i,b} + \alpha_b + e_{i,b}, \tag{3}$$

where $y_{i,b}$ is a placebo outcome for migrant $i$ in lottery $b$, $\beta$ is the coefficient of interest, $\text{success}_{i,b}$ indicates whether migrant $i$ was successful in lottery $b$, $\alpha_b$ is a lottery fixed effect, and $e_{i,b}$ is an orthogonal error. (Different lotteries have different probabilities of success. The lottery fixed effect ensures that we compare successful entrants only to unsuccessful in the same lottery.) Unsuccessful entrants can reenter later lotteries, so we observe some workers in more than one lottery. We estimate the equation with ordinary least squares, and to account for the correlation between different observations of the same worker we cluster standard errors at the worker level.

Table 4 reports these placebo estimates. Conditional on their lottery, successful and unsuccessful entrants have similar ages and numbers of dependants, and they have been in New Zealand for a similar length of time. They are similarly likely to be male, to live in Auckland, and to live in a major city. They have similar baseline employment rates and earnings. They are somewhat more likely to have switched firms in the 6 months prior to the lottery; given that we see no other evidence of imbalance between the successful and unsuccessful entrants we view this difference as spurious. The p-value testing the hypothesis that there is no difference across any outcome is 0.349.

**Results.** In Figure 4 we report OLS estimates of the coefficients $\beta_t$ from the equation

$$y_{i,b,t} = \beta_t\text{success}_{i,b} + \alpha_{b,t} + e_{i,b,t}, \tag{4}$$

where $i$ is a migrant who entered lottery $b$, and $t$ equals the number of months since lottery $b$ was drawn. In Panel A the dependent variable is an indicator for having received a resident visa $t$ months after the lottery. Evidently, winning the lottery has a very large effect on the likelihood that a migrant receives a resident visa, reaching a maximum of about 70 percentage points one year after the lottery. Thereafter, resident visas for successful entrants begin to plateau while those for unsuccessful entrants begin to catch up.

In Figure 4 Panel B the dependent variable is an indicator for having worked for a new firm at any point during the $t$ months since the lottery. Winning a lottery has a substantial effect on

the likelihood that a migrant switches firms. In Figure 4 Panel C the dependent variable is log earnings in the $t$th month since the lottery. There is no evidence that winning a lottery increases a migrant's earnings.

To provide point estimates, we use the lottery as an instrument for whether a migrant holds a resident visa. Specifically, we estimate the linear system

$$y_{i,b,t} = \beta \text{resident}_{i,b,t} + \alpha_b + \epsilon_{i,b,t},$$
$$\text{resident}_{i,b,t} = \delta \text{success}_{i,b} + \gamma_b + u_{i,b,t}, \tag{5}$$
$$\text{success}_{i,b} \perp \epsilon_{i,b,t}.$$

The key assumption is that the lottery only affects outcomes through its effect on migrants' visa status. Given the institutional structure we study, that assumption is plausible. In our baseline specification we estimate the system using outcomes 12–36 months after the lottery (which Figure 4 indicates is the period in which our instrument has the largest effect on visa status).

Results are presented in Table 5. Receiving a resident visa increases the monthly job-switching rate by about 1.5 percentage points. However we find no evidence that a resident visa affects migrants' earnings; we can rule out any effect on log earnings larger than 0.01. These results are robust to various alternative specifications which control for baseline outcomes, which expand the set of months for which we measure outcomes, which omit workers who held an Essential Skills in Demand list occupation at the time of the lottery (for whom we might expect smaller effects), and which change the functional form of the estimator.

Appendix Table A4 reestimates our instrumental variables system to study how receiving a resident visa affects other outcomes. One might worry that receiving a resident visa affects the probability that a worker is employed in New Zealand, introducing a selection bias into our regression estimates. The result in Column (1) suggests this is not the case: receiving a resident visa has no detectable effect on the likelihood that a migrant is employed in New Zealand (although, as shown in Column (2), this is because a positive effect on being in New Zealand is offset by a negative effect on being employed conditional on being in New Zealand). In Column (3) of Appendix Table A4 we repeat the exercise presented in Subsection 5.1, where we ask whether a resident visa induces workers to move into higher-paying firms. We find no evidence that it does.

Our preferred specification, reported in Column (2) of Table 5, implies that obtaining a resident visa *decreases* migrants' earnings by about 6%. While this effect is not significant at the 5% level, it is consistent with a major concern with our analysis thus far: new migrants may be moving to lower-paying, higher-amenity jobs. Such behavior is consistent with models in which wages are set through bargaining, and so our results thus far do not refute such models. In the following section, we study an unambiguous prediction of bargaining models: that increasing a

25

worker's job options will increase the earnings of those who remain at their original job.

## 5.3   The effect of a resident visa among workers who do not switch jobs

The results discussed above demonstrate that expanding a worker's job options does not, on average, increase their wages: though new residents often switch jobs, their average earnings are unaffected. In bargaining models of wage-setting, expanding a worker's job options can affect their wages in two ways: the worker might move to one of their new job options, or the worker might use their improved outside job options to negotiate a higher wage at their existing job. Though the latter effect is unambigiously positive, the former effect could be either positive or negative. In concrete terms, new residents appear to be moving to higher-amenity jobs. If higher-amenity jobs tend to pay lower wages, a negative *job-switching effect* could be obscuring a positive *bargaining effect*.

Per Proposition 1, the ideal test of bargaining asks whether receiving a resident visa increases the earnings of those workers who choose not to switch jobs. In this subsection, we estimate 'stayers average treatment effect' using Subsection 5.2's sample of workers who enter a resident visa lottery.

**Identification.** Workers who are paid poorly at their current job will, if given the chance, be more likely to switch jobs. As such, if we simply condition on workers who stay at their prior job, the visa lottery will no longer be independent of workers' potential outcomes. Nonetheless, under plausible assumptions, the stayers average treatment effect *can* be identified.

We observe the realized earnings of lottery-winning job stayers. The identification challenge is thus to identify *counterfactual* earnings for lottery-winning job-stayers: what they would have earned, on average, had they lost the lottery. To do so, we must infer how average counterfactual earnings among lottery-winning job-stayers differ from average earnings among lottery-losers. Given that the lottery is random, we can infer this 'selection bias' by asking how a lottery-winner's decision to switch jobs depends on their counterfactual earnings.

We do not observe the relationship between a lottery-winner's job-switching and their *counterfactual* earnings. However, we do observe the relationship between a lottery-winner's job-switching and their *pre-lottery* earnings. We also observe the relationship between lottery-losers' pre-lottery earnings and lottery-losers' post-lottery earnings. In Appendix B, we present conditions under which these two observed relationships can be combined to identify the relationship between a lottery-winner's job-switching and their counterfactual earnings — and thus identify the stayers average treatment effect. The key assumption is that job-switching is Markovian in counterfactual earnings: conditional on a worker's *current* counterfactual earnings, their decision to switch jobs does not depend on their past counterfactual earnings. We view this as-

sumption as plausible over short time frames when (for example) wealth effects are unlikely to be important.

We prove nonparametric identification in a stylized setting under which lottery losers *never* switch jobs. In practice, some lottery losers do switch jobs (though they switch less often than do lottery winners). We thus cannot nonparametrically identify the data generating process for counterfactual earnings.[18] We instead impose a parametric structure.

**Estimation.** Associate each worker $i$ with a lottery $l(i)$. Consider a worker $i$ and time $t$, where time is measured relative to the date of the worker's lottery (*i.e.* $t = 0$ is the quarter in which the lottery was held).[19] Let $Y_{i,t}(W, M)$ indicate their potential log earnings, where $W$ indicates that the worker won their lottery and $M$ indicates that the worker has moved firms between quarter 0 and quarter $t$. In turn, their decision to move firms will depend on whether they won the lottery, which we represent with another potential outcome $M_{i,t}(W)$. Letting $W_i$ indicate whether the worker won their lottery, a worker's realized log earnings are thus $Y_{i,t} = Y_{i,t}(W_i, M_{i,t}) = Y_{i,t}(W_i, M_{i,t}(W_i))$.

The key economic question is whether workers can use success in the lottery to bargain a higher wage at their existing firm: *i.e.*, whether $Y_{i,t}(1,0) > Y_{i,t}(0,0)$. As such, our target estimand is the stayers average treatment effect — the average effect of winning the lottery, among workers who do not move firms as a result:

$$\text{ATE}_{\text{stayers}} \equiv \mathbb{E}\left[ Y_{i,t}(1,0) - Y_{i,t}(0,0) \,\Big|\, M_{i,t}(1) = M_{i,t}(0) = 0; t \in 4, ..., 11 \right].$$

To match the results reported in the previous subsection, we measure outcomes 4–11 quarters after the lottery. Note that $\text{ATE}_{\text{stayers}}$ measures the effect of winning the lottery, rather than the effect of receiving a resident visa. As such, it is most comparable to the 'intent-to-treat' estimates reported in Column (1) of Table 5, rather than the IV estimates reported in later columns.

To estimate $\text{ATE}_{\text{stayers}}$, we first condition on the population who have a consistent employer in the quarter prior to the lottery: $M_{i,-1} = 0$. Among this population, we impose the following nonparametric assumptions:

1. If a worker who lost the lottery moves, she would have moved had she won the lottery: $M_{i,t}(1) \geq M_{i,t}(0)$.

2. The lottery has no effect on earnings before it is held: $Y_{i,-1}(1,0) = Y_{i,-1}(0,0)$.

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[18]This is a 'full support' issue, closely related to the 'identification at infinity' issue in identifying the Roy model (Taber & Vejlin, 2020).

[19]In this subsection we measure outcomes at the quarterly level, rather than at the month level, to minimize transitory measurement error due, for example, to some months having more fortnightly pay cycles than others. This simplifies the DGP for counterfactual earnings that we must specify.

In our baseline specification, we additionally impose the following parametric assumptions:

3. The decision to move, among workers who have not done so already, is probit in $W_i$, $Y_{i,t}(0,0)$, and their interaction, with a lottery effect:

$$\mathbb{P}\left[M_{i,t} = 1 \mid W_i, \left(Y_{i,s}(0,0)\right)_{s \leq t}, M_{i,t-1} = 0\right] = \Phi\left(\beta_0 + \beta_1 W_i + \beta_2 Y_{i,t}(0,0) + \beta_3 W_i Y_{i,t}(0,0) + \delta_{l(i),t}\right);$$

where $\Phi$ is the normal CDF.

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

$$Y_{i,t}(0,0) = \alpha_0 + \alpha_1 Y_{i,t-1}(0,0) + \gamma_{l(i),t} + \epsilon_{i,t}; \quad \epsilon_{i,t} \sim N(0, \sigma_\epsilon).$$

5. Lottery effects are joint-normally distributed:

$$\left(\delta_{b,t}, \gamma_{b,t}\right) \sim N\left(0, \Sigma_{\delta\gamma}\right).$$

We calculate the Bayesian posterior of the above model, given uninformative priors, using a Gibbs sampler described in Appendix C.

**Results.** Estimates are presented in Table 6. In Column (1), we report the specification above. We find no evidence that winning a resident visa lottery increases the earnings of job-stayers. Our point estimate is negative, and our posterior distribution places very low probability on economically significant positive effects.

Table 6 also lists estimates of the model parameters. These are plausible: moving firms is positively associated with winning the lottery and is negatively associated with counterfactual earnings, with lottery-winners being particularly sensitive to their counterfactual earnings.

In the results presented in Column (2), we weaken our assumption that job-switching is Markovian in counterfactual earnings. Specifically, we add a lag of counterfactual earnings to the selection equation

$$\mathbb{P}\left[M_{i,t} = 1 \mid W_i, \left(Y_{i,s}(0,0)\right)_{s \leq t}, W_{i,t-1} = 0\right]$$
$$= \Phi\left(\beta_0 + \beta_1 W_i + \beta_2 Y_{i,t}(0,0) + \beta_3 W_i Y_{i,t}(0,0) + \beta_4 Y_{i,t-1}(0,0) + \beta_5 W_i Y_{i,t-1}(0,0) + \delta_{l(i),t}\right).$$

Again, we find no evidence that winning a resident visa lottery increases the earnings of those who stay at their original firms.

# 6  How Loosening Restrictions in an Occupation Affects Wages in that Occupation

In the previous section, we showed that expanding a worker's job options does not tend to increase their earnings. However, this *individual-level* result need not imply that a *market-level*

shock to workers' job options will have no effect. As shown by Proposition 2, in a Bertrand wage-posting equilibrium, expanding the job options of many workers can increase both their wages and the wages of other workers. In this section, we test the effects of market-level shocks directly.

To do so, we study how wages in an occupation change when that occupation is added or removed from an Essential Skills in Demand list. As discussed in Section 3, in occupations included on one of these lists, migrants could work for any firm willing to employ them. We ask how expanding migrants' job options affects both their wages and the wages of their non-migrant colleagues.

**Data.** Over our sample period, the relevant Essential Skills in Demand lists were the 'Construction and Infrastructure Skill Shortage List', the 'Canterbury Skill Shortage List', the 'Immediate Skill Shortage List', the 'Long Term Skill Shortage List' and the 'Regional Skill Shortage List'. These lists differed mostly in the process used to amend them, in whether they only applied to certain sub-national regions, and whether they were also used to assess applications for a resident visa. We obtained historic lists from government archives and from the Internet Archive.

We treat an occupation as being included on a list in a given month if it was included in any list on the first of that month. Some lists only expanded migrants' job options in certain regions. To avoid *a priori* assumptions about migrants' willingness to move across regional boundaries, we consider an occupation treated if it was included for any region. We observe workers' occupations at the ANZSCO 6-digit level (e.g. 'Electrical Engineer'). Occasionally, the occupation included on an Essential Skills in Demand list is more specific (e.g. 'Power Systems Engineer'); in such cases we consider the entire ANZSCO 6-digit occupation as being treated.

We conduct our analysis using an occupation-by-month panel. The panel is described in Appendix Table A5. Occupations which were sometimes or always on an Essential Skills in Demand list had somewhat higher earnings than other occupations.

**Identifying variation.** We identify the effect of Essential Skills in Demand lists by asking how earnings change when an occupation is added or removed from these lists. The Immediate Skill Shortage List (which was later renamed as the Regional Skill Shortage List) and the Long Term Skill Shortage List were together amended in a single process. During the first years of our sample, these lists were supposed to be reviewed twice-yearly, though reviews were often delayed or postponed. During the later years of our sample, these lists were reviewed yearly. Amendments were proposed either by industry bodies or by the responsible government agency. These proposals were assessed internally, and final decision-making authority lay with a senior bureaucrat (for the Immediate Skill Shortage List) or with a government minister (for the Long Term Skill Shortage List).

In September 2011 — following the September 2010 and February 2011 earthquakes in the Canterbury region — the government introduced a special skill list for occupations required

29

in the post-quake rebuild. This list initially included only occupations which were already included in other lists. In later iterations it included some occupations which were absent from other lists. This list was later renamed the Construction and Infrastructure Skill Shortage List, at which point it begun to include regions other than Canterbury. These lists were reviewed somewhat more regularly and informally than the lists described in the paragraph prior.

The criteria for including an occupation changed over time and varied between lists, but were most explicit for the Immediate Skill Shortage List in the latter half of our sample. During that period, proposals to amend the Immediate Skill Shortage List were assessed according to three criteria: 'skill level', 'scale', and 'shortage'. The 'skill level' criterion was satisfied provided the occupation was coded as sufficiently skill-intensive. The 'scale' criterion was satisfied provided the occupation either included at least 2000 workers, or had at least 50 Essential Skills visas approved in the prior 12 months. The 'shortage' criterion was assessed using various factors including (a) the number of unemployed 'jobseekers' registered with the New Zealand welfare agency, (b) the number of online job listings, (c) the number of recent visa approvals in that occupation, and (d) historic and forecast employment growth in the occupation.[20]

Some of these criteria are plausibly orthogonal to demand and supply shocks. For example, the 'scale' criterion was used to justify removing several small occupations during the later years of our sample, including upholterer, glider pilot instructor, rheumatologist, and geophysicist. However, the use of employment forecasts to assess the shortage criterion does threaten our differences-in-differences identification strategy: if occupations are listed in anticipation of future demand shocks, our estimated effect on earnings will be upwards-biased. We will assess this threat by using Australian data as a proxy for labor demand.

**Results.** We begin by estimating a linear panel event-study model (Freyaldenhoven, Hansen, Pérez, & Shapiro, 2021). That is — letting $o$ index occupation, letting $t$ index months, letting $\text{list}_{o,t}$ indicate inclusion on an Essential Skills in Demand list and letting $\Delta$ be the first difference operator — we estimate the linear equation

$$\text{mean log earnings}_{o,t} = \delta_{-13}\left(1 - \text{list}_{o,t+12}\right) + \sum_{s=-12}^{36} \delta_s \Delta \text{list}_{o,t-s} + \delta_{37}\text{list}_{o,t-37} + \alpha_o + \gamma_t + \epsilon_{o,t}$$

with ordinary least squares, subject to the constraint $\delta_{-1} = 0$.

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[20]The memorandum summarizing the December 2016 decision to remove 'upholsterer' from the Immediate Skill Shortage List is representative: "The Furniture and Cabinetmaking Asociation of NZ Inc. advised that with low cost imports coming into New Zealand, there are only a few small businesses now operating. There is little upholstery manufacturing going on in New Zealand, and apprentice numbers are low. They are quite relaxed about the removal of this occupation from a shortage list. There are small numbers of employees in this occupation and numbers of work visas granted over the last few years have been low. Occupation growth has been negative over the last five years and forecast growth is quite low. There are a small number of jobseekers registered with MSD who have claimed at least 12 months' work experience as an upholsterer."

We depict these estimates in Figure 5. Earnings are stable before an occupation is added to a skill list. They increase quickly after an occupation is added, stabilizing at about 3.5% higher 6 months after the occupation is added. This result is consistent with wages being set in a Bertrand wage-posting equilibrium: when an occupation is added to an Essential Skills in Demand list, migrants' job options expand. This increases the elasticity of their labor supply; firms respond by setting more generous wages.

The event study depicted in Figure 5 suggests that the effect of listing an occupation can be well-approximated by a model in which the effect is instantaneous and lasts indefinitely:

$$\text{mean log earnings}_{o,t} = \beta \, \text{list}_{o,t} + \alpha_o + \gamma_t + \epsilon_{o,t}, \tag{6}$$

where $\text{list}_{o,t}$ indicates that the occupation is included on an Essential Skills in Demand list, $\alpha_o$ is an occupation fixed effect, $\gamma_t$ is a month fixed effect, and $\beta$ is the parameter of interest. We estimate the two-way fixed effects model in Equation (6) with ordinary least squares. The estimated effect — depicted in Column (1) of Table 7 — is equal to about 0.03. This is consistent with the estimates of the linear panel event-study model.

Proposition 2 told us that expanding migrant's job options can increase *both* migrants' and residents' earnings. In Columns (2) and (3) of Table 7 we assess this prediction. We find that listing an occupation increases the earnings of both migrants and residents.

Our identification strategy will be threatened if occupations are added to an Essential Skills in Demand list in anticipation of positive labor demand shocks. We assess this threat in two ways. We first test whether our estimates are sensitive to the inclusion of controls. Column (4) of Table 7 reestimates our two-way fixed effect model, additionally controlling for log firm value-added and for the log number of workers at a firm. (We construct these variables at the worker level, and then take occupation averages.) Column (5) includes these controls and additionally controls for occupation-specific linear time trends. In both columns (4) and (5), the estimated effect is similar to that in our baseline specification.

We next assess whether occupations are listed in anticipation of positive labor demand shocks by studying a proxy for labor demand shocks: wages in Australia. It is unlikely that New Zealand work visa policy affects Australian wages.[21] Thus, were we to find that Australian wages increase when an occupation is included on a New Zealand Essential Skills in Demand list, we would conclude that occupations are being listed in anticipation of positive demand shocks.[22]

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[21]Though some workers do move from New Zealand to Australia, they are a small proportion of the Australian labor force. In 2012, 2.5% of Australian residents were born in New Zealand `https://web.archive.org/web/20240306215258/https://www.abs.gov.au/statistics/people/population/australias-population-country-birth/latest-release`.

[22]Wages in Australia and New Zealand tend to co-move, suggesting that the two countries face correlated labor

We operationalize this test using publicly available data on mean Australian earnings, by occupation, provided in Table 14B of the Australian Tax Office's Individuals Statistics release. This data is released at the 4-digit ANZSCO occupation level, for each Australian tax year. Recall our New Zealand data is available at the 6-digit ANZSCO-by-month level: For this comparison we aggregate the New Zealand data to the 4-digit ANZSCO-by-year level. We consider a 4-digit ANZSCO occupation as treated in a given year if any of its component 6-digit occupations are included on an Essential Skills in Demand list at any point during that year. The Australian data is available beginning from the July 2010–June 2011 tax year. In the Australian data we do not observe mean *log* earnings; we instead take the log of mean earnings.

Figure 6 presents linear panel event study estimates which ask how both New Zealand earnings and Australian earnings are affected by the inclusion of an occupation on a New Zealand Essential Skills in Demand list. As in the more granular specification presented in Figure 5, New Zealand earnings increase when an occupation is included on a New Zealand Essential Skills in Demand list. There is no similar effect on Australian earnings. (We do find weak evidence of a pre-trend in the Australian data. Given that this pretrend ends when an occupation is listed, and that we find no similar pre-trend in the New Zealand data, we interpret it as spurious.)

Columns (6) and (7) of Table 7 exploit the Australian data to estimate point estimates for the effect of the Essential Skills in Demand list on New Zealand earnings. Column (6) estimates a triple-difference specification:

$$\text{New Zealand mean log earnings}_{o,t} - \text{Australian log mean earnings}_{o,t} = \beta \, \text{list}_{o,t} + \alpha_o + \gamma_t + \epsilon_{o,t}.$$

Column (7) presents the Freyaldenhoven, Hansen, and Shapiro (2019) estimator, in which Australian log mean earnings are used as a proxy for an unobserved confound. Both approaches result in point estimates similar to our baseline estimate.

Two-way fixed effects models — like that in Equation (6) — can perform poorly when treatment effects are heterogeneous (De Chaisemartin & d'Haultfoeuille, 2020). The Essential Skills in Demand lists will likely have greatest effect when many workers are migrants. As such, we now consider an estimator which recovers an average effect of inclusion on an Essential Skills in Demand list.

In Appendix D we define our estimator formally. The key insight is that a literal difference-in-differences — earnings growth in a newly-treated occupation minus earnings growth in a control occupation — *is* an unbiased estimator of the treatment effect in the newly-treated oc-

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demand shocks. An OLS estimate of the linear equation

$$\text{log mean Australia earnings}_{o,t} = \beta \, \text{mean log New Zealand earnings}_{o,t} + \alpha_o + \gamma_t + \epsilon_{o,t}$$

yields a slope coefficient of 0.218, with a standard error (allowing for within-occupation clustering) of 0.078.

cupation if the treatment and control occupations had both been untreated for long enough that any effects of historical treatments had dissipated (De Chaisemartin & d'Haultfoeuille, 2020; De Chaisemartin & d'Haultfoeuille, 2024). We study events in which an occupation is either added to an Essential Skills in Demand list after being absent for at least 24 months or is removed after being included for at least 24 months. For each event we identify a set of control occupations with the same pre-event status. We calculate the simple difference-in-difference for each event-control pair, measuring outcomes up to 36 months after the event. We then average these estimates to construct a single point estimate.

This point estimate is presented in Column (8) of Table 7. It is very similar to our baseline estimate but is slightly more precise.

One convenient feature of the nonparametric average treatment effect estimator is that it can easily be decomposed into subsets of occupations. In Appendix Figure A2 we report the average effect, conditional on the proportion of workers in the treated occupation who hold an Essential Skills visa. The results are noisy, but we do generally find larger point estimates in occupations with a greater proportion of Essential Skills migrants. This relationship is robust to whether we population-weight occupations when calculating average effects.

**Mechanisms.** In Table 8 we ask how including an occupation in an Essential Skills in Demand list affects intermediate outcomes. In Column (1), the dependent variable measures the proportion of workers, in an occupation, employed at a firm for the first time during that month. We find including an occupation in an Essential Skills in Demand list increases job-switching by about 10% of the baseline rate. This is consistent with the Essential Skills in Demand lists increasing labor market competition.

Proposition 2 told us that, in a competitive equilibrium, expanding the set of firms eligible to employ migrants should have no effect on wages. This prediction would seem to be rejected by the results in this section, which has found that expanding the set of firms eligible to employ migrants increases wages. However, the hypothesis of Proposition 2 shut down two channels through which expanding the set of firms might affect wages: Proposition 2 both assumed that firms have a homogeneous production function and it assumed that this production function exhibits constant returns to scale. When either of these conditions fail, expanding migrants' job options *can* decrease competitive equilibrium wages. The remaining columns of Table 8 test these conditions directly.

Columns (2) and (3) of Table 8 ask whether our results can be explained by concavity in firms' production functions. In Column (2) the dependent variable is simply the log number of workers in that occupation during the month; in Column (3) the dependent variable is the mean of the log number of workers across each worker's firm. Using either dependent variable we find that including an occupation in an Essential Skills in Demand list *increases* the number of workers,

as prospective migrants can more easily obtain work visas. As such, the positive effects we have found on workers' earnings cannot be explained by concavity in firms' production functions.

Columns (4) and (5) of Table 8 use firm-level financial data to assess whether our results can be explained by the reallocation of workers to more productive firms.[23] For both columns we first construct a firm-by-year productivity measure. We then form the occupation-by-month dependent variable by taking the mean (across all workers in that occupation during that month) of the productivity of each worker's employer during that month. In Column (4), the productivity measure is the log ratio of a firm's revenue to its expenditure on intermediate inputs (which is a proxy for TFP). In Column (5), the productivity measure is log value-added per worker, where value-added is the firm's revenue minus its expenditure on intermediate inputs.

Positive coefficients in columns (4) and (5) of Table 8 would suggest either that inclusion in an Essential Skills in Demand list reallocates workers to more productive firms or that occupations are being listed in anticipation of positive productivity shocks. We find no evidence of either force. The coefficient in Column (4) is a precise zero, suggesting no relationship between inclusion in an Essential Skills in Demand list and firm productivity. The coefficient in Column (5) is negative. This negative coefficient is consistent with firms' production functions exhibiting decreasing returns to scale, with the increase in firm sizes (reported in Column (3)) reducing workers' average productivity.

Including an occupation in an Essential Skills in Demand list appears to increase wages despite the fact that listing an occupation increases the number of workers in that occupation. In other words, any reduction in workers' marginal product is more than offset by the fact that expanding migrants' job options reduces firms' market power. In the following section, we will isolate the effects of migrants' job options by estimating a structural model of the labor market.

# 7   Specifying and Estimating a Structural Wage-Posting Model

This paper asks how restricting migrants' job options affects wages, profits, and welfare. Our analysis of market-level shocks has shown that restricting migrants' job options reduces average wages. Our analysis of individual-level shocks suggests that non-pecuniary preferences are also important: when an individual migrant's job restrictions are lifted, they often move firms despite not, on average, receiving higher wages.

However, these reduced-form analyses have limitations. We do not observe individual workers' preferences over firms, and thus a reduced-form analysis cannot identify welfare effects. Moreover, restricting migrants' job options will certainly affect different workers differently. This

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[23]The underlying data for these outcome variables comes from firm surveys and firm tax returns, compiled in the Longitudinal Business Database (Fabling & Maré, 2019).

treatment effect heterogeneity is not, without further assumptions, identified in a reduced-form analysis (Heckman, Smith, & Clements, 1997). Finally, though restricting migrants' job options reduces average wages, these restrictions might not increase average profits — in particular, firms which cannot access migrant labor are likely to suffer. Identifying profit effects with a reduced-form analysis of occupation-level shocks would be difficult given that firms typically employ many occupations.

In this section we overcome these issues by estimating a structural model of the labor market. The results in the previous sections were consistent with wages being set in a Bertrand wage-posting equilibrium, and so our estimation procedure will assume that this is the case. The model is similar to that presented in Section 2. To facilitate estimation we impose functional forms on production and preferences. We will estimate our model using panel data, so we add a time dimension to our model, but the model will remain essentially static in the sense that agents' choice sets are unaffected by historical actions.[24] We also add workers' occupations and productivity as explicit components of the model (as in the theoretical extension provided in Appendix A).

In Section 8 we will use the model to understand the equilibrium effects of the Essential Skills visa system and to ask how the Essential Skills visa system mediates the wage effects of migration. To that end, the model quantifies two mechanisms by which restricting migrants' job options could affect the wage distribution:

1. Restricting migrants' job options will decrease the elasticity of their labor supply. When firms set wages they trade off the desire to attract more workers against the desire to pay lower wages. This trade-off is weaker when workers' labor supply is less elastic, and so restricting migrants' job options will encourage firms to pay lower wages.

2. Restricting migrants' job options will segregate them into certain firms. If production exhibits decreasing returns to scale, then increasing the number of workers employed at a firm will decrease their marginal product of labor, and so decrease wages. The excluded firms, at which migrants cannot work, will employ fewer workers. Wages at these excluded firms would thus increase — unless there are complimentarities between different occupations, in which case the wages of some occupations might also decrease.

Quantifying the first mechanism requires that we quantify how restricted migrants' job op-

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[24]In particular, we model only the *static* restrictions imposed by the Essential Skills visa system — Essential Skills migrants can work only at certain firms — and ignore the *dynamic* restrictions — Essential Skills migrants who switch firms must obtain a new visa. Our sense is that this assumption is innocuous: the cost of obtaining a new visa was relatively low (typically about two days' wages, and often free). However insofar as dynamic restrictions are important, our structural estimates will understate the restrictiveness of the Essential Skills visa system.

tions are in practice. For example, if we tell a Wellington-based carpenter that he can only work for one Wellington construction firm — but that he can work for any construction firm in Christchurch — have we substantially reduced his job options? We estimate workers' willingness to move both across firms and across space.

Quantifying the second mechanism requires that we quantify how employment of one worker will affect the marginal product of other workers. For example, if we allow a construction firm to employ migrant carpenters, will the marginal product of unskilled laborers increase or decrease? We estimate production functions allowing for both decreasing returns to scale and for complementarities between different occupations.

## 7.1 The Structural Model

We estimate a partial-equilibrium perfect-information model. In each period $t$, the model comprises a continuum of workers $\mathbf{I}_t$ and a finite set of firms $\mathbf{F}_t$.

During each period $t$, each worker $i \in \mathbf{I}_t$ has an (exogenous) occupation $o_{i,t}$ and each firm $f \in \mathbf{F}_t$ utilizes a set of occupations $\mathbf{O}_{f,t}$. Let $\mathbf{F}_{o,t} \equiv \{f \in \mathbf{F}_t : o \in \mathbf{O}_{f,t}\}$ denote the set of firms which employ occupation-$o$ workers during period $t$.

**Workers' choice sets.** In each period $t$, each worker $i$ chooses a single firm $f_{i,t}$ at which she will be employed. The set of firms from which she can choose depends on her occupation and on her visa status. Specifically, each worker is either a *migrant* or a *resident*. Let $\mathbf{F}_{o,t}^{migrant} \subset \mathbf{F}_{o,t}$ denote the subset of firms at which migrants in occupation $o$ can work in period $t$. Residents can work at any firm. Let $\mathbf{F}_{i,t} \in \left\{\mathbf{F}_{o_i,t}^{migrant}, \mathbf{F}_{o_i,t}\right\}$ denote the set of firms at which worker $i$ can work. In each period $t$, let $\mathbf{I}_t^{migrant} \subset \mathbf{I}_t$ denote the subset of workers who are migrants and let $\mathbf{I}_t^{resident} \equiv \mathbf{I}_t \setminus \mathbf{I}_t^{migrant}$ denote the subset who are residents.

**Production.** During each period $t$, each worker $i \in \mathbf{I}_t$ supplies effective labor $l_{i,t}$ to firm $f_{i,t} \in \mathbf{F}_{i,t}$. The effective labor supplied by each worker $l_{i,t} = h_{i,t}\omega_{i,t}$ varies both because of variation in their hours worked $h_{i,t}$ (which is observed) and because of variation in their idiosyncratic productivity $\omega_{i,t}$ (which is unobserved); both $h_{i,t}$ and $\omega_{i,t}$ are exogenous. The total effective labor supplied to each firm in each occupation integrates over the effective labor supplied by each worker:

$$L_{f,o,t} \equiv \int_{i:f_{i,t}=f,o_{i,t}=o} l_{i,t} di.$$

Each firm $f$ combines their labor to produce output using a CES production function:

$$y_{f,t}\left(\left(L_{f,o,t}\right)_{o \in \mathbf{O}_{f,t}}\right) = \left(\sum_{o \in \mathbf{O}_{f,t}} e^{\phi_{f,o,t}} L_{f,o,t}^{\rho}\right)^{\frac{\nu}{\rho}}, \tag{7}$$

where $\phi_{f,o,t}$ measures the firm's labor-augmenting productivity in occupation $o$, $\nu$ measures returns to scale and $\rho$ measures firms' ability to substitute across occupations.

Output is sold at unit price in a competitive market.

**Workers' preferences.** Workers' firm choices are determined by their preferences over earnings and over non-wage the amenities provided by each firm. Each firm $f$ has an exogenous, time-invariant location $c_f \in \mathbf{C}$. Denote the set of firms employing occupation-$o$ workers in location $c$ as $\mathbf{F}_{c,o,t} \equiv \{f \in \mathbf{F}_{o,t} : c_f = c\}$. Each worker $i$ has a time-invariant demographic type $x_i \in \mathbf{X}$. (This demographic type is unaffected by and distinct from the worker's visa status.) We assume that each worker $i$'s preferences across firms $f$ and earnings $W$ can be represented by this utility function:[25]

$$u_{i,t}\left(W, f\right) = \tau \log\left(W\right) + \bar{\xi}_{c_f, o_i, x_i, t} + \xi_{f, o_i, x_i, t} + \frac{1}{\lambda}\zeta_{i, c_f, t} + \epsilon_{i, f, t}, \tag{8}$$

where $\tau$ measures the relative importance of earnings, $\bar{\xi}_{c,o,x,t}$ measures the typical amenity-value of location $c$ among type-$x$ workers in occupation $o$, $\xi_{f,o,x,t}$ measures the typical amenity-value of employment at firm $f$ among type-$x$ workers in occupation $o$, $\zeta_{i,c,t}$ measures $i$'s idiosyncratic preferences across locations $c$ (the importance of which is measured by the parameter $\lambda$) and $\epsilon_{i,f,t}$ measures $i$'s idiosyncratic preferences across firms.[26]

We assume that workers' idiosyncratic preferences and type are independent of both their effective labor and their idiosyncratic productivity. We also assume that in the cross-section idiosyncratic preferences follow a nested extreme value distribution, where the nests are the locations $\mathbf{C}$.[27] We leave the dependence of idiosyncratic preferences across time unrestricted.

**Equilibrium.** In each period $t$, each firm $f \in \mathbf{F}_t$ chooses a vector of occupation-specific wages $\vec{w}_{f,t} \equiv \left(w_{f,o,t}\right)_{o \in \mathbf{O}_{f,t}}$. A worker $i$ employed at firm $f_i$ in occupation $o_i$ will receive earnings $W_{i,t} = w_{f_i, o_i, t} l_{i,t}$. Given wages, each worker $i \in \mathbf{I}_t$ chooses the firm that will maximize their utility:

$$f_{i,t} \in \underset{f \in \mathbf{F}_{i,t}}{\arg\max}\, u_{i,t}\left(w_{f,o_i,t} l_{i,t}, f\right). \tag{9}$$

Wages are set in Bertrand competition. Let $\vec{w}_{-f,t}$ denote the salaries chosen by firms other than firm $f$. Let $\vec{L}_{f,t}\left(\vec{w}_{f,t}, \vec{w}_{-f,t}\right)$ denote the labor vector supplied to firm $f$, given the wages

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[25]This utility function is a monotonic transformation of that assumed in Section 2. Such a transformation has no effect on the wage-posting equilibrium, though it would affect the bargaining equilibrium because the Nash bargaining solution is affected by nonlinear transformations of agents' payoffs.

[26]We normalize the within-location amenity values $\xi_{f,o,x,t}$ by requiring that, within each location-occupation-type-year $c, o, x, t$: $\log\sum_{f \in \mathbf{F}_{c,o,t}} \exp\xi_{f,o,x,t} = 0$. We normalize the between-market amenity values $\bar{\xi}_{c,o,x,t}$ by requiring that, within each occupation-type-period $o, x, t$: $\log\sum_{c \in \mathbf{C}} \exp\bar{\xi}_{c,o,x,t} = 0$.

[27]That is, they have CDF $\mathbb{P}\left[\left(\zeta_{i,c_f,t} + \lambda\epsilon_{i,f,t}\right)_{f \in \mathbf{F}_{o_{i,t},t}} \leq \left(x_j\right)_{f \in \mathbf{F}_{o_{i,t},t}}\right] = \exp\left(\sum_{c \in \mathbf{C}}\left(\sum_{f \in \mathbf{F}_{c,o,t}} \exp\left(\frac{-x_f}{\lambda}\right)\right)^\lambda\right)$.

$\vec{w}_{f,t}, \vec{w}_{-f,t}$. Equilibrium wages will thus satisfy

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

## 7.2 Characterizing Equilibrium.

We will now characterize equilibrium wages and labor supply. We will use this characterization to derive structural residuals and simulate counterfactuals.

**Wages.** Equilibrium wages will satisfy the first order conditions

$$\frac{\partial L_{f,o,t}}{\partial w_{f,o,t}} \left( \frac{\partial y_{f,t}}{\partial L_{f,o,t}} - w_{f,o,t} \right) - L_{f,o,t} = 0. \tag{10}$$

Rearranging Equation (10) yields the markdown equation

$$w_{f,o,t} = \frac{\partial y_{f,t}}{\partial L_{f,o,t}} \left( 1 + \frac{1}{\eta_{f,o,t}} \right)^{-1}, \tag{11}$$

where $\eta_{f,o,t}$ is the period-$t$ elasticity of occupation-$o$ labor supplied to firm $f$.

Differentiating Equation (7) yields the marginal product of labor

$$\frac{\partial y_{f,t}}{\partial L_{f,o,t}} = \nu \left( \sum_{o' \in \mathbf{O}_{f,t}} e^{\phi_{f,o',t}} L_{f,o',t}^{\rho} \right)^{\frac{\nu-\rho}{\rho}} e^{\phi_{f,o,t}} L_{f,o,t}^{\rho-1}. \tag{12}$$

**Labor supply.** Given the utility function (8), a worker's choice of firm will be unaffected by her effective labor:

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

It follows that, conditional on worker type $x_i$ and visa status, labor supply follows a standard nested-logit model. For occupation $o$, firm $f$ and period $t$, define the mean utility of type-$x$ residents as

$$\delta_{f,o,x,t}^{resident} = \tau \log(w_{f,o,t}) + \xi_{f,o,x,t}, \tag{13}$$

and define migrants' mean utility as

$$\delta_{f,o,x,t}^{migrant} = \begin{cases} \tau \log(w_{f,o,t}) + \xi_{f,o,x,t} & \text{if } f \in \mathbf{F}_{o,t}^{migrant} \\ -\infty & \text{otherwise} \end{cases}.$$

For either $status \in \{resident, migrant\}$, define mean utility for occupation-$o$ type-$x$ workers in location $c$ as

$$\delta_{c,o,x,t}^{status} = \lambda \log \left( \sum_{f \in \mathbf{F}_{c,o,t}} \exp \left( \delta_{f,o,x,t}^{status} \right) \right) + \bar{\xi}_{c,o,x,t}. \tag{14}$$

The probability that a type-$x$ occupation-$o$ worker with $status \in \{resident, migrant\}$ will be employed at firm $f$ in location $c$ during period $t$, conditional on being employed by any firm within $c$, is given by:

$$\sigma^{status}_{f,o,x,t|c} \equiv \mathbb{P}\left[f_{i,t} = f \middle| i \in \mathbf{I}^{status}_t, o_{i,t} = o, x_i = x, c_{f_{i,t}} = c\right] = \frac{\exp \delta^{status}_{f,o,x,t}}{\sum_{f' \in \mathbf{F}_{c,o,t}} \exp \delta^{status}_{f',o,x,t}}. \tag{15}$$

Similarly, the probability that a type-$x$ occupation-$o$ worker with $status \in \{resident, migrant\}$ will be employed at any firm in location $c$ is given by:

$$\sigma^{status}_{c,o,x,t} \equiv \mathbb{P}\left[c_{f_{i,t}} = c \middle| i \in \mathbf{I}^{status}_t, o_{i,t} = o, x_i = x\right] = \frac{\exp \delta^{status}_{c,o,x,t}}{\sum_{c' \in \mathbf{C}} \exp \delta^{status}_{c',o,x,t}}. \tag{16}$$

Let $\sigma^{status}_{f,o,x,t} = \sigma^{status}_{f,o,x,t|c_f} \sigma^{status}_{c_f,o,x,t}$ denote the overall proportion of type-$x$ occupation-$o$ workers with $status \in \{resident, migrant\}$ employed at firm $f$ during period $t$. The supply elasticity of such workers to firm $f$ will be

$$\eta^{status}_{f,o,x,t} = \tau \left(1 - (1-\lambda)\sigma^{status}_{f,o,x,t|c_f} - \lambda \sigma^{status}_{f,o,x,t}\right). \tag{17}$$

The overall supply elasticity to firm $f$ aggregates over visa status and types:

$$\eta_{f,o,t} = \sum_{x \in \mathbf{X}} \left(\sigma_{x,resident|f,o,t} \eta^{resident}_{f,o,x,t} + \sigma_{x,migrant|f,o,t} \eta^{migrant}_{f,o,x,t}\right), \tag{18}$$

where $\sigma_{x,resident|f,o}$ is the proportion of firm $f$'s occupation-$o$ period-$t$ workers who are type-$x$ residents and $\sigma_{x,migrant|f,o}$ is the proportion of firm $f$'s occupation-$o$ period-$t$ workers who are type-$x$ migrants.[28]

## 7.3 Estimation

We will estimate the parameter vector $\tau, \lambda, \rho, \nu$ using GMM, given dynamic restrictions on the joint evolution of labor augmenting productivity and amenities. This estimation routine requires that, given a candidate vector, we can calculate the structural residuals $\phi_{f,o,t}, \bar{\xi}_{c,o,x,t}, \xi_{f,o,x,t}$. We provide explicit forms for these residuals in Appendix E; the intuition for how we calculate them is as follows:

1. We calculate the location and firm amenity values $\bar{\xi}_{c,o,x,t}, \xi_{f,o,x,t}$ using Berry (1994) inversion and the observed labor supply of residents — that is, we invert equations (13), (14), (15) and (16).

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[28]Under our assumption that workers' effective labor is independent of their preferences and their type, labor supply elasticities equal *effective* labor supply elasticities .

2. We calculate type-by-visa status labor supply elasticities $\eta^{status}_{f,o,x,t}$ using Equation (17), given observed market shares and the parameters $\tau, \lambda$.

3. We calculate the overall labor supply elasticities $\eta_{f,o,t}$ by aggregating over visa statuses and worker types, given the observed demographic mix of workers at each job, using Equation (18).

4. We can then use these labor supply elasticities to calculate the occupation-specific marginal product of labor at each firm by inverting Equation (11).

5. Finally, we can use these marginal products, observed employment levels, and the production parameters $\rho, \nu$ to calculate labor-augmenting productivity $\phi_{f,o,t}$ using Equation (12).

As far as we are aware, this paper is the first to estimate production functions using the marginal product of labor, inferred from wages. More typically, production functions are estimated using firm financial data. The primary advantage of our approach is that it provides observations at the firm-by-occupation level, rather than just at the firm level. This helps us estimate firms' ability to substitute across occupations.

While estimating production functions using *marginal products* is novel, it is similar to the practice in the differentiated products literature of estimating production functions using marginal costs (Berry et al., 1995; Berry & Haile, 2016). In the differentiated products literature, firms' marginal costs are inferred from prices, given an estimated product demand system and an assumed conduct assumption. These marginal costs can then be used to estimate a production function. This approach differs from ours only in that we exploit a model a labor market rather than a model of a product market.

**Data.** Because our estimation procedure requires that we observe all workers' occupations, we estimate the system using a short firm-occupation-year panel constructed using the 2013 and 2018 censuses. Specifically, our underlying sample of workers is similar to that studied in Section 4: full-time employees with non-zero earnings at a unique employer. Unlike Section 4, we measure wages using the 3 months of earnings prior to the census, rather than the 12 months prior, and we include all workers with a unique firm over those 3 months rather than only workers with a unique firm over the 12 month period. This expanded sample increases the precision with which we measure firms' labor utilization, at the cost of increased measurement error in wages. We discuss how we account for measurement error below.

Our sample also differs from that in Section 4 by additionally including migrants who hold temporary visas other than the Essential Skills visa. This also increases the precision with which we measure firms' labor utilization. We assume that these other temporary visa holders have

unrestricted job options and so treat them as residents. This assumption is correct for the most common temporary visas other than the Essential Skills visa (the Partner of a Worker Work Visa and working holiday visas), but is incorrect for some more unusual visas (such as the Thai Chefs Work Visa, which requires that its holder work as a Thai chef).

We exclude a small number of occupations in which all workers are employed by a single employer.

In our baseline specification, we define a worker's type $x_i$ as just indicating whether they were born in New Zealand. Let $x_i = NZ$ indicate that the worker was born in New Zealand and let $x_i = abroad$ indicate that the worker was born elsewhere.

Location is defined using Statistics NZ's 'functional urban areas'.

**Using a split-sample to allow for measurement error in wages.** We do not observe workers' idiosyncratic productivity $\omega_{i,t}$. As such, wages will be measured with error. Under our assumption that idiosyncratic productivity $\omega_{i,t}$ is orthogonal to preferences and types, this measurement error will be classical. Nonetheless, it would bias estimation: As we explain below, we identify the model under the assumption that shocks to the amenity value of employment are orthogonal to shocks to productivity. Measurement error in wages would introduce mechanical correlation between amenities and productivity, because both are calculated using wages.

We account for measurement error in wages by randomly allocating all worker-year observations to one of two samples; in our baseline specification we stratify this randomization within firm-occupation-year cells. Given a candidate parameter vector, we thus calculate the sample-specific estimates of the structural residuals $\hat{\phi}^s_{f,o,t}, \hat{\xi}^s_{f,o,x,t}, \hat{\bar{\xi}}^s_{c,o,x,t}$ using only the sample-specific vector of log wages $\left( \log w^s_{o,f,t} \right)$, where $\log w^s_{o,f,t}$ is the mean log hourly wage among workers in sample $s$, occupation $o$ and firm $f$ during year $t$. The moment conditions that we specify below only impose orthogonality between the two samples.

**Baseline moment conditions.** We identify the model under the assumption that shocks to the amenity-value of employment are orthogonal to both productivity shocks and baseline productivity. This assumption is similar to that used by MacKay and Miller (in press) to identify price parameters in their analysis of product market demand. In our context, it requires that the non-wage reasons why a worker might choose to work at a particular firm — *e.g.* cultural fit, ease of public transport access, or amenities in the surrounding neighbourhood — change in a manner that is both independent of coincident changes in the firm's productivity and independent of the firm's historic productivity. We view this assumption as plausible in the New Zealand context, where employment amenities rarely impose a literal cost on the employer — for example, employer-sponsored health insurance is rare. Of course there are situations in which this assumption would fail. For our purposes, the most important test of our estimates is whether they can account for the market-level shock estimated in the previous section. We show below

41

that they can.

Recall that a worker's type indicates whether they were born in New Zealand. Because many occupation-by-firm cells include *only* workers born in New Zealand, the mean amenity for those born abroad $\xi_{f,o,abroad,t}$ is often undefined. Our moment conditions thus restrict only the mean amenity for those born in New Zealand $\xi_{f,o,NZ,t}$.

Specifically, in our baseline specification we impose four moment conditions. First, we assume that, within a location-by-occupation labor market, amenity shocks measured using one sample are orthogonal to baseline residual productivity measured using the other sample:

$$\Delta\hat{\xi}^s_{f,o,NZ,t} \perp \hat{\phi}^{-s}_{f,o,t-1} \mid o, c(f), \tag{19}$$

where $\Delta$ is the first-difference operator and $-s$ denotes the sample which is not $s$. Given that productivity exhibits mean-reversion, restriction (19) allows lagged productivity to be used as a wage-shifting instrument to estimate the labor supply parameter $\tau$.

Second, we assume that, within a location-by-occupation labor market, productivity shocks are orthogonal to amenity shocks:

$$\Delta\hat{\xi}^s_{f,o,NZ,t} \perp \Delta\hat{\phi}^{-s}_{f,o,t} \mid o, c(f). \tag{20}$$

We interpret restriction (20) as allowing amenity shocks $\Delta\hat{\xi}^s_{f,o,NZ,t}$ to be used as a quantity-shifting instrument to identify the production function parameters $\rho, \nu$.

Third, to identify returns to scale $\nu$ we construct a instrument to shift firm-level 'aggregate labor' $\log\left(\sum_{o\in\mathbf{O}_{f,t}} e^{\phi_{f,o,t}+\rho\log l_{f,o,t}}\right)$. We first residualize the firm-by-occupation amenity shocks $\Delta\hat{\xi}^s_{f,o,NZ,t}$ on a location-by-occupation-by-sample fixed effect; let $\tilde{\xi}^s_{f,o,NZ,t}$ denote these residualized shocks. We then form the firm-level aggregate amenity shock $\check{\xi}^s_{f,t}$ as

$$\check{\xi}^s_{f,NZ,t} \equiv \log\left( \sum_{o\in\mathbf{O}_{f,t}} \hat{e}^{\hat{\phi}^s_{f,o,t-1}+\rho\tilde{\xi}^s_{f,o,NZ,t}} \right).$$

We assume that these firm-level aggregate amenity shocks are also orthogonal to productivity shocks:

$$\check{\xi}^s_{f,NZ,t} \perp \Delta\hat{\phi}^{-s}_{f,o,t}. \tag{21}$$

Finally, we identify the inter-location labor supply parameter $\lambda$ by requiring that productivity shocks be orthogonal to market-level amenity shocks:

$$\Delta\bar{\xi}^s_{c_f,o,NZ,t} \perp \Delta\hat{\phi}^{-s}_{f,o,t} \mid o. \tag{22}$$

**Baseline estimates.** Our model is just-identified. We calculate the structural residuals using all firm-occupation-sample-year observations, but our moment conditions are only defined for

those observations which are observed in both years. Given that the moment restrictions (19), (20) and (22) condition on location and/or occupation, we within-difference the relevant residuals before forming the empirical moments. We weight observations by their baseline (year 2013) number of workers. Standard errors allow clustering between both enterprises and occupations, calculated using the approach given by Cameron, Gelbach, and Miller (2011).

The resultant estimates are presented in Column (1) of Table 9. The labor supply elasticity facing an atomistic employer, $\tau$, is equal to 3.446. This is similar to estimates in the existing literature (Sokolova & Sorensen, 2021). Workers exhibit a moderate willingness to substitute across space: we estimate $\lambda = 0.483$. This means that a firm which has saturated its local labor market but which is atomistic nationally will face a labor supply elasticity of about $0.483 \times 3.446 = 1.664$. We find that firms can substitute across occupations easily ($\rho = 0.970$), but face diminishing returns to scale ($\nu = 0.541$).

**Over-identification.** An important test of our estimates is whether they can account for market-level shocks to migrants' job options. Note that our estimation procedure did not use the Essential Skills in Demand lists — our estimation procedure only required that we observe migrants' market shares $\sigma^{migrant}_{f,o,x,t}$. As such, shocks to the Essential Skills in Demand lists can be used to test the model.

Adding an occupation to an Essential Skills in Demand list will decrease the market share of firms which could initially employ migrants. By equations (17) and (18), a reduction in market shares will make labor supply more elastic, reducing firms' market power and increasing wages.[29] That effect will be bigger when workers are less willing to substitute away from their local market — *i.e.* when $\lambda$ is low. As such, our model restricts how a shock to market shares should affect wages.

We operationalize our test by asking whether the shock to market shares is orthogonal to residual productivity (Roussille & Scuderi, 2023). We estimate the linear equation

$$\Delta\hat{\phi}^s_{f,o,t} = \beta_0 + \beta_1 \Delta\text{list}_{c_f,o,t} + \epsilon_{s,o,f}, \tag{23}$$

where $\text{list}_{c,o,t}$ indicates that occupation $o$ was included in an Essential Skills in Demand list in location $c$ during period $t$. We estimate the equation using OLS, weighting by the baseline

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[29] Equations (11), (17) and (18) together imply that the wage set by firm $f$ for occupation $o$ will depend on $\bar{\sigma}_{f,o,t|c_f}$: the average market share in that occupation, where the average is taken across types and visa statuses:

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

Let $\text{list}_{c,o,t}$ indicate that occupation $o$ was included in an Essential Skills in Demand list in location $c$ during period $t$. Regressing $\Delta\bar{\sigma}_{f,o,t|c_f}$ on $\Delta\text{list}_{c_f,o,t}$ using our estimation sample, weighting by the baseline number of workers, yields a slope coefficient of -0.0203 [0.0177].

number of workers. Under the hypothesis that the model is correctly specified, $\beta_1 = 0$. The resultant p-value, presented in Table 9, indicates that the test is not rejected.

**Additional estimates.** Columns (2)–(5) of Table 9 assess the robustness of our structural estimates. In Column (2), we denote a worker's type $x_i$ as their country of birth, rather than just an indicator for being born in New Zealand. Estimates are very similar to those in our baseline specification.[30]

In Column (3), we form our split-sample by randomizing *workers* (whereas in our baseline specification we randomized worker-years, stratified by occupation and firm). The estimates in Column (2) are thus robust to persistent measurement errors in hours of work, though this comes at the cost of a reduced sample size. Estimates are similar to our baseline estimates, with a slight reduction in firms' ability to substitute across occupations.

In Column (4), we allow the production parameters $\nu, \rho$ to vary across the primary, manufacturing and services sectors. Though the resultant estimates are a little noisy, we do find that the primary sector features less convexity. This may reflect the primary sector featuring more competitive goods markets.

In Column (5), we measure firms' labor utilization as the number of workers employed, rather than the number of worker-hours employed. While this is a noisier measure of labor utilization, it is much simpler for us to simulate counterfactuals if we assume that workers supply a homogenous number of hours. These estimates are again very similar to our baseline estimates.

# 8   Equilibrium Effects and Policy Counterfactuals

In this section we use the structural model — estimated in Section 7 — to understand both the overall effects of the Essential Skills visa system and how these effects might be mitigated. For simplicity, we study only the population at the 2018 census, and we drop time subscripts from notation. We first describe how we calculate equilibria, and then present the equilibrium effects of the Essential Skills visa system on wages, profits and output. We then use our model to ask how the Essential Skills visa system mediates the wage effects of increased immigration.

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[30]Although our structural model can be estimated using any firm-occupation observations for which type-*NZ* workers are observed, the counterfactuals in the following section will require we impute amenities for any firm-occupation-type cells for which no workers are observed. This problem is much more common with a richer definition of worker type, and thus we prefer the simpler definition of worker type used in our baseline estimates.

## 8.1 Calculating equilibria

**Data.** We use the same underlying population of workers used in the prior section: workers with 3 months of earnings at a unique firm prior to the population census. We define a worker's type $x_i$ as indicating whether they were born in New Zealand. We calculate the model using the parameter vector reported in Column (5) of Table 9. We calculate the log wage of an occupation-by-firm job by taking the mean log wage of all workers in that job (having estimated our structural parameters, there is no longer any need to divide workers by split-sample). In forming a worker's log wage we subtract their log hours from their log earnings, but we do not otherwise use their hours in calculating equilibria; as in the estimates reported in Column (5) of Table 9, we measure a firm's use of occupation-$o$ labor as just the number of occupation-$o$ workers employed by that firm.

We calculate labor-augmenting and total-factor productivity using the equations derived in Appendix E. For firms or markets in which we observe type-$x$ workers, we also calculate amenities using the equations derived in Appendix E. When we observe no type-$x$ residents, we impute amenities using an algorithm described in Appendix subsection F.1.

Simulating an equilibrium requires that we specify the set of firms which can employ migrants in each occupation.[31] We assume that a location-$c$ firm can employ occupation-$o$ migrants if either that firm was observed employing occupation-$o$ migrants or occupation $o$ was included in an Essential Skills in Demand list for location $c$.

**Solving for an equilibrium.** We solve for an equilibrium treating labor as continuous. We find the equilibrium wage vector by iteration: given an initial wage vector $\log w_r$, we find the mass of workers employed at each firm, and then find the implied wage vector $\log w_r'$ using equations (11) and (12). We then form the next wage vector by taking a convex combination of the initial wage vector and the implied wage vector: $\log w_{r+1} = 0.75 \times \log w_r + 0.25 \times \log w_r'$. We iterate this algorithm until convergence. We initialize this algorithm at the observed wage vector when finding the initial equilibrium and at the initial equilibrium when finding counterfactual equilibria.[32]

Our labor supply system is sufficiently flexible that our model could have multiple equilibria. We have found that starting the above fixed point routine from alternative starting values leads to a virtually identical equilibrium, which is consistent with there being a unique equilibrium at our estimated parameter vector.

**Calculating worker-level effects.** We are interested in both average effects and the distribution of effects. To calculate the latter, we allocate workers discretely across firms, given both an

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[31]This set did not need to be specified for estimation — market shares sufficed.

[32]Because we do not use migrants when calculating amenities, the observed wage vector need not be an equilibrium of our model. The correlation between observed wages and wages in our initial equilibrium is 0.987.

initial equilibrium wage vector and a counterfactual equilibrium wage vector. Doing so requires a novel algorithm for drawing nested extreme value random variables, described in appendix subsection F.2.

## 8.2 How the Essential Skills visa system affects wages, profits and welfare

In our primary counterfactual, we allow Essential Skills migrants to work for any firm: $\forall o \in \mathbf{O}$ : $\mathbf{F}_o^{migrant} = \mathbf{F}_o$. In Figure 7 Panel A, we depict how this counterfactual affects mean log wages.[33] Specifically, we depict the mean effect by both a worker's own visa status and by the proportion of her colleagues who themselves hold an Essential Skills visa. Regardless of their own visa status, workers who work with many migrants would experience a large increase in wages, were migrants' job options unrestricted. In contrast, migrants who work with few other migrants would actually tend to receive slightly lower wages were their job options unrestricted, because they tend to move toward lower-paying, higher-amenity firms.

On average, expanding migrants' job options would increase their equilibrium wage by about 8%. As discussed in Section 3, the typical resident works with few migrants, both because migrants are segregated into different firms and because relatively few workers are migrants. As such, the average worker is unaffected by the expansion of migrants' job options.

Figure 7 also depicts the distribution of effects across migrants (in Panel B) and residents (in Panel C). While most migrants receive a large wage increase, a substantial minority prefer a lower-paying job. The vast majority of residents are essentially unaffected. About 0.7% of residents would see their wage decrease by more than 2%, while 2.1% would see their wage increase by more than 2%. About 0.5% of residents would receiving a wage increase greater than 10%.

In Appendix Table A6 we describe the subpopulations of workers represented in each bar of the Figure 7 histograms. Migrants who would have a lower wage, were migrants' job options unrestricted, typically have a higher baseline wage. Among residents this relationship between wage effects and baseline wage is non-monotonic: the groups with the lowest baseline wages are those who suffer a moderate wage decrease and those who enjoy a large wage increase. Residents who would a log wage increase of at least 0.02 have an average log wage of 3.35 — much less than the average log wage among all residents, which is 3.57. Workers who receive a large wage increase typically worked with more migrants at baseline.

The final column of Appendix Table A6 depicts the proportion of workers whose utility is greater in the counterfactual equilibrium than in the initial equilibrium. Expanding migrants'

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[33]Occupations in which migrants' job choices are already unrestricted, because they are included on a nationwide Essential Skills in Demand List, are excluded from the population used to generate Figure 7 and Table A6.

job options benefits almost all migrants: though many migrants have a substantially lower wage in the counterfactual equilibrium, these migrants have always moved to a new firm, and their overall utility is higher. Residents who receive a higher wage in the counterfactual equilibrium almost always prefer the counterfactual equilibrium. In addition, some residents who receive a lower wage in the counterfactual equilibrium are nonetheless better off: these are residents who are enticed to move to a lower-paying firm, because that firm pays more than it did initially.

**Effects on profit and output.** In Figure 8 we depict the effects on firm profit (in Panel A) and output (in Panel B). Both profits and output increase in firms which initially employ few migrants, and decrease in firms which initially employ many migrants. The overall effect — in both logs and levels — is negative for profit and positive for output. Average effects are close to zero, because the large negative effects on the few firms which employ many migrants cancel out the small positive effects on the many firms which employ few migrants. Nonetheless, expanding migrants' job options would decrease aggregate profits by about \$56m, and increase aggregate output by about \$9m.

In Appendix Table A7 we compare the characteristics of firms which are benefited or harmed by the expansion in migrants' job options. Firms which benefit are typically smaller and lower productivity. They rarely employed many migrants in the initial equilibrium. Firms which are substantially harmed almost always employed migrants in the initial equilibrium, though there is an interesting group of firms who are slightly worse off despite employing no migrants initially: these are firms who lose their resident workers due to other firms' wage increases (or who would lose their residents, were they not to counter with their own wage increases).

The hetereogeneity of profit effects might explain the somewhat complicated politics of migrant job restrictions. In 2019 the New Zealand government proposed a mandatory accreditation scheme for employers of temporary migrants. While the scheme aimed to reduce extreme cases of migrant exploitation, it was generally seen as making it more difficult for employers to hire migrants. In consultation, 62% of employers supported the scheme (in whole or in part) while 25% were opposed.[34] Similarly, in 2018 the New Zealand government changed the Post Study Work Visa to allow these migrants to switch employers. In consultation, 41% of employers supported the proposal while 59% were opposed.[35]

**Effects on welfare.** We now calculate the effect of the Essential Skills visa restrictions on overall welfare. Let $w_{o,f}$ denote the initial wage paid by firm $f$ to occupation $o$ during period

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[34]https://web.archive.org/web/20240523053252/https://www.mbie.govt.nz/assets/summary-of -submissions-consultation-on-employer-assisted-work-visas-and-regional-workforce-planning .pdf.

[35]https://web.archive.org/web/20240523231921/https://www.mbie.govt.nz/assets/c2a0e57f7e/ cabinet-paper-report-back-on-consultation-on-proposed-changes-to-immigration-settings-for -international-students.pdf

$t$, and let $w'_{o,f}$ denote the counterfactual wage. Let $f_i$ denote worker $i$'s initial employer during period $t$, and let $f'_i$ denote her counterfactual employer. Let $s_i = w_{o_i,f_i} h_i$ denote worker $i$'s initial earnings and let $s'_i = w'_{o_i,f'_i} h_i$. We measure a worker $i$'s 'money-metric' welfare $WTP_i$ as their willingness to pay for their counterfactual employer and earnings:

$$u_{i,t}\left(s'_i - WTP_i, f'_i\right) = u_i\left(s_i, f_i\right).$$

Given the form of the utility function (8), this equation has solution

$$WTP_i = s'_i - s_i \exp\left(\frac{v_i - v'_i}{\tau}\right), \tag{24}$$

where $v_i \equiv \bar{\xi}_{c_{f_i},o_i,x_i} + \xi_{f_i,o_i,x_i} + \frac{1}{\lambda}\zeta_{i,c_{f_i}} + \epsilon_{i,f_i}$ is the non-pecuniary amenity $i$ receives from her initial firm, and $v'_i$ is the non-pecuniary amenity $i$ receives from her counterfactual firm. We further decompose $WTP_i$ into a term representing the pure effect of earnings changes, and a term representing changes to the amenity value of employment:

$$WTP_i = \underbrace{s'_i - s_i}_{\text{earnings}} + \underbrace{s_i\left(1 - \exp\left(\frac{v_i - v'_i}{\tau}\right)\right)}_{\text{amenity value of employment}}. \tag{25}$$

Because we assume a competitive, perfectly-elastic output market, the overall welfare effect aggregates over workers' $WTP_i$ and firms' profit changes.

The result is depicted Figure 9. The overall welfare loss of the Essential Skills visa restrictions is \$292.9m. This is large, equal to about 30% of migrants' baseline earnings. Strikingly, the overall welfare effect is driven by non-pecuniary factors: although expanding migrants' job options increases aggregate earnings, it also decreases profits, and the net effect on output is relatively small. The large effect on migrants' non-pecuniary value for their firms is consistent with the result in Section 5 that new residents often switch employers, despite doing so yielding no average benefit to their earnings.

## 8.3 How the Essential Skills visa system mediates the wage effects of migration

In Section 7, we found that firms' production functions exhibit decreasing returns to scale. As such, migration can decrease residents' wages by decreasing the marginal product of labor. In this subsection, we ask whether the Essential Skills visa system protects residents from the wage effects of increased migration.

In principle, the Essential Skills visa system could either ameliorate or exacerbate the wage effects of migration. When migrants are segregated into certain firms, residents in other firms

will be insulated from increased migration. However, increasing migration will have a particularly negative effect on residents in those firms in which migrants can work — both because such firms will suffer from a decreasing marginal product and because, as the migrant share of the firms' employees grows, firms' monopsony power over their employees will grow as well (Amior & Stuhler, 2024). Here, we use our structural model to quantify how the Essential Skills visa system mediates the wage effects of migration.

We focus on a subset of occupations which were not included on an Essential Skills in Demand list during 2018 and which had at least 50 Essential Skills migrants. For each such occupation, we calculate three counterfactual equilibria, in addition to the initial equilibrium which we have already calculated. In counterfactual (1), the number of migrants is increased by 5%. In counterfactual (2), migrants' job options are unrestricted. In counterfactual (3), the number of migrants is increased by 5% *and* migrants' job options are unrestricted.

Our object of interest is the *migration elasticity*: the change in residents' mean log wages, scaled by the change in the log number of workers in the occupation:

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

For each occupation, we calculate two migration elasticities. The *restricted migration elasticity* compares the two equilibria in which migrants job options are restricted (i.e. counterfactual (1) *vs.* the initial equilibrium). The *unrestricted migration elasticity* compares the two equilibria in which migrants job options are unrestricted (i.e. counterfactual (3) *vs.* counterfactual (2)).

Panel A in Figure 10 compares these two migration elasticities, across occupations. Restricted migration elasticities are typically negative: the Essential Skills visa system does not prevent increased migration from reducing residents' wages. In typical occupations, increasing the number of workers by 10% would decrease wages by less than 1% — though for bus drivers, hair dressers and painters, such an increase would decrease wages by more than than 2%.

While the Essential Skills visa system does not *prevent* migration from reducing residents' wages, does it at least weaken this effect? We find no consistent relationship between the restricted and unrestricted migration elasticities: in some occupations one is greater while in other occupations the other is greater.

Panel B of Figure 10 shows that this difference can be explained by migrants' baseline segregation. When migrants typically work with nonmigrants, the Essential Skills visa system accentuates the wage effects of migration: the unrestricted migration elasticity is weaker than the restricted migration elasticity. When migrants typically work with other migrants, the Essential Skills visa system attenuates the wage effects of migration: the restricted migration elasticity is weaker. In sum, the Essential Skills visa system only protects residents from the wage effects of migration when it segregates migrants into separate firms.

# 9 Conclusion

How wages are set is a fundamental question that any model of the labor market must address. When wages are bargained individually, the allocation of workers to firms is constrained efficient; the balance of market power matters only for the distribution of surplus (Silbert & Townsend, 2024). Moreover, models of individual wage bargaining typically assume that each worker's wage will be bargained independently of the wage bargained by another — if my employer gives me a raise, its bargain with its other workers will be unaffected.[36]

This paper has argued that assuming individual wage bargaining can be misleading. Our evidence is consistent with a very different wage-setting protocol. Specifically, the firms we study appear to engage in wage-posting: they demonstrate either no ability or no willingness to tailor wages to individual workers. This wage-setting protocol has important consequences for the design of immigration policy: it implies that restrictions on migrants' job options can hurt not only migrants but also the existing residents with whom they work.

More generally, wage-posting links the bargaining power of different groups of workers. As another example, in ongoing work (joint with Savannah Noray) we are studying whether whether the wage gap between men in majority-female occupations and men in majority-male occupations can be explained by womens' weaker job mobility.

This paper has also argued that workers' non-pecuniary preferences are an important policy consideration. When migrants transition from an Essential Skills visa to a resident visa, they very often switch firms but do not, on average, earn any more. By revealed preference, non-pecuniary preferences must be important. When we considered a counterfactual equilibrium in which migrants' job options are unrestricted, we found that these non-pecuniary considerations accounted for 81% of the increase in worker welfare and 97% of the increase in overall welfare.

Crucially, expanding migrants' job options increases *residents*' non-pecuniary welfare. Given that wages are set through wage-posting, a resident might avoid working for their most preferred firm because that firm has a captive pool of migrant labor, and so pays a low wage. When migrants' job options are expanded, the firm increases its wage, allowing the resident to work at the firm she prefers without having to suffer a heavy wage penalty.

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[36]There are exceptions. In the Stole and Zwiebel (1996) model, employers value marginal workers in part because marginal workers reduce the bargaining power of inframarginal workers. In the Cullen and Pakzad-Hurson (2023) model, employers are wary of paying one worker a more generous wage because doing so would risk disclosing their ability to pay all workers more.

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Figure 1: The relationship between a worker's earnings and her colleagues' visa status
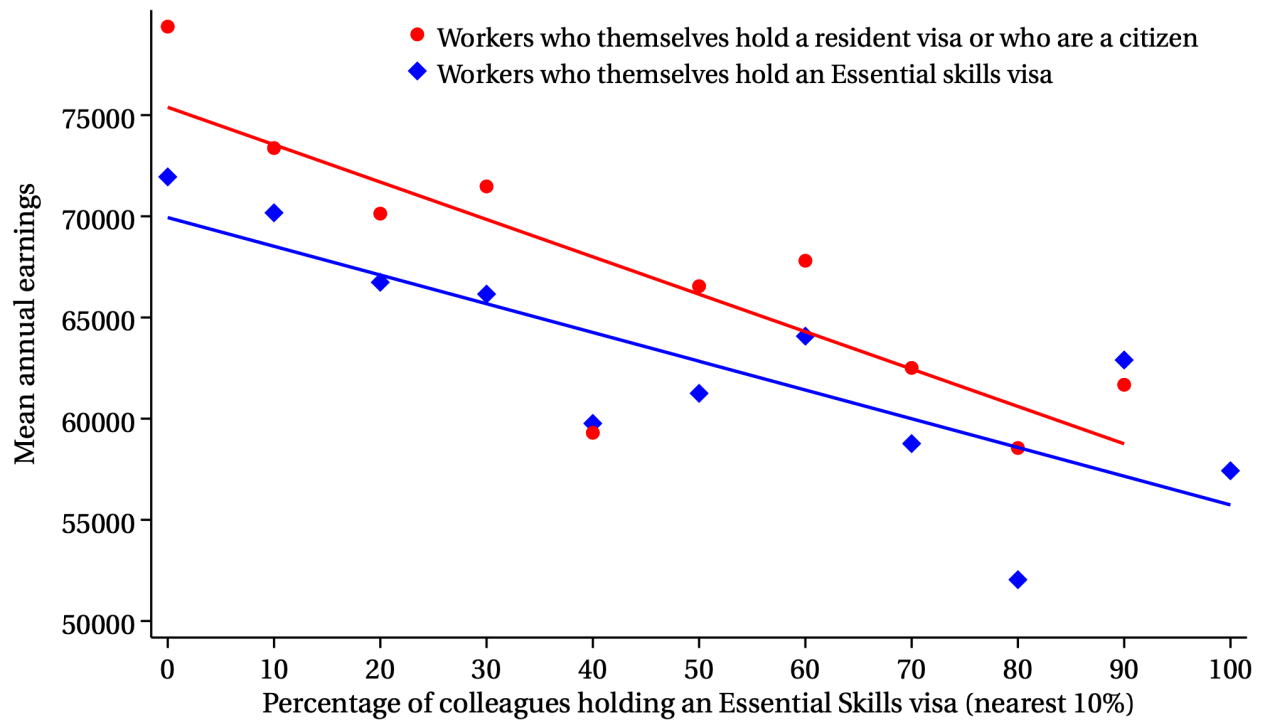


This binned scatter plot presents mean employee earnings, conditional on both a worker's own visa status and on the proportion of the workers in the modal worker's occupation × firm cell who hold an Essential Skills visa. Earnings are measured in 2020 New Zealand dollars. The figure is constructed using both the 2013 and 2018 population censuses; the sample are full-time paid employees with a unique employer. See Section 3 for data sources and Section 4 for details on the analytic sample.

Figure 2: How job-switching and earnings change when a migrant becomes a resident
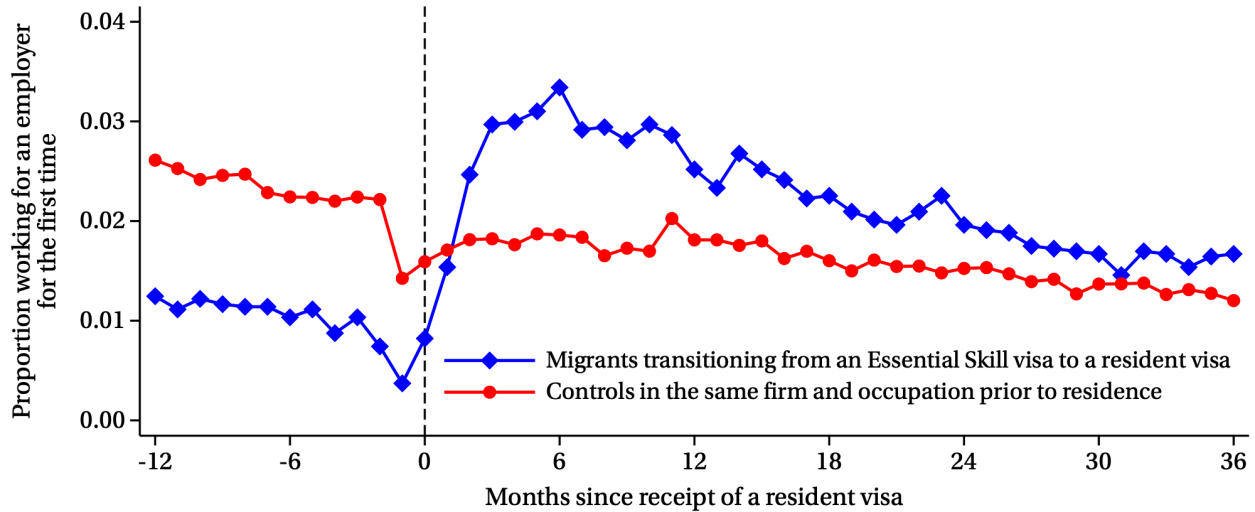


Panel A: Job-switching
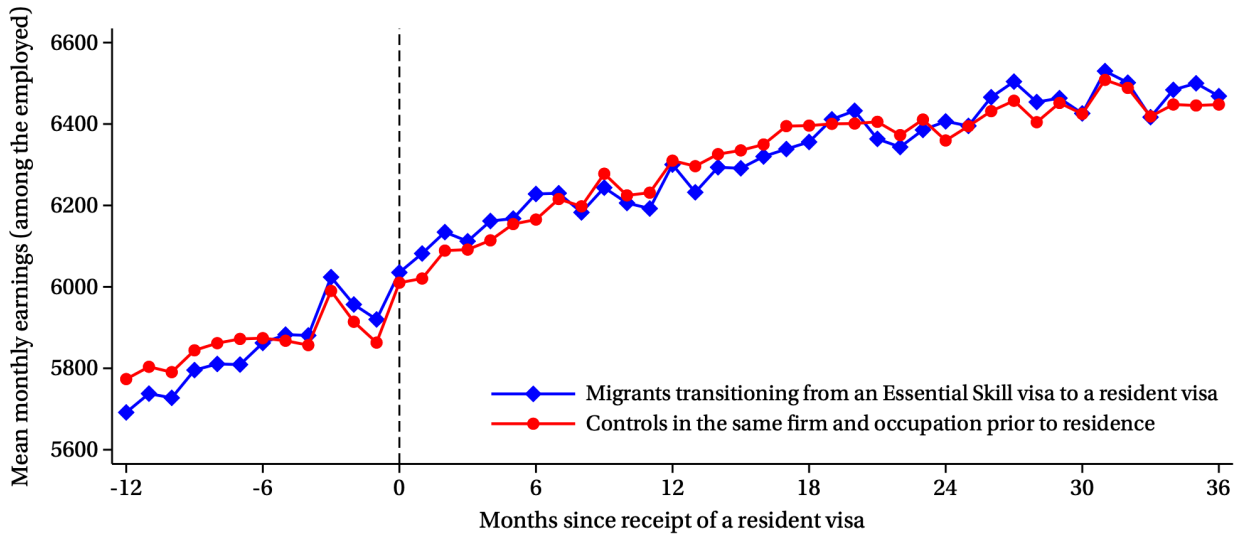


Panel B: Earnings

This figure depicts how job-switching (Panel A) and earnings (Panel B) change around the month that a migrant transitions from an Essential Skills visa to a resident visa. The dependent variable in Panel A indicates a worker being employed at a particular firm for the first time. The dependent variable in Panel B is monthly labor earnings (in 2020 New Zealand dollars). Both figures comprise only workers who held an Essential Skills visa for at least 18 months prior to receiving a resident visa; Panel B additionally restricts to workers with positive earnings. The red series comprises workers who worked in the same firm and occupation as the modal migrant in the month prior to the modal migrant receiving a resident visa. The dip in the baseline month in Panel A is due to our requirement that both the new resident and her controls have a unique firm in that month. See Section 3 for data sources and Subsection 5.1 for details on the analytic sample.

# Figure 3: How receiving a resident visa affects a worker's earnings
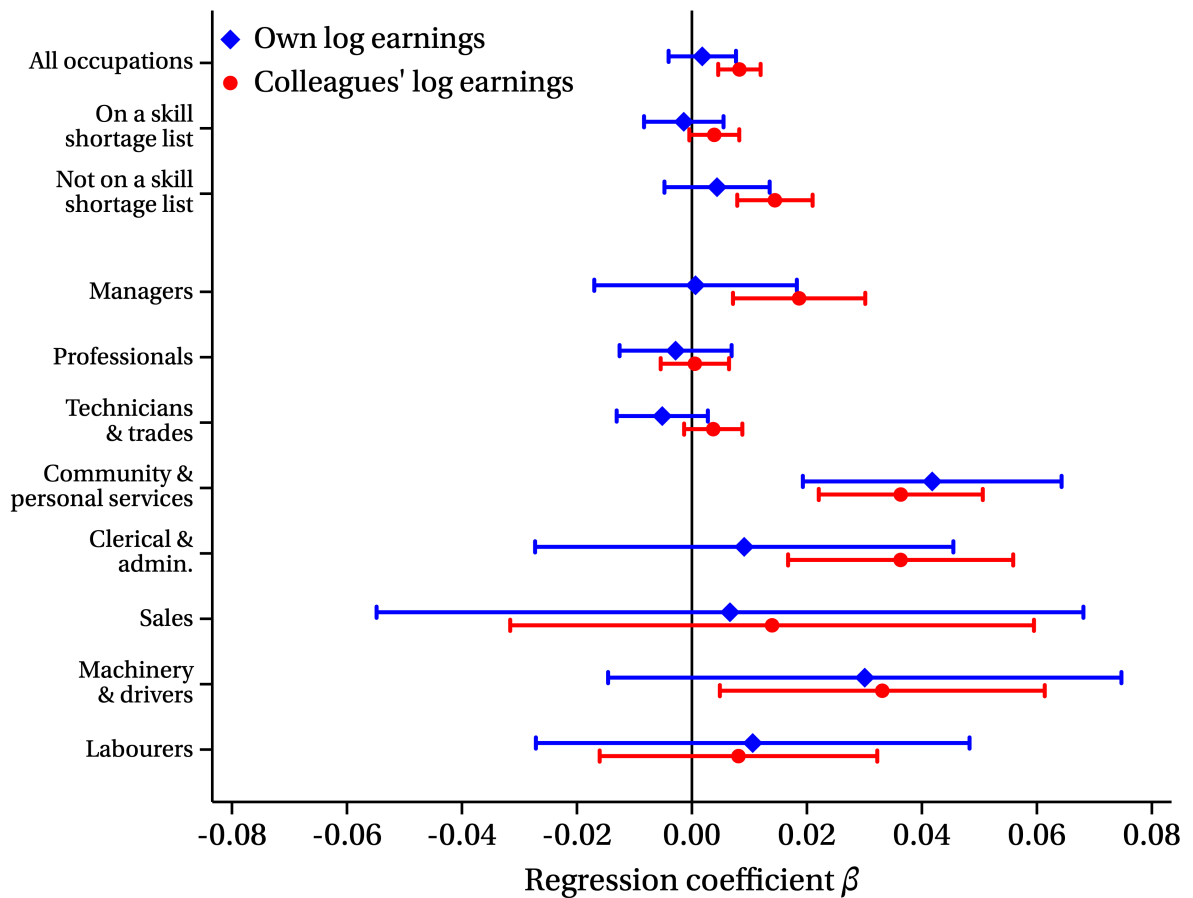


This figure depicts estimated effects of receiving a resident visa on earnings using the matched-control estimator of Equation (2). The dependent variable in the blue diamond series is a worker's monthly log earnings. The dependent variable in the red circle series is the average monthly log earnings among a worker's colleagues. Both series comprise only workers who held an Essential Skills visa for at least 18 months prior to receiving a resident visa and who have positive earnings. The red series additionally restricts to workers with a unique firm and excludes the first and last month of employment at a firm. Bars represent 95% confidence intervals. See Section 3 for data sources and Subsection 5.1 for details on the analytic sample and estimator. The underlying data for this figure is available in Appendix Table A2.

Figure 4: How winning a resident visa lottery affects a worker's visa status, job-switching and earnings
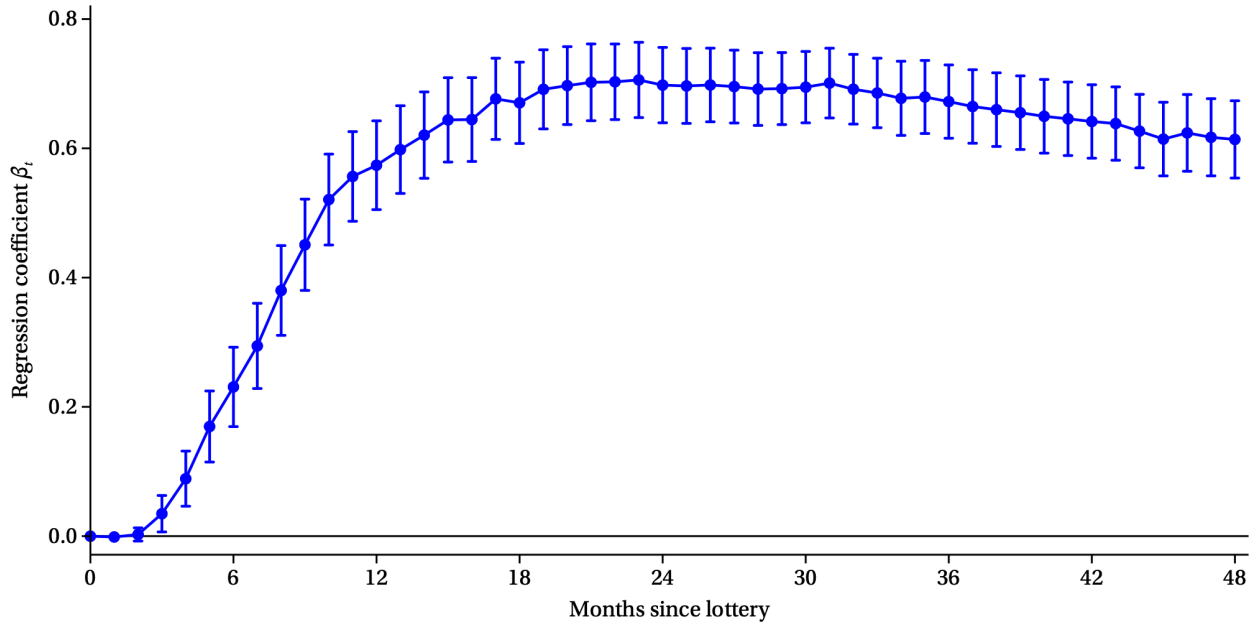


Panel A: Effects on visa status
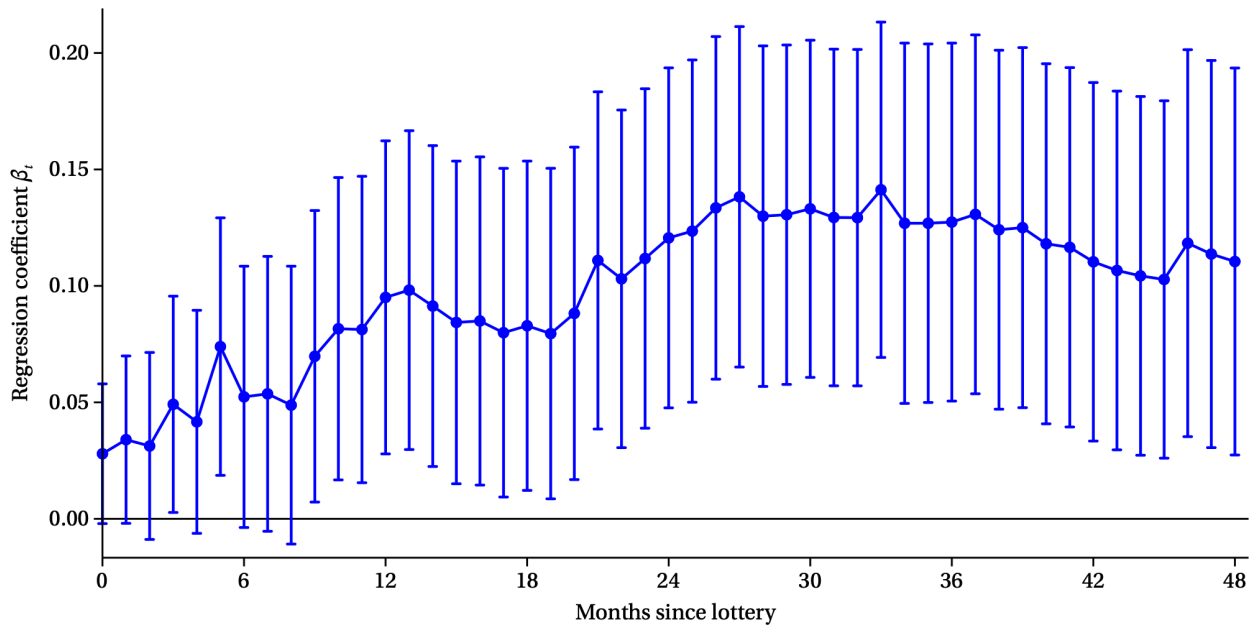


Panel B: Effects on job-switching

Figure 4 (continued): How winning a resident visa lottery affects a worker's visa status, job-switching and earnings
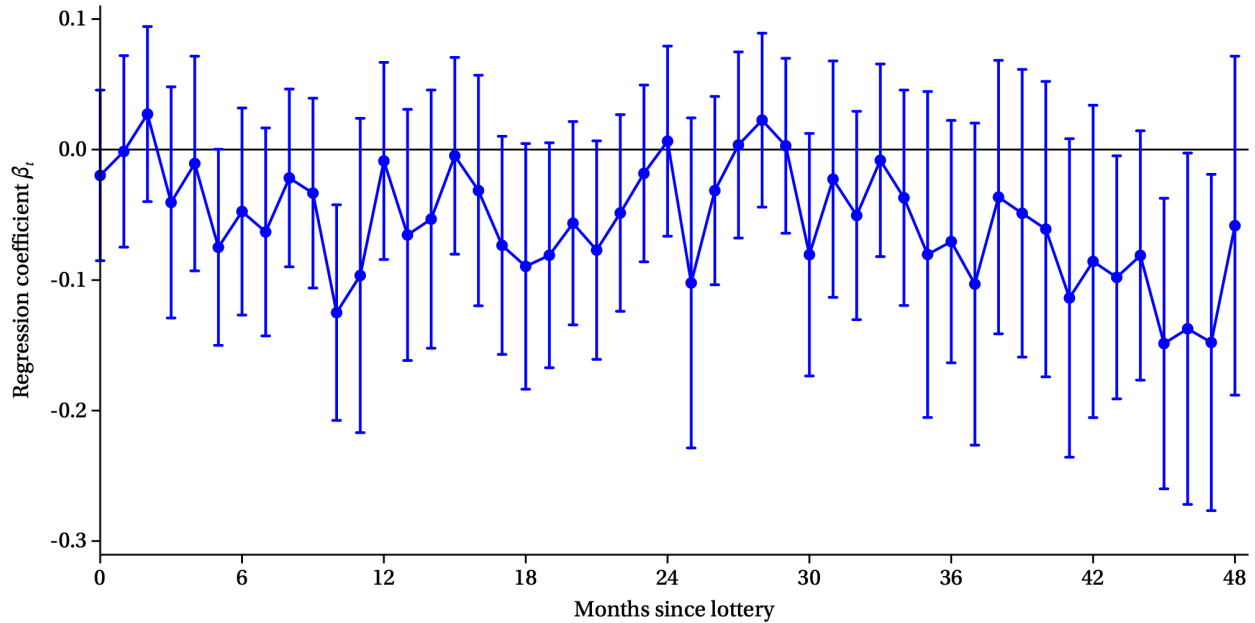


Panel C: Effects on log earnings

The figure presents regression estimates of Equation (4) to study the effects of winning a resident visa lottery, varying the month $t$ at which outcomes are measured. In Panel A, the dependent variable is an indicator for having obtained a resident visa $t$ months after the lottery. In Panel B, the dependent variable is an indicator for having worked for a new firm at any point during the $t$ months since the lottery. In Panel C, the dependent variable is log earnings $t$ months after the lottery. Bars represent 95% confidence intervals. See Section 3 for data sources and Subsection 5.2 for details on the analytic sample and estimator.

## Figure 5: How earnings change when an occupation is included on an Essential Skills in Demand list
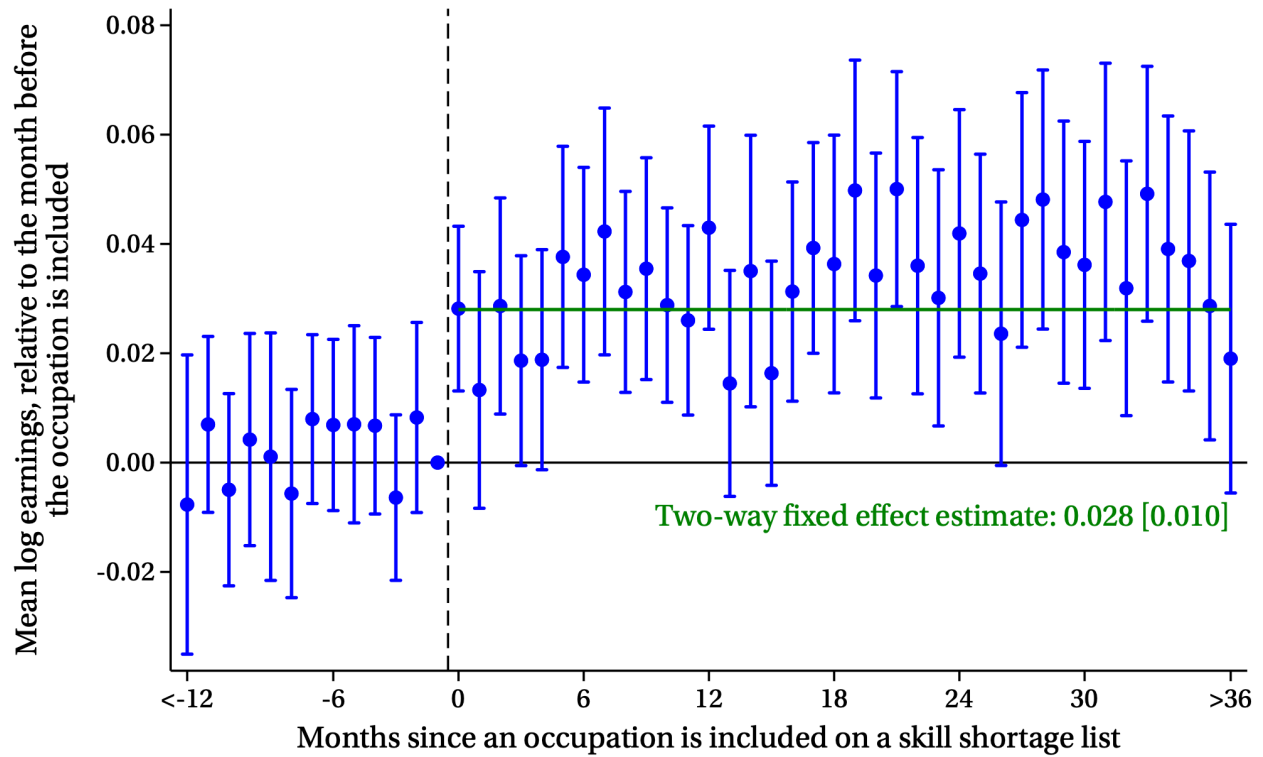


This figure reports coefficient estimates from the Freyaldenhoven et al. (2021) linear panel event-study model, asking how log earnings in an occupation (in New Zealand or in Australia) typically change when the occupation is added to or removed from a New Zealand Essential Skills in Demand list. Bars represent 95% confidence intervals. See Section 3 for data sources and Section 6 for details on the analytic sample.

Figure 6: How earnings in New Zealand and Australia change when an occupation is included on a New Zealand Essential Skills in Demand list
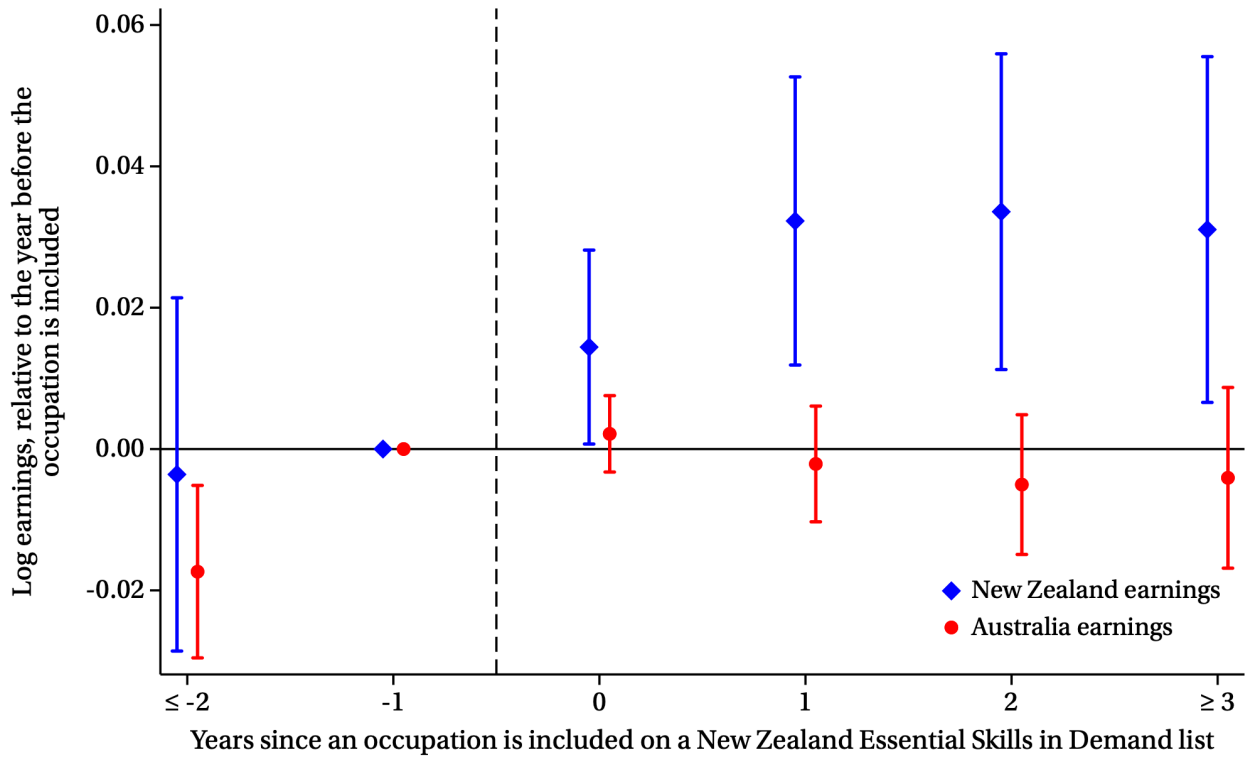


This figure reports coefficient estimates from the Freyaldenhoven et al. (2021) linear panel event-study model, asking how log earnings in an occupation typically change when the occupation is added to or removed from an Essential Skills in Demand list. Bars represent 95% confidence intervals. See sections 3 and 6 for data sources and Section 6 for details on the analytic sample.

## Figure 7: How expanding migrants' job options affects wages
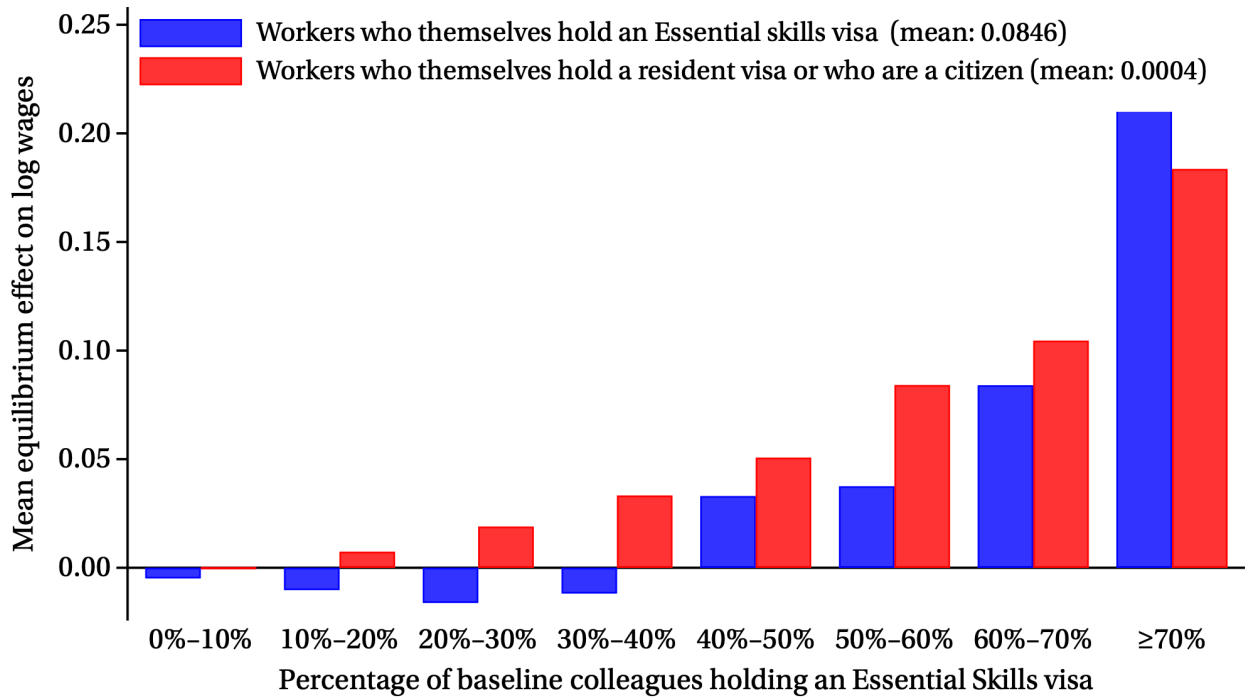


Panel A: Mean effects by own visa status and the visa status colleagues
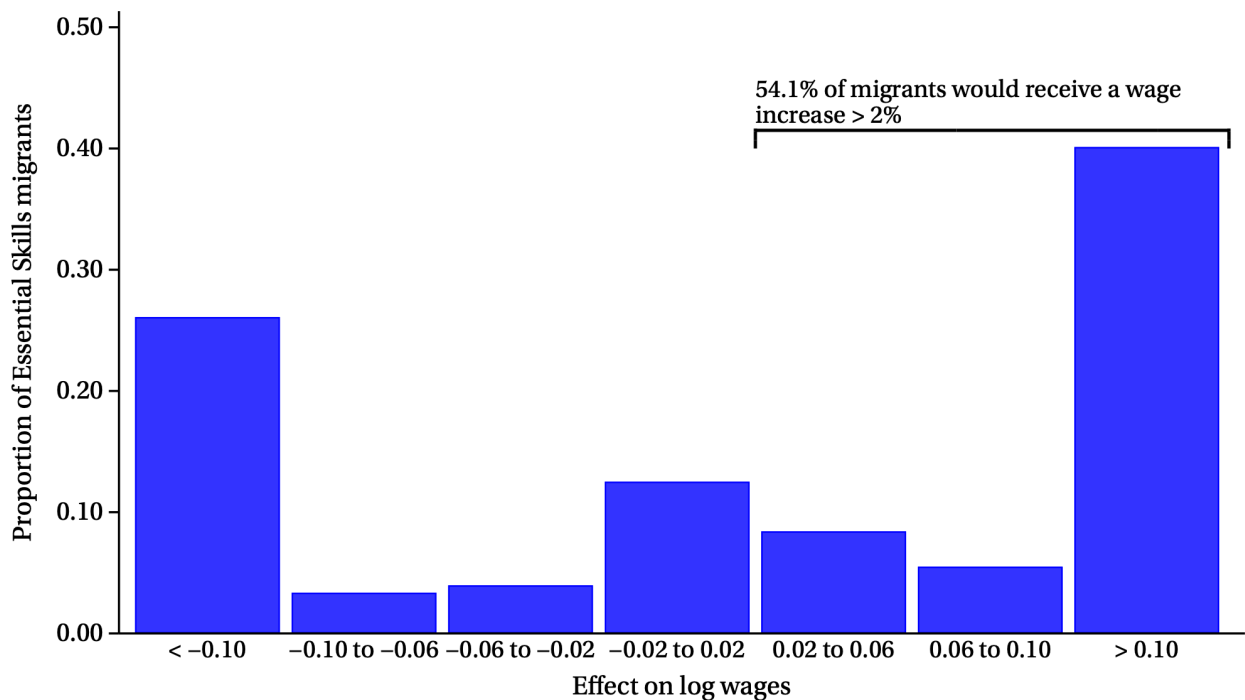


Panel B: The distribution of effects on migrants' log wages

# Figure 7 (continued): How expanding migrants' job options affects wages
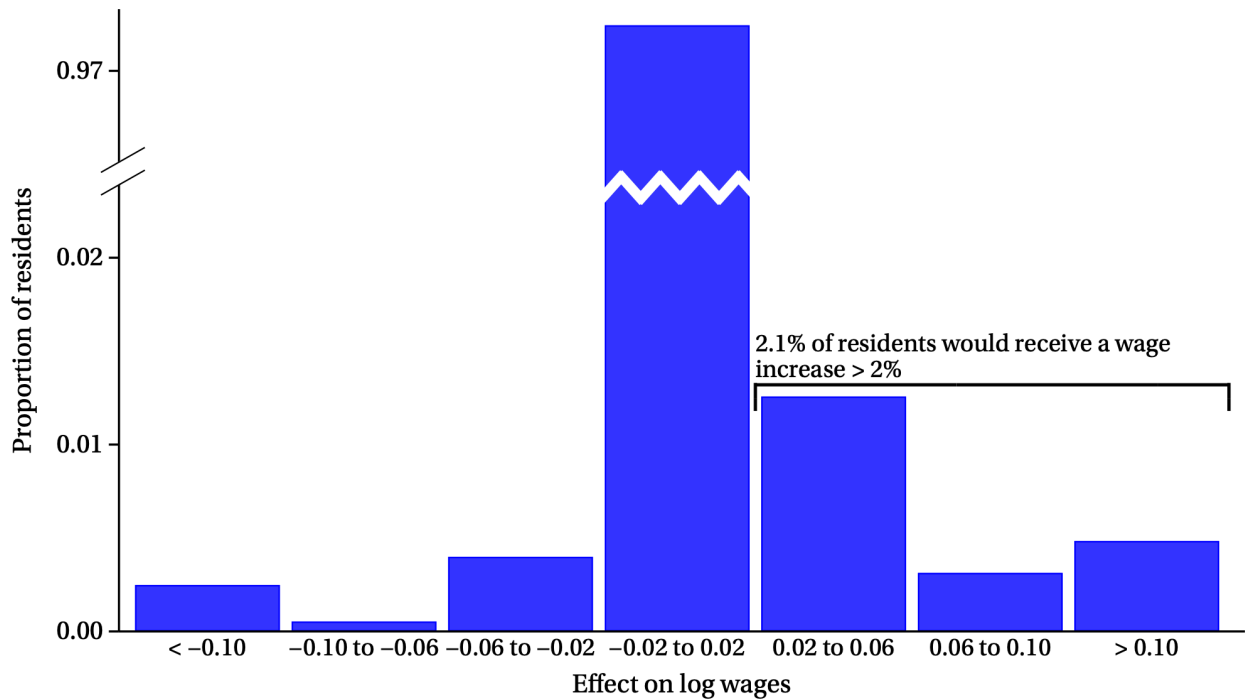


Panel C: The distribution of effects on residents' log wages

This figure depicts how allowing migrants to work at any firm would affect workers' log wages, using the equilibrium simulations discussed in Section 8. Panel A depict the mean effect on log wages, by a worker's own visa status and by the percentage of their baseline colleagues who themselves hold an Essential Skills visa. Panel B depicts the distribution of effects among Essential Skills migrants while Panel C depicts the distribution of effects among residents. Workers whose occupation is already included on a nation-wide Essential Skills in Demand list are excluded from the population used to generate the figure. Workers whose occupation is already included on a nation-wide Essential Skills in Demand list are excluded from the population used to generate the figure.

# Figure 8: How expanding migrants' job options affects firm profit and output
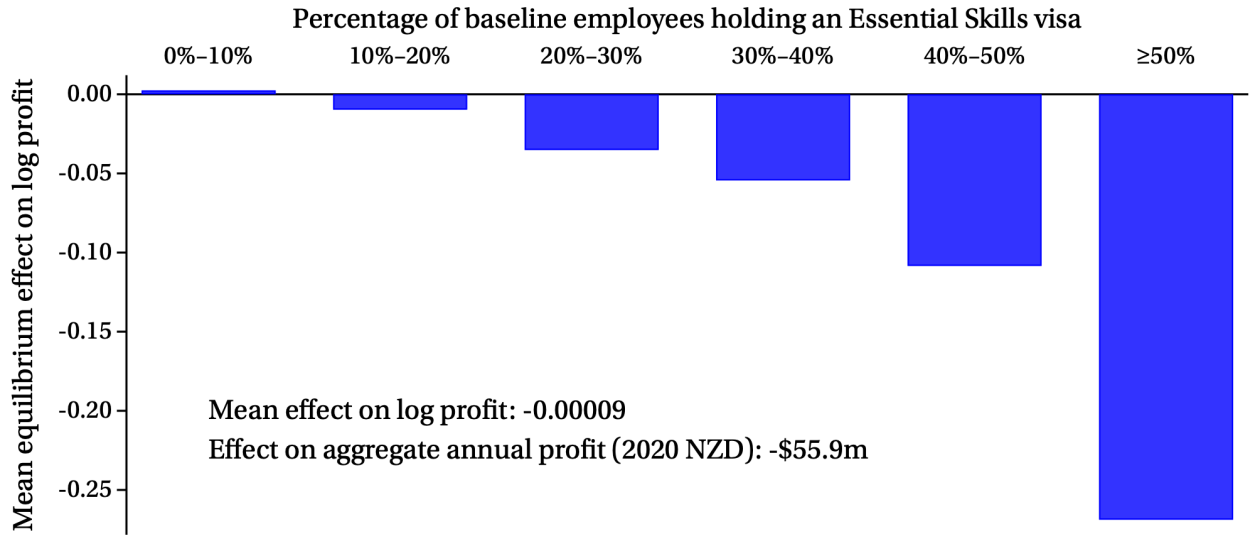


Panel A: Mean effects on log profit, by visa status among employees
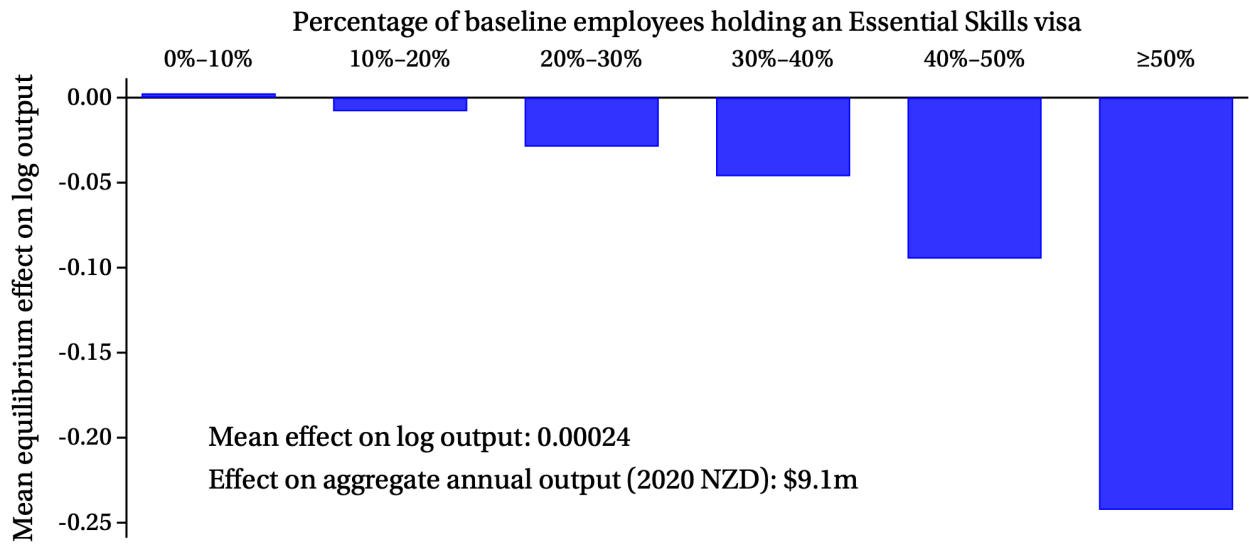


Panel B: Mean effects on log output, by visa status among employees

This figure depicts how allowing migrants to work at any firm would affect firms' profits and output, using the equilibrium simulations discussed in Section 8. Panel A depicts the mean effect on log profit by the percentage of the firm's employees who hold an Essential Skills visa. Panel B depicts the mean effect on log output by the percentage of the firm's employees who hold an Essential Skills visa.

Figure 9: How expanding migrants' job options affects aggregate welfare
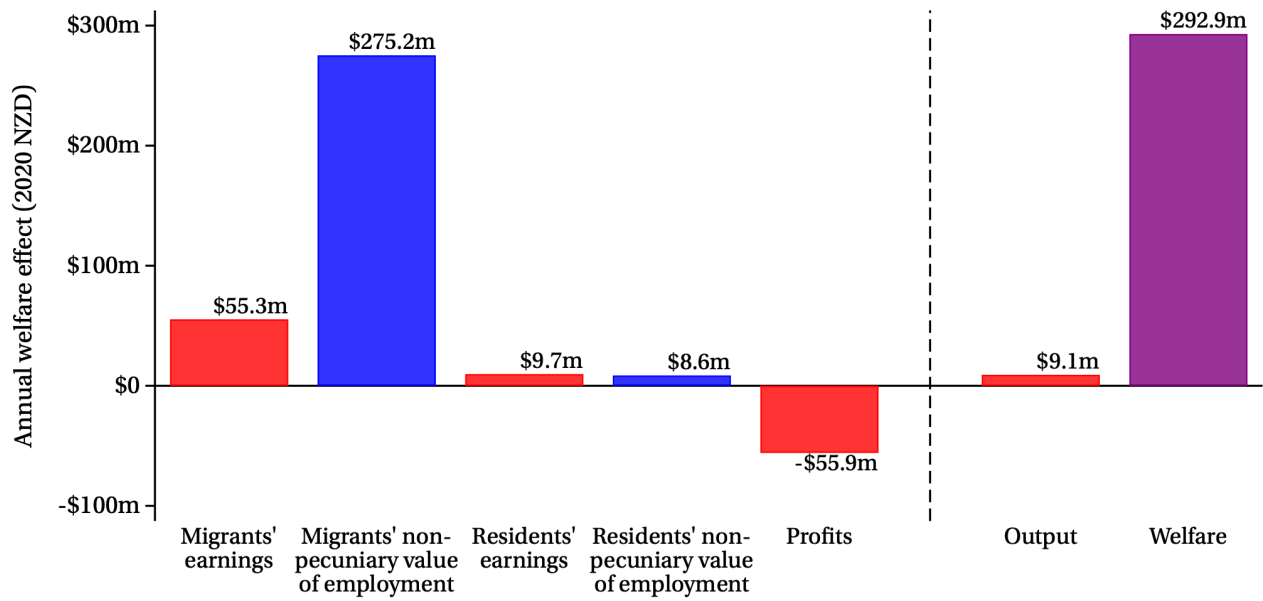


This figure depicts how allowing migrants to work at any firm would affect aggregate welfare and its subcomponents, using the equilibrium simulations discussed in Section 8. Worker welfare is measured as in equations (24) and (25).

Figure 10: How the Essential Skills visa system mediates the effects of migration
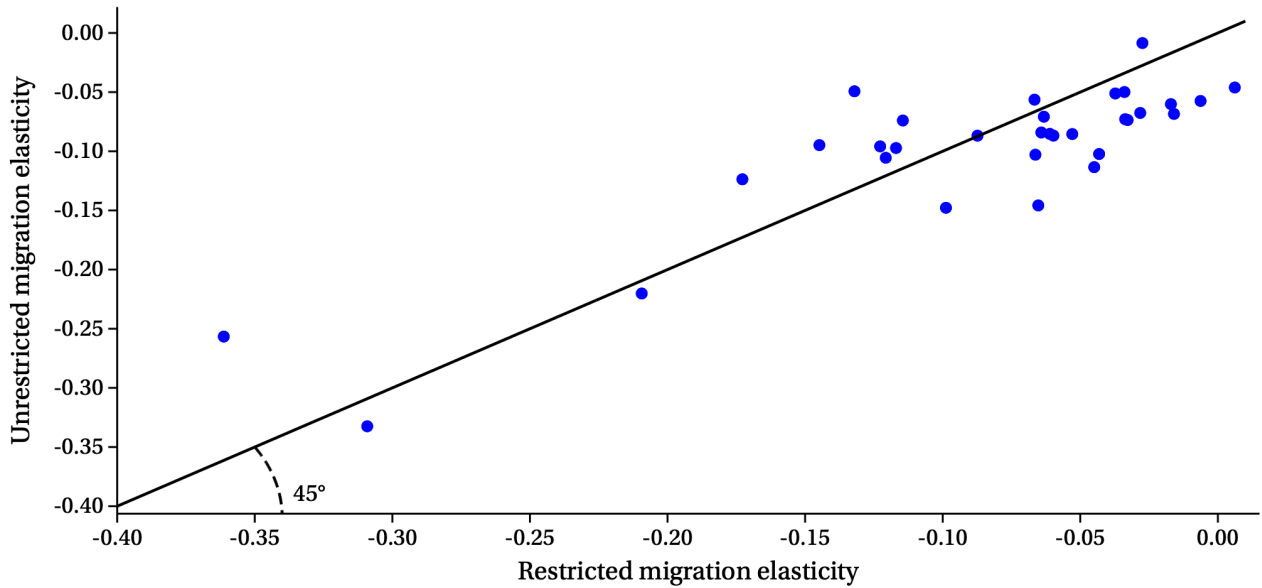


Panel A: The restricted and unrestricted migration elasticities
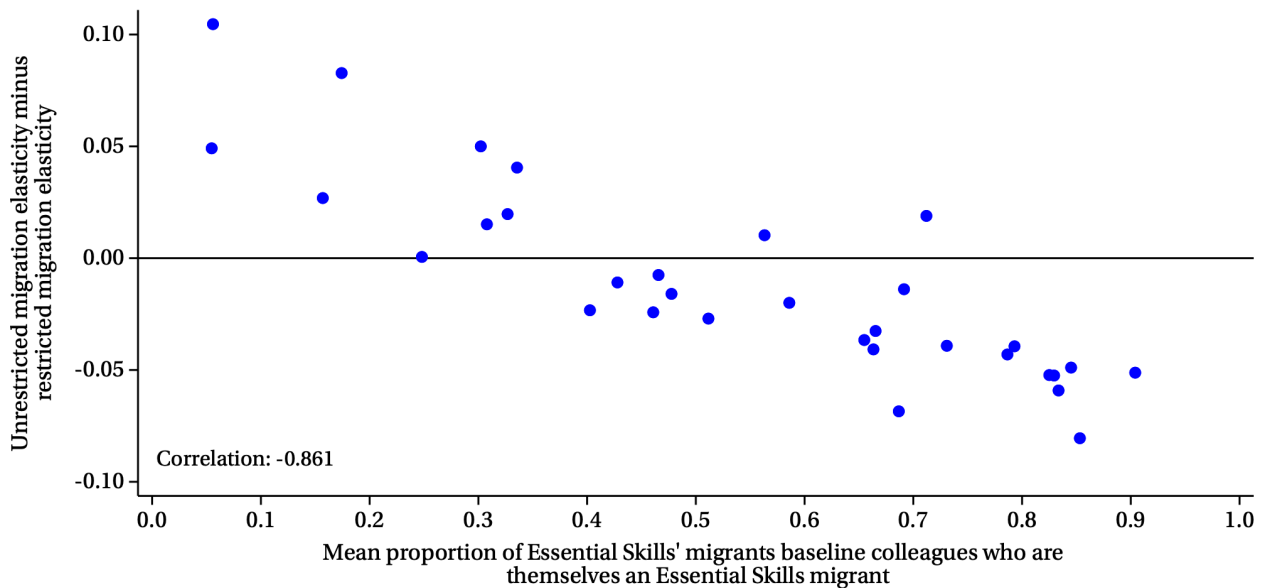


Panel B: Migrant segregation predicts the difference between the two migration elasticities

This figure depicts how increasing the number of migrants would affect residents' wages — and how this affect would differ, were migrants' job options unrestricted. The underlying simulations are described in subsection 8.3. In both panels the unit of observation is an occupation. Panel A compares the restricted migration elasticity (the wage effect of migration, given that migrants can only work at certain firms) to the unrestricted migration elasticity (the wage effect of migration, if migrants could work at any firm). Panel B compares the difference between these two elasticities to the mean proportion of Essential Skills' migrants baseline colleagues who are themselves an Essential Skills migrant.

# Table 1: Summary statistics

**Panel A: All worker-month observations**

| | By visa status: | | | All workers |
| | Essential Skills | Other temporary visa | Resident or citizen | |
|---|---|---|---|---|
| Proportion male | 0.715 | 0.561 | 0.496 | 0.502 |
| Mean real earnings | 5067.0 | 3564.2 | 5215.4 | 5135.8 |
| Proportion living in: | | | | |
|    Auckland | 0.315 | 0.373 | 0.266 | 0.271 |
|    any major urban area | 0.540 | 0.578 | 0.510 | 0.514 |
| Number of worker-month observations | 4069371 | 13074444 | 261511728 | 278655552 |
| Number of distinct workers | 205875 | 872676 | 3386520 | 3840834 |

**Panel B: During the 2018 Population Census**

| | By visa status: | | | All workers |
| | Essential Skills | Other temporary visa | Resident or citizen | |
|---|---|---|---|---|
| Proportion male | 0.726 | 0.522 | 0.489 | 0.494 |
| Mean age | 35.1 | 31.0 | 43.1 | 42.5 |
| Proportion living in: | | | | |
|    Auckland | 0.410 | 0.528 | 0.355 | 0.362 |
|    any major urban area | 0.842 | 0.918 | 0.883 | 0.883 |
| Proportion born in: | | | | |
|    New Zealand | 0.001 | 0.003 | 0.716 | 0.679 |
|    United Kingdom | 0.105 | 0.092 | 0.065 | 0.066 |
|    India | 0.124 | 0.205 | 0.025 | 0.033 |
|    China | 0.061 | 0.131 | 0.021 | 0.026 |
|    South Africa | 0.058 | 0.038 | 0.022 | 0.023 |
|    Fiji | 0.051 | 0.026 | 0.017 | 0.018 |
|    Australia | — | 0.005 | 0.018 | 0.017 |
|    Philippines | 0.266 | 0.093 | 0.018 | 0.024 |
| Proportion by highest qualification: | | | | |
|    none | 0.057 | 0.043 | 0.116 | 0.113 |
|    high school | 0.386 | 0.287 | 0.372 | 0.369 |
|    trade qualification | 0.177 | 0.147 | 0.196 | 0.194 |
|    bachelor's degree | 0.242 | 0.291 | 0.180 | 0.185 |
|    postgraduate degree | 0.138 | 0.232 | 0.135 | 0.139 |
| Proportion paid employees | 0.994 | 0.989 | 0.949 | 0.950 |
| Proportion working full-time in their primary job | 0.958 | 0.750 | 0.801 | 0.801 |
| Proportion with a secondary job | 0.015 | 0.056 | 0.069 | 0.068 |
| Mean real labor income in prior year | 50794.2 | 31668.4 | 61337.1 | 60020.0 |
| Mean num. months of income in prior year | 10.4 | 8.4 | 11.2 | 11.0 |
| Mean num. employers in prior year | 1.3 | 1.7 | 1.4 | 1.4 |
| Number of workers | 19152 | 56355 | 1435512 | 1511019 |
| Prop. of sample matched to a Census form | 0.759 | 0.658 | 0.926 | 0.909 |

Table 1 describes our sample of worker-month observations. Panel A includes all person-months with positive earnings, while Panel B includes the subset of such observations from March 2018 (when the 2018 Population Census was conducted) who filled out a 2018 Census form. Visa status is from administrative records. In Panel A, gender and location are from both survey and administrative records, while earnings are from administrative tax records. In Panel B, all variables are from the 2018 Population Census, except for labor income and employer counts, which are from administrative tax records. Earnings are expressed in 2020 New Zealand dollars.

## Table 2: The most common occupations among Essential Skills migrants

| Occupation | Num. Essential Skills migrants | Prop. of Essential Skills migrants in this occupation | Prop. of occupation who are an Essential Skills migrant | Prop. of occupation who are an Essential Skills migrant, among Essential Skills migrants' firms |
|---|---|---|---|---|
| Dairy Cattle Farm Worker | 951 | 0.056 | 0.341 | 0.856 |
| Chef | 918 | 0.054 | 0.095 | 0.634 |
| Carpenter | 903 | 0.053 | 0.166 | 0.707 |
| Aged or Disabled Carer | 633 | 0.037 | 0.179 | 0.506 |
| Dairy Cattle Farmer | 525 | 0.031 | 0.090 | 0.701 |
| Cafe or Restaurant Manager | 438 | 0.026 | 0.106 | 0.789 |
| Retail Supervisor | 420 | 0.025 | 0.126 | 0.825 |
| Retail Manager (General) | 366 | 0.022 | 0.024 | 0.704 |
| Metal Fabricator | 261 | 0.015 | 0.113 | 0.712 |
| Personal Care Assistant | 255 | 0.015 | 0.026 | 0.204 |
| Cook | 252 | 0.015 | 0.118 | 0.911 |
| Registered Nurse (Aged Care) | 180 | 0.011 | 0.067 | 0.308 |
| Truck Driver (General) | 171 | 0.010 | 0.010 | 0.396 |
| Commercial Housekeeper | 165 | 0.010 | 0.129 | 0.669 |
| Motor Mechanic (General) | 162 | 0.010 | 0.022 | 0.475 |
| Sales Assistant (General) | 159 | 0.009 | 0.005 | 0.548 |
| Resident Medical Officer | 150 | 0.009 | 0.041 | 0.080 |
| Diesel Motor Mechanic | 147 | 0.009 | 0.043 | 0.545 |
| Massage Therapist | 141 | 0.008 | 0.427 | 0.871 |
| Waiter | 129 | 0.008 | 0.051 | 0.595 |
| All occupations | 16992 | 1.000 | 0.017 | 0.635 |

Table 2 lists the 20 most common occupations for Essential Skills migrants, during March 2018. Counts and proportions are calculated using all workers with positive earnings who can be assigned an occupation either because they completed a census form or because their occupation is included in administrative immigration records. To construct the final column, we first calculate the proportion of each occupation-firm cell who hold an Essential Skills visa, and then take the average of these proportions weighting each cell by its number of Essential Skills migrants.

## Table 3: Cross-sectional wage regressions

|  | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Sample: 2013 Population Census** | | | | | | |
| Slope coefficient on Essential Skills visa | -0.194 | -0.184 | -0.048 | -0.025 | -0.010 | -0.032 |
|  | [0.006] | [0.005] | [0.004] | [0.005] | [0.006] | [0.006] |
| Number of workers | 714915 | 696870 | 679533 | 696870 | 679533 | 696648 |
| **Sample: 2018 Population Census** | | | | | | |
| Slope coefficient on Essential Skills visa | -0.222 | -0.189 | -0.049 | -0.048 | -0.004 | -0.026 |
|  | [0.003] | [0.003] | [0.003] | [0.004] | [0.005] | [0.005] |
| Number of workers | 772842 | 770367 | 750789 | 770367 | 750789 | 753039 |
| Controls: | No | Yes | Yes | Yes | Yes | No |
| Fixed effects: | None | None | Occupation | Firm | Occ. × firm | Occ. × firm |

Table 3 reports cross-sectional regressions in which the dependent variable is an employee's log earnings (in the 12 months prior to either the 2013 Population Census or the 2018 Population Census). These regressions are estimated using full-time paid employees with a unique employer (see Section 4 for a detailed description of the sample). The controls included in columns (2)-(5) are log hours of work, indicators for decadal age bins, and indicators for the worker having as their highest qualification a high school certificate, a trade certificate or diploma, a bachelor's degree, or a postgraduate degree. (Estimated slope coefficients for these controls, along with $R^2$ values, are reported in Appendix Table A1). Standard errors (robust to heteroskedasticity) are in parentheses.

## Table 4: Resident visa lottery placebo analysis

| | Control mean | Slope coefficient | Standard error | P-value | Num. workers | Num. obs. |
|---|---|---|---|---|---|---|
| Age | 34.805 | -0.436 | [0.553] | 0.430 | 3465 | 6123 |
| Number of dependants | 1.894 | 0.021 | [0.154] | 0.890 | 2985 | 5070 |
| Months in New Zealand | 44.441 | 3.759 | [2.485] | 0.130 | 3465 | 6123 |
| Male | 0.793 | -0.008 | [0.032] | 0.800 | 3456 | 6108 |
| In Auckland | 0.456 | -0.019 | [0.040] | 0.641 | 3081 | 5283 |
| In major city | 0.665 | -0.013 | [0.037] | 0.724 | 3081 | 5283 |
| In the six months prior to the lottery: | | | | | | |
|     Employed in NZ | 0.952 | 0.015 | [0.015] | 0.325 | 3465 | 6123 |
|     Log monthly NZ earnings | 9.950 | -0.061 | [0.052] | 0.241 | 3315 | 5829 |
|     Starting a new job | 0.088 | 0.045 | [0.025] | 0.077 | 3465 | 6123 |
| Pooled test that all coefficients = 0 | | | | 0.349 | 3465 | 52065 |

Table 4 reports estimates of Equation (3), in which the dependent variable is a 'placebo' outcome which is known to be unaffected by the lottery. Standard errors are clustered at the worker level. The pooled test is conducted using a stacked regression in which lottery success and the lottery fixed effects are both interacted with indicators for each dependent variable. See Section 3 for data sources and Subsection 5.2 for details on the analytic sample and estimator.

## Table 5: How winning a resident visa lottery affects job-switching and earnings

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Panel A: Dependent variable indicates that a worker is employed at a firm for the first time in that month** | | | | | | |
| | Intent-to-treat; 12–36 months after lottery | Linear IV; 12–36 months after lottery | Linear IV with baseline control; 12–36 months after lottery | Linear IV; 12–48 months after lottery | Linear IV; 12–36 months after lottery; no skill-list occupations | Probit IV average partial effect; 12–36 months after lottery |
| Second-stage (or ITT) slope coefficient | 0.010 [0.003] | 0.015 [0.004] | 0.014 [0.004] | 0.013 [0.004] | 0.017 [0.005] | 0.014 [0.003] |
| First-stage slope coefficient | — | 0.676 [0.027] | 0.721 [0.024] | 0.705 [0.023] | 0.734 [0.026] | — |
| First-stage F statistic | — | 635.423 | 444.939 | 976.873 | 772.716 | — |
| Control mean | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 |
| Number of observations | 149433 | 149433 | 149433 | 205446 | 93768 | 148806 |
| Number of workers | 3465 | 3465 | 3465 | 3465 | 2148 | 3459 |

| | Intent-to-treat; 12–36 months after lottery | Linear IV; 12–36 months after lottery | Linear IV with baseline control; 12–36 months after lottery | Linear IV; 12–48 months after lottery | Linear IV; 12–36 months after lottery; no skill-list occupations | Dep. variable is earnings; Linear IV; 12–36 months after lottery |
|---|---|---|---|---|---|---|
| **Panel B: Dependent variable is monthly log earnings (or, in Column (6), monthly earnings)** | | | | | | |
| Second-stage (or ITT) slope coefficient | -0.041 [0.025] | -0.057 [0.034] | -0.025 [0.032] | -0.080 [0.038] | -0.019 [0.040] | -110.476 [225.791] |
| First-stage slope coefficient | — | 0.723 [0.024] | 0.677 [0.027] | 0.665 [0.026] | 0.680 [0.031] | 0.676 [0.027] |
| First-stage F statistic | — | 918.178 | 319.274 | 648.478 | 476.048 | 635.423 |
| Control mean | 8.406 | 8.406 | 8.408 | 8.424 | 8.350 | 3778.4 |
| Number of observations | 126987 | 126987 | 123771 | 171894 | 77898 | 149439 |
| Number of workers | 3237 | 3237 | 3153 | 3243 | 1983 | 3465 |

Table 5 presents instrumental variable (or intent-to-treat) estimates of the effect of receiving a resident visa on job-switching (Panel A) or on earnings (Panel B). Column (1) presents estimates from ordinary least squares regressions. Columns (2)–(5) (in Panel A) or (2)–(6) (in Panel B) present two-stage least squares estimates of the linear IV system (5). Column (6) in Panel A presents the average partial effect from a probit IV system which replaces the first equation of system (5) with the assumption that $y_{i,b,t} = 1\{\beta \text{resident}_{i,b,t} + \alpha_b + e_{i,b,t} > 0\}$, and additionally assumes that $e_{i,b,t}, u_{i,b,t}$ are joint normal. Column (4) is estimated using months 12–48 following the lottery, other columns are estimated using months 12–36 following the lottery. Columns (1)–(5) of Panel B additionally restrict to observations with positive earnings. Column (5) excludes entries in which the entrant held an occupation on an Essential Skills in Demand list at the time of the lottery. Standard errors are clustered at the worker level. See Section 3 for data sources and Subsection 5.2 for details on the analytic sample and estimator.

## Table 6: How winning a resident visa lottery affects the earnings of those who don't switch firms

| | (1) | (2) |
|---|---|---|
| Job-switching depends on: | Current earnings | Current and lagged earnings |
| Average effect of lottery success on log earnings, among job-stayers | -0.050 [0.029] | -0.027 [0.029] |
| Job-switching selection equation | | |
| $\beta_0$ | 1.624 [0.253] | 1.554 [0.349] |
| $\beta_1$ | 2.761 [2.723] | -0.585 [2.544] |
| $\beta_2$ | -0.364 [0.027] | -0.060 [0.070] |
| $\beta_3$ | -0.277 [0.295] | -0.226 [0.491] |
| $\beta_4$ | — | -0.299 [0.049] |
| $\beta_5$ | — | 0.305 [0.461] |
| $\mathrm{var}(\delta)$ | 0.121 [0.016] | 0.112 [0.015] |
| Earnings D.G.P. | | |
| $\alpha_0$ | 3.394 [0.045] | 3.424 [0.045] |
| $\alpha_1$ | 0.636 [0.005] | 0.633 [0.005] |
| $\mathrm{var}(\epsilon)$ | 0.121 [0.001] | 0.121 [0.001] |
| $\mathrm{var}(\gamma)$ | 0.030 [0.002] | 0.029 [0.002] |
| $\mathrm{cov}(\delta,\gamma)$ | 0.012 [0.005] | 0.000 [0.005] |
| Number of observations | 62361 | 61704 |
| Number of workers | 2982 | 2982 |

Table 6 reports posterior means of the parameters in the system described in Subsection 5.3, with which we infer how winning a resident visa lottery affects the earnings of those who remain at their baseline firms. Posterior standard deviations are included in parentheses.

Table 7: The effect of including an occupation in an Essential Skills in Demand list on earnings

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Earnings measured among | All workers | Essential Skills migrants | Residents | All workers | All workers | All workers | All workers | All workers |
| Estimator | Two-way fixed effects | Two-way fixed effects | Two-way fixed effects | Two-way fixed effects with controls | Two-way fixed effects with controls & occ.-specific slopes | Triple-difference with Australian earnings | Proxy-confound with Australian earnings | Nonparametric average treatment effect |
| Effect of the Essential Skills in Demand list | 0.028 [0.010] | 0.042 [0.011] | 0.025 [0.012] | 0.023 [0.009] | 0.023 [0.008] | 0.019 [0.010] | 0.034 [0.011] | 0.025 [0.008] |
| Number of occ.-month obs. | 150375 | 120231 | 143706 | 131334 | 131334 | 3567 | 3210 | 141564 |
| Number of occupations | 1029 | 993 | 1029 | 1023 | 1023 | 357 | 357 | 1029 |

Table 7 reports estimates of how including an occupation in an Essential Skills in Demand list affects log earnings. Column (1) measures log earnings using all workers. Column (2) measures log earnings using only Essential Skills migrants, Column (3) measures log earnings using only residents and citizens, other columns measure log earnings using all workers. Columns (1), (2), (3) and (8) estimate the two-way fixed effect equation (6) using ordinary least squares. Columns (4) and (5) add controls for mean log firm value-added and for the mean log number of workers at a worker's firm, and Column (5) additionally controls for occupation-specific linear time trends. Columns (6) and (7) compare New Zealand earnings to Australian earnings; Australian data is only available at the year-by-4 digit occupation level, and so these specifications are estimated at that level (whereas other specifications are estimated at the month-by-6 digit occupation level). Column (6) presents a two-way fixed effect estimate with log New Zealand earnings minus log Australian earnings as the dependent variable. Column (7) presents the Freyaldenhoven et al. (2019) estimator, in which Australian log earnings are used as a proxy for an unobserved confound. Column (8) presents the nonparametric average treatment effect estimator discussed in Appendix D. Standard errors, clustered at the occupation level, are in parentheses. See Section 3 for data sources and Subsection 6 for details on the analytic sample and estimators.

## Table 8: The effect of including an occupation in an Essential Skills in Demand list on intermediate outcomes

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Outcome variable | Proportion of workers employed at a firm for the first time | Log number of workers in the occupation | Mean log number of workers across workers' firms | Mean log TFP across workers' firms | Mean log value-added-per-worker across workers' firms |
| Effect of skill shortage listing | 0.0035 | 0.2362 | 0.1033 | 0.0090 | -0.0537 |
| | [0.0011] | [0.0554] | [0.0540] | [0.0176] | [0.0201] |
| Outcome mean | 0.0325 | 4.7268 | 4.3578 | 0.9961 | 11.4019 |
| Number of occ.-month obs. | 161301 | 161301 | 127521 | 127521 | 127302 |
| Number of occupations | 1029 | 1029 | 1020 | 1020 | 1020 |

Table 7 reports estimates of how including an occupation in an Essential Skills in Demand list affects intermediate outcomes. All specifications are estimated using a two-way fixed effect equation like (6) (but with alternative outcome variables) using ordinary least squares. The dependent variable in Column (1) measures the proportion of workers who are observed working for a firm for the first time in that month. The dependent variable in Column (2) measures the log number of workers in the occupation. The dependent variable in Column (3) measures the mean log number of workers (in any occupation) across each worker's firm. The dependent variable in Column (4) is the mean log ratio of revenue to intermediate expenditures across each worker's firm. The dependent variable in Column (5) is the mean log value-added-per-worker across each worker's firm.

Table 9: Structural estimates

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Worker type definition | Born NZ vs. abroad | Country of birth | Born NZ vs. abroad | Born NZ vs. abroad | Born NZ vs. abroad |
| Firms' labor measured as | Num. worker-hours | Num. worker-hours | Num. worker-hours | Num. worker-hours | Num. workers |
| Split-samples formed | Within occ.-firm-year | Within occ.-firm-year | Randomizing workers | Within occ.-firm-year | Within occ.-firm-year |
| **Coefficient estimates** | | | | | |
| $\tau$ (labor supply elasticity for an atomistic firm) | 3.446 [0.544] | 3.547 [0.614] | 3.564 [0.614] | 3.356 0.537 | 3.314 [0.544] |
| $\lambda$ (workers' willingness to substitute across space) | 0.483 [0.242] | 0.513 [0.305] | 0.682 [0.294] | 0.463 0.225 | 0.456 [0.216] |
| | | | | Primary / Manuf. / Services | |
| $\rho$ (firms' ability to substitute across occupations) | 0.970 [0.026] | 0.963 [0.029] | 0.919 [0.032] | 1.023 [0.080] / 0.930 [0.046] / 0.975 [0.029] | 0.969 [0.026] |
| $\nu$ (returns to scale) | 0.541 [0.097] | 0.536 [0.089] | 0.473 [0.093] | 0.822 [0.132] / 0.541 [0.178] / 0.547 [0.101] | 0.550 [0.092] |
| **Over-ID test using Essential Skills in Demand lists** | | | | | |
| Slope coefficient | 0.005 [0.009] | 0.013 [0.011] | 0.030 [0.026] | -0.872 [0.767] | 0.006 [0.009] |
| p. value | 0.580 | 0.241 | 0.259 | 0.256 | 0.517 |
| Number of occupation-firm-sample observations | 104760 | 104622 | 67900 | 102885 | 104760 |
| Number of enterprises | 16287 | 16269 | 11100 | 15981 | 16287 |
| Number of occupations | 855 | 849 | 810 | 855 | 855 |

Table 9 presents estimates of the structural model of wage-setting described in Section 7. In columns (1), (3), (4) and (5) a worker's type indicates whether they were born in New Zealand; In Column (2) a worker's type indicates their country of birth. In columns (1)-(4) the labor used in a firm-by-occupation is measured as the number of worker-hours; in Column (5) labor is measured as just the number of workers. In columns (1), (2), (4) and (5) split-samples are formed by randomizing worker-year observations within occupation-firm-year cells; in Column (3) split-samples are formed by randomizing workers. In Column (4), the production parameters $\rho$ and $\nu$ are allowed to vary across high-level industries, whereas in the other columns these parameters are assumed constant. Standard errors, allowing two-way clustering within occupations and firms, are in parentheses.

76

# A  Three Models of Wage-Setting, with heterogeneous workers

In this section we extend the theoretical framework of Section 2 to allow workers to have varying roles in production. Specifically, we allow workers to have both heterogeneous (and firm-specific) productivity, and to each have an occupation (where different firms may make different use of different occupations, and occupations may be substitutes or complements). The model in this section generalizes the model in Section 2, and thus the proofs in this section serve also as proofs for the analogous results in Section 2.

We consider a static, partial-equilibrium, perfect-information labor market comprising a unit continuum of workers $\mathbf{I}$ and a finite set of firms $\mathbf{F}$. Each worker $i \in \mathbf{I}$ will be employed at a single firm $f_i \in \mathbf{F}$. Each worker $i \in \mathbf{I}$ has an (exogenous) occupation $o_i \in \mathbf{O}$ and each firm $f \in \mathbf{F}$ utilizes a set of occupations $\mathbf{O}_f \subseteq \mathbf{O}$. Let $\mathbf{F}_o \equiv \{f \in \mathbf{F} : o \in \mathbf{O}_f\}$ denote the set of firms which employ workers in occupation $o$.

**Production.** Worker $i \in \mathbf{I}$ would have productivity $l_{i,f} \in \mathbb{R}^+$, were they to work at firm $f$. Let $l_i \equiv (l_{i,f})_{f \in \mathbf{F}}$. The effective labor supplied to each firm in each occupation integrates over worker productivity: $L_{f,o} \equiv \int_{i:f_i=f,o_i=o} l_{i,f} di$. Each firm $f$ is endowed with a production function $y_f : \mathbb{R}^{|\mathbf{O}_f|} \to \mathbb{R}^+$, with which produces output using the vector of effective labor $\vec{L}_f \equiv (L_{f,o})_{o \in \mathbf{O}_f}$. We assume that each production function $y_f$ is differentiable and concave. We assume that output is sold at unit price in a competitive market.

**Labor supply.** Each worker is either a *migrant* or a *resident*. Residents can be employed at any firm while migrants can only be employed at a subset of firms. Let $\mathbf{F}_o^{\mathrm{migrant}} \subset \mathbf{F}_o$ denote the subset of occupation-$o$ firms at which migrants can work. Let $\mathbf{I}^{\mathrm{migrant}} \subset \mathbf{I}$ denote the subset of workers who are migrants and let $\mathbf{I}^{\mathrm{resident}} = \mathbf{I} \setminus \mathbf{I}^{\mathrm{migrant}}$ denote the subset who are residents. For each worker $i$, let $\mathbf{F}_i \in \left\{\mathbf{F}_{o_i}^{\mathrm{migrant}}, \mathbf{F}_{o_i}\right\}$ denote the set of firms at which she can work.

Workers have preferences over their income and the firm to which they are matched. We assume that the preferences of each worker $i \in \mathbf{I}$ over their earnings $W$ and firm $f$ can be represented as

$$u_i(W, f) = W e^{v_{i,f}},$$

where $v_{i,f}$ measures $i$'s taste for working at $f$. We assume that the distribution of $v_i \equiv (v_{i,f})_{f \in \mathbf{F}}$ is absolutely continuous, conditional on visa status.

In each of the solution concepts specified below, a worker's earnings will be proportional to their productivity: $W_i = W_i l_{i,f_i}$. For each firm $f$, let $\vec{L}_f(\vec{w}_f; \vec{w}_{-f})$ be the vector of effective labor supplied who would choose firm $f$, were it to pay the occupation-specific wage vector

77

$\vec{w}_f \equiv (w_{f,o})_{o \in \mathbf{O}_f}$ and other firms were to pay wage vector $\vec{w}_{-f}$:

$$\vec{L}_f(\vec{w}_f; \vec{w}_{-f}) \equiv (L_{f,o}(w_{f,o}; w_{-f,o}))_{o \in \mathbf{O}_f};$$

$$L_{f,o}(w_{f,o}; w_{-f,o}) \equiv L_{f,o}^{\text{resident}} + L_{f,o}^{\text{migrant}};$$

$$L_{f,o}^{\text{resident}}(w_{f,o}; w_{-f,o}) \equiv \int_{i: o_i = o, f \in \arg\max_{g \in \mathbf{F}_i}\left\{u_i\left(w_{g,o_i} l_{i,f}, g\right)\right\}, i \in \mathbf{I}^{\text{resident}}} l_{i,f} \, di;$$

$$L_{f,o}^{\text{migrant}}(w_{f,o}; w_{-f,o}) \equiv \int_{i: o_i = o, f \in \arg\max_{g \in \mathbf{F}_i}\left\{u_i\left(w_{g,o_i} l_{i,f}, g\right)\right\}, i \in \mathbf{I}^{\text{migrant}}} l_{i,f} \, di.$$

(By the absolute continuity of the distribution of $\nu_i$, measure zero workers will be indifferent between firms.) We assume that labor supply functions for both migrants and residents $L_{f,o}^{\text{resident}}, L_{f,o}^{\text{migrant}}$ are twice differentiable.

**Defining equilibrium.** We compare three solution concepts. In each solution concept we require that wages be strictly positive.

A *competitive equilibrium* comprises an assignment of workers to firms $(f_i)_{i \in \mathbf{I}}$ and a firm-occupation-specific wage schedule $(w_{f,o})_{o \in \mathbf{O}_f, f \in \mathbf{F}}$ such that each worker's firm yields her the maximal utility from her choice set:

$$\forall i \in \mathbf{I}: f_i \in \underset{f \in \mathbf{F}_i}{\arg\max}\, u_i\left(w_{f,o_i} l_{i,f}, f\right),$$

and the mass of labor assigned to each firm maximizes its profits, taking wages as fixed:

$$\forall f \in \mathbf{F}: \vec{L}_f(\vec{w}_f; \vec{w}_{-f}) \in \underset{\vec{L} \in \mathbf{R}^{|\mathbf{O}_f|}}{\arg\max}\left\{y_f(\vec{L}) - \vec{w}_f' \cdot \vec{L}\right\}.$$

Let $\Delta_{i,f}$ denote the marginal product of worker $i$ at firm $f$, given the equilibrium assignment of other workers to their firms:

$$\Delta_{i,f} = l_{i,f} \frac{\partial}{L_{f,o_i}} y_f(\vec{L}_f).$$

A *bargaining equilibrium* comprises an assignment of workers to firms $(f_i)_{i \in \mathbf{I}}$ and a worker-specific wage schedule $(w_i)_{i \in \mathbf{F}}$ such that each worker is assigned to that firm which could yield her maximal utility, were she paid her marginal product

$$\forall i \in \mathbf{I}: f_i \in \underset{f \in \mathbf{F}_i}{\arg\max}\, u_i(\Delta_{i,f}, f),$$

and her earnings are bargained *a la* Nash (1950):

$$\forall i \in \mathbf{I}: W_i \in \underset{W \in \mathbf{R}^+}{\arg\max}\left\{\left(u_i(W, f_i) - u_i^{\text{option}}\right)^\beta (\Delta_{i,f} - W)^{1-\beta}\right\}, \tag{26}$$

where $\beta \in (0,1)$ measures workers' bargaining power, and $u_i^{\text{option}}$ is the maximal utility that $i$ could receive at an alternative firm:

$$\forall i \in \mathbf{I} : u_i^{\text{option}} \equiv \max_{f \in \mathbf{F}_i \setminus \{f_i\}} u_i \left( \Delta_{i,f}, f \right).$$

A *wage-posting equilibrium* comprises an assignment of workers to firms $(f_i)_{i \in \mathbf{I}}$ and a firm-occupation-specific wage schedule $(w_{f,o})_{o \in \mathbf{O}_f, f \in \mathbf{F}}$ such that each worker's firm yields her the maximal utility from her choice set:

$$\forall i \in \mathbf{I} : f_i \in \underset{f \in \mathbf{F}_i}{\arg\max}\, u_i \left( w_{f,o_i} l_{i,f}, f \right),$$

and each firm's wages are chosen to maximize its profits, given the wages set by the other firms:

$$\forall f \in \mathbf{F} : \vec{w}_f \in \underset{\vec{w} \in \mathbf{R}^{|O_f|}}{\arg\max} \left\{ y_f \left( \vec{L}_f \left( \vec{w}; \vec{w}_{-f} \right) \right) - \vec{w}' \cdot \vec{L}_f \left( \vec{w}; \vec{w}_{-f} \right) \right\}.$$

We assume that there exists a unique competitive equilibrium wage schedule, a unique bargaining equilibrium wage schedule, and a unique wage-posting equilibrium wage schedule.

**Relationship between this model and the model presented in Section 2.** The model in Section 2 is a special case of the model in this section, corresponding to the case in which there is only a single occupation and all workers have unit productivity: $\forall i \in \mathbf{I}, f \in \mathbf{F} : l_{i,f} = 1$. In this section we explicitly assumed that labor supply functions are twice-differentiable; for the model presented in Section 2 that follows from the assumption that the random vector $v_i$ is absolutely continuous, with a differentiable PDF.

## A.1  Predictions for wage-setting

We now show that analogues to lemmas 1–3 hold in our richer environment.

**Lemma A.1.** *Under a competitive equilibrium, each firm $f \in \mathbf{F}$ will pay a wage vector equal to its marginal product: $\vec{w}_f = \nabla y_f \left( \vec{L}_f \right)$.*

*Proof.* Each firm $f$ has the objective $\max_{\vec{L}} \left\{ y_f \left( \vec{L} \right) - \vec{w}_f' \cdot \vec{L} \right\}$. By the assumption that $y_f$ is concave and differentiable, the objective will be concave and differentiable, and thus equilibrium labor demand will satisfy the vector-valued first order conditions

$$\nabla y_f \left( \vec{L}_f \right) - \vec{w}_f = 0.$$

$\square$

**Lemma A.2.** *Under a bargaining equilibrium, each worker $i \in \mathbf{I}$ will receive wage*

$$w_i = \frac{\beta \Delta_{i,f_i} + (1-\beta) \exp\left(v_{i,f_i^{option}} - v_{i,f_i}\right) \Delta_{i,f_i^{option}}}{l_{i,f_i}}$$

*where $f_i^{option}$ is the worker's outside option:*

$$f_i^{option} \in \underset{f \in \mathbf{F}_i \setminus \{f_i\}}{\arg\max}\, u_i\left(\Delta_{i,f}, f\right).$$

*Proof.* From Expression (26), earnings for worker $i$ maximize

$$\left(u_i\left(W, f_i\right) - u_i^{option}\right)^{\beta} \left(\Delta_{i,f} - W\right)^{1-\beta}$$

Substituting in the utility function $u_i(W, f) = W e^{v_{i,f}}$ and differentiating yields the first order condition

$$\frac{\partial}{\partial W}\left[\left(W e^{v_{i,f_i}} - u_i^{option}\right)^{\beta} \left(\Delta_{i,f} - W\right)^{1-\beta}\right]_{W=W_i} \propto \frac{\beta e^{v_{i,f_i}}}{W_i e^{v_{i,f_i}} - u_i^{option}} - \frac{1-\beta}{\Delta_{i,f} - W_i} = 0.$$

Solving that equation for $W_i$ implies that

$$W_i = \beta \Delta_{i,f} + (1-\beta) u_i^{option} e^{-v_{i,f_i}}.$$

By the definition of $u_i^{option}$ and the assumed form of the utility function:

$$u_i^{option} = \max_{f \in \mathbf{F}_i \setminus \{f_i\}} \left\{\Delta_{i,f} e^{v_{i,f}}\right\} = \Delta_{i,f_i^{option}} e^{v_{i,f_i^{option}}}.$$

and by definition, $W_i = w_i l_{i,f_i}$. $\qquad\qquad\square$

**Lemma A.3.** *Under a wage-posting equilibrium, the wage paid by each firm $f \in \mathbf{F}$ to occupation $o \in \mathbf{O}_f$ will be given by*

$$w_{f,o} = \left(\frac{1}{1 + \frac{1}{\eta_{f,o}}}\right) \frac{\partial y_f}{\partial L_{f,o}}$$

*where $\eta_{f,o}$ is the firm-occupation-specific elasticity of labor supply:*

$$\eta_{f,o} = \frac{w_{f,o}}{L_{f,o}} \frac{\partial L_{f,o}\left(w_{f,o}; w_{-f,o}\right)}{\partial w_{f,o}}.$$

*Proof.* Each firm $f$ has the objective

$$\max_{\vec{w}}\left\{y_f\left(\vec{L}_f\left(\vec{w}, \vec{w}_{-f}\right)\right) - \vec{w}' \cdot \vec{L}_f\left(\vec{w}, \vec{w}_{-f}\right)\right\}.$$

By assumption, both the function $y_f(\cdot)$ and the function $\vec{L}_f(\cdot, \cdot)$ are differentiable. The objective is thus differentiable. We have additionally assumed that equilibrium wages are positive, and so the wage vector chosen by the firm will satisfy the first-order conditions

$$\frac{\partial}{\partial w_{o,f}} \left[ y_f\left(\vec{L}_f\left(\vec{w}, \vec{w}_{-f}\right)\right) - \vec{w}' \cdot \vec{L}_f\left(\vec{w}, \vec{w}_{-f}\right) \right]\Big|_{\vec{w}=\vec{w}_f} = \frac{\partial y_f}{\partial L_{f,o}} \frac{\partial L_{f,o}}{\partial w_{f,o}} - L_{f,o} - w_{f,o} \frac{\partial L_{f,o}}{\partial w_{f,o}} = 0.$$

Solving that equation for $w_{f,o}$ yields the result. □

We now show that analogues to propositions 1 and 2 also hold.

**Proposition A.1.** *Consider a migrant $i$ whose bargaining equilibrium firm $f_i$ would be unchanged, were she a resident:*

$$f_i = \operatorname*{arg\,max}_{f \in \mathbf{F}_{o_i}^{migrant}} u_i\left(\Delta_{i,f}, f\right) \in \operatorname*{arg\,max}_{f \in \mathbf{F}_{o_i}} u_i\left(\Delta_{i,f}, f\right).$$

*Making her a resident will increase her bargaining equilibrium earnings provided that her new outside option is better than her old, i.e. provided that*

$$\max_{f \in \mathbf{F}_{o_i} \setminus \{f_i\}} u_i\left(\Delta_{i,f}, f\right) > \max_{f \in \mathbf{F}_{o_i}^{migrant} \setminus \{f_i\}} u_i\left(\Delta_{i,f}, f\right).$$

*Proof.* Let $f_i^{\text{migrant option}}$ denote $i$'s outside option as a migrant:

$$f_i^{\text{migrant option}} = \operatorname*{arg\,max}_{f \in \mathbf{F}^{migrant} \setminus \{f_i\}} u_i\left(\Delta_{i,f}, f\right),$$

and let $f_i^{\text{resident option}}$ denote $i$'s outside option as a resident:

$$f_i^{\text{resident option}} = \operatorname*{arg\,max}_{f \in \mathbf{F} \setminus \{f_i\}} u_i\left(\Delta_{i,f}, f\right).$$

(Without loss of generality, assume these firms are uniquely defined.) By assumption, $f_i^{\text{migrant option}} \neq f_i^{\text{resident option}}$ and so

$$u_i\left(\Delta_{i, f_i^{\text{resident option}}}, f_i^{\text{resident option}}\right) > u_i\left(\Delta_{i, f_i^{\text{migrant option}}}, f_i^{\text{migrant option}}\right).$$

Given the assumed utility function, this implies that

$$\exp\left(v_{i, f_i^{\text{resident option}}}\right) \Delta_{i, f_i^{\text{resident option}}} > \exp\left(v_{i, f_i^{\text{migrant option}}}\right) \Delta_{i, f_i^{\text{migrant option}}}.$$

The result thus follows from Lemma A.2. □

As in Proposition 2, we provide an unambiguous prediction for the effect of a market-level shock under the assumption that firms' marginal products are homogeneous and constant. Specifically, we make the following assumption:

**Assumption A.1.** *Firms have a homogeneous production function in which each occupation has a constant marginal product:*

$$\exists y : \mathbb{R}^{|\mathbf{O}|} \to \mathbb{R}^+ \text{ such that } \forall f \in \mathbf{F} : y_f = y \text{ and } \forall o \in \mathbf{O}, \vec{L}, \vec{L}' \in \mathbb{R}^{|\mathbf{O}|} : \frac{\partial}{L_o} y(\vec{L}) = \frac{\partial}{L_o'} y(\vec{L}').$$

We modify Assumption 2 by additionally assuming that migrants and residents' productivity distributions are proportional:

**Assumption A.2.** *Migrants' preferences and residents' preferences over firms share the same distribution:*

$$\forall x : \mathbb{P}\left[ v_i \le x \,\big|\, i \in \mathbf{I}^{migrant} \right] = \mathbb{P}\left[ v_i \le x \,\big|\, i \in \mathbf{I}^{resident} \right].$$

*and their productivity distributions are also equal, up to a scalar multiple:*

$$\exists \alpha \in \mathbb{R}^+ \text{ such that } \forall x : \mathbb{P}\left[ \alpha l_i \le x \,\big|\, i \in \mathbf{I}^{migrant} \right] = \mathbb{P}\left[ l_i \le x \,\big|\, i \in \mathbf{I}^{resident} \right].$$

Similarly, we modify Assumption 3 by assuming that *effective* labor supply elasticities are increasing in other firms' wages. Given the occupation-$o$ wage schedule $(w_{f,o})_{g \in \mathbf{F}_o}$, denote the firm-by-occupation elasticity of residents' effective labor supply as $\eta_{f,o}^{\text{resident}}\left( (w_{g,o})_{g \in \mathbf{F}_o} \right)$:

$$\eta_{f,o}^{\text{resident}}\left( (w_{g,o})_{g \in \mathbf{F}_o} \right) \equiv \frac{\partial}{\partial \log w_{f,o}} \log\left( L_{f,o}^{\text{resident}} \right).$$

**Assumption A.3.** *Each firm-by-occupation elasticity of effective resident labor supply is increasing in other firms' wages:*

$$\forall o \in \mathbf{O}, \forall (w_{g,o})_{g \in \mathbf{F}_o}, \forall h \ne f \in \mathbf{F}_o : \frac{\partial}{\partial w_{h,o}} \eta_{f,o}^{\text{resident}}\left( (w_{g,o})_{g \in \mathbf{F}_o} \right) > 0.$$

Our analysis of a market-level shock will use the following lemma:

**Lemma A.4.** *Consider a function $f : \mathbb{R} \times X \to \mathbb{R}$ where $X$ is a partially-ordered set. Let $f$ be decreasing in its first argument and increasing in its second, and let the equation $w = f(w, x)$ have a solution for all $x \in X$. The solution $w(x)$ of the equation $w = f(w, x)$ is increasing in $x$.*

*Proof.* Consider $x_2 > x_1$. Decompose $w(x_2) - w(x_1)$ as

$$w(x_2) - w(x_1) = f(w(x_2), x_2) - f(w(x_1), x_1)$$
$$= f(w(x_2), x_2) - f(w(x_1), x_2) + f(w(x_1), x_2) - f(w(x_1), x_1).$$

Assume towards a contradiction that $w(x_2) \leq w(x_1)$. Given that $f$ is decreasing in its first element: $f(w(x_2), x_2) \geq f(w(x_1), x_2)$. But $f$ is increasing in its second element, so $f(w(x_1), x_2) > f(w(x_1), x_1)$. Thus $f(w(x_2), x_2) - f(w(x_1), x_2) + f(w(x_1), x_2) - f(w(x_1), x_1) > 0$ and so $w(x_2) - w(x_1) > 0$. This contradicts the assumption that $w(x_2) \leq w(x_1)$. $\square$

Lemma A.4 is an implicit function theorem for monotone functions. It is very similar to existing results in monotone comparative statics (Milgrom & Shannon, 1994), though we are unaware of it having been stated explicitly. With it in hand, we can ask how expanding migrants' job options affects wages:

**Proposition A.2.** *Consider expanding $\mathbf{F}_o^{migrant}$ such that occupation-$o$ migrants can work at any firm: $\mathbf{F}_o^{migrant} = \mathbf{F}_o$. Under a competitive equilibrium, Assumption A.1 implies that workers' wages will be unchanged. Under a wage-posting equilibrium, assumptions A.1, A.2 and A.3 imply that wages at every firm will increase.*

*Proof.* Given Assumption A.1, the marginal product of each occupation $o$ is exogenous. The claim about competitive equilibrium follows from Lemma A.1.

We will now prove that in a Bertrand wage-posting equilibrium, when A.2, A.3 and A.1 hold, allowing migrants to work at any firm will increase wages at every firm.

In what follows, let $\mathbf{F}_o^{migrant,0}$ denote the set of firms at which migrants could work initially. Let $\eta_{f,o}^{migrant}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{migrant}\right)$ denote the elasticity of migrant labor supply to the firm $f$, when migrants can work at firms $\mathbf{F}_o^{migrant} \in \left\{\mathbf{F}_o^{migrant,0}, \mathbf{F}_o\right\}$. We continue to use $\eta_{f,o}^{resident}\left((w_{g,o})_{g \in \mathbf{F}_o}\right)$ to denote the elasticity of resident labor supply to firm $f$ (conditional on wages, the labor supply of residents does not depend on $\mathbf{F}_o^{migrant}$).

Let $\eta_{f,o}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{migrant}\right)$ denote the overall elasticity of labor supply to firm $f$. This overall elasticity is a weighted average of the group-specific elasticities:

$$\eta_f\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{migrant}\right) = \sigma_{o,f}^{migrant}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{migrant}\right) \eta_{f,o}^{migrant}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{migrant}\right)$$
$$+ \sigma_{o,f}^{resident}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{migrant}\right) \eta_{f,o}^{resident}\left((w_{g,o})_{g \in \mathbf{F}_o}\right), \quad (27)$$

where $\sigma_{o,f}^{migrant}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{migrant}\right)$ is the (endogenous) share of effective labor supplied by migrants and $\sigma_{o,f}^{resident}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{migrant}\right)$ is the share supplied by residents.

The remainder of the proof consists of 6 steps.

*Step 1: For every wage schedule $(w_{g,o})_{g\in\mathbf{F}_o}$ and firm $f$: $\frac{\partial}{\partial\log w_f}\eta_{f,o}^{resident}\left((w_{g,o})_{g\in\mathbf{F}_o}\right) < 0$.*
Given the assumed form for the utility function $u_i(w,f) = we^{\nu_{i,f}}$, if for any two firms $f,g$ it's the case that $u_i\left(w_f,f\right) > u_i\left(w_g,g\right)$ then, for any $c > 0$, it must be the case that $u_i\left(cw_f,f\right) > u_i\left(cw_g,g\right)$. It follows that

$$\forall f \in \mathbf{F}_o: \sum_{g\in\mathbf{F}_o}\frac{\partial}{\partial\log w_{g,o}}\log\left(L_{f,o}^{\text{resident}}\right) = 0.$$

As such:

$$\eta_{f,o}^{\text{resident}} = -\sum_{g\in\mathbf{F}_o\backslash\{f\}}\frac{\partial}{\partial\log w_{g,o}}\log\left(L_{f,o}^{\text{resident}}\right).$$

Differentiating both sides of that equation with respect to $\log w_{f,o}$ implies that

$$\frac{\partial}{\partial\log w_{f,o}}\eta_{f,o}^{\text{resident}} = -\frac{\partial}{\partial\log w_{f,o}}\sum_{g\in\mathbf{F}\backslash\{f\}}\frac{\partial}{\partial\log w_{g,o}}\log\left(L_{f,o}^{\text{resident}}\right)$$

$$= -\sum_{g\in\mathbf{F}\backslash\{f\}}\frac{\partial}{\partial\log w_{g,o}}\frac{\partial}{\partial\log w_{f,o}}\log\left(L_{f,o}^{\text{resident}}\right)$$

$$= -\sum_{g\in\mathbf{F}\backslash\{f\}}\frac{\partial}{\partial\log w_{g,o}}\eta_{f,o}^{\text{resident}}.$$

By Assumption A.3, for each $g \neq f$: $\frac{\partial}{\partial\log w_{g,o}}\eta_{f,o}^{\text{resident}} > 0$. Thus $\frac{\partial}{\partial\log w_{f,o}}\eta_{f,o}^{\text{resident}} < 0$.

*Step 2: When migrants can work at any firm, the elasticity of labor supply facing each firm equals the elasticity of resident labor supply: $\eta_f\left((w_{g,o})_{g\in\mathbf{F}_o},\mathbf{F}_o\right) = \eta_{f,o}^{resident}\left((w_{g,o})_{g\in\mathbf{F}_o}\right)$.*
By Assumption A.2: $\eta_{f,o}^{\text{migrant}}\left((w_{g,o})_{g\in\mathbf{F}_o},\mathbf{F}_o\right) = \eta_{f,o}^{\text{resident}}\left((w_{g,o})_{g\in\mathbf{F}_o}\right)$. With Equation (27), this implies that $\eta_f\left((w_{g,o})_{g\in\mathbf{F}_o},\mathbf{F}_o\right) = \eta_{f,o}^{\text{resident}}\left((w_{g,o})_{g\in\mathbf{F}_o}\right)$.

*Step 3: When migrants can work at any firm, wages are strategic complements.*
By Lemma A.3, each firm $f$'s wage solves the equation

$$w_{f,o} = \left(\frac{1}{1 + \frac{1}{\eta_{f,o}\left(w_{f,o},w_{-f,o},\mathbf{F}_o^{\text{migrant}}\right)}}\right)y'_{f,o},$$

where $y'_{f,o}$ is the marginal product of occupation-$o$ workers at firm $f$; by Assumption A.1 $y'_{f,o}$ is a constant. By Step 2, $\eta_{f,o}\left(w_{f,o},w_{-f,o},\mathbf{F}_o\right) = \eta_{f,o}^{\text{resident}}\left(w_{f,o},w_{-f,o}\right)$. As such, when migrants can work at any firm (i.e. when $\mathbf{F}_o^{\text{migrant}} = \mathbf{F}_o$), then:

$$w_{f,o} = \left(\frac{1}{1 + \frac{1}{\eta_{f,o}^{\text{resident}}\left(w_{f,o},w_{-f,o}\right)}}\right)y'_{f,o}, \tag{28}$$

By Assumption A.3, $\eta_{f,o}^{\text{resident}}$ is increasing in $w_{-f,o}$. By Step 1, $\eta_{f,o}^{\text{resident}}$ is decreasing in $w_{f,o}$. The right hand side of Equation (28) is increasing in $\eta_{f,o}^{\text{resident}}$. Thus, by Lemma A.4, $w_{f,o}$ is increasing in $w_{-f,o}$.

*Step 4: Allowing migrants to work at any firm increases the best response schedules of firms which could initially employ migrants.*

In this step, fix a firm $f^* \in \mathbf{F}_o^{\text{migrant},0}$. Let *effective*$\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{G}\right)$ denote the vector-valued function

$$\left[\textit{effective}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{G}\right)\right]_f = \begin{cases} w_{f,o} & \text{if } f \in \mathbf{G}; \\ 0 & \text{if } f \notin \mathbf{G}. \end{cases}$$

By Assumption A.2, migrants' preferences over firms are the same as residents would be, were wages at firms *not* in $\mathbf{F}^{\text{migrant}}$ sufficiently low that no resident would want to work there. Thus:

$$\eta_{f^*,o}^{\text{migrant}}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{\text{migrant},0}\right) = \eta_{f^*}^{\text{resident}}\left(\textit{effective}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{\text{migrant},0}\right)\right). \tag{29}$$

By construction, $(w_{g,o})_{g \in \mathbf{F}_o} > \textit{effective}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{\text{migrant},0}\right)$ (where $>$ is the standard vector partial order), and given that $f^* \in \mathbf{F}_o^{\text{migrant},0}$: $w_{f^*} = \textit{effective}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{\text{migrant},0}\right)_{f^*}$. Thus, by Assumption A.3,

$$\eta_{f^*,o}^{\text{resident}}\left(\textit{effective}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{\text{migrant},0}\right)\right) < \eta_{f^*,o}^{\text{resident}}\left((w_{g,o})_{g \in \mathbf{F}_o}\right). \tag{30}$$

Combining expressions (29) and (30) implies that

$$\eta_{f^*,o}^{\text{migrant}}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{\text{migrant},0}\right) < \eta_{f^*,o}^{\text{resident}}\left((w_{g,o})_{g \in \mathbf{F}_o}\right) \tag{31}$$

Equation (27) implies that $\eta_{f^*}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{\text{migrant},0}\right)$ is a convex combination of $\eta_{f^*,\text{resident}}\left((w_{g,o})_{g \in \mathbf{F}_o}\right)$ and of $\eta_{f^*,\text{migrant}}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{\text{migrant},0}\right)$. By Step 2: $\eta_{f^*}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o\right) = \eta_{f^*}^{\text{resident}}\left((w_{g,o})_{g \in \mathbf{F}_o}\right)$. Given inequality (31), it must therefore be the case that

$$\eta_{f^*,o}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o\right) > \eta_{f^*,o}\left((w_{g,o})_{g \in \mathbf{F}_o}, \mathbf{F}_o^{\text{migrant},0}\right). \tag{32}$$

By Lemma A.3, firm $f^*$'s best-response schedule $w_{f^*,o}\left(w_{-f^*,o}; \mathbf{F}_o^{\text{migrant}}\right)$ solves the equation

$$w_{f^*,o} = \left(\frac{1}{1 + \frac{1}{\eta_f\left(w_{f^*,o}, w_{-f^*,o}, \mathbf{F}_o^{\text{migrant}}\right)}}\right) y'_{f^*,o}. \tag{33}$$

Treating $w_{-f^*,o}$ as fixed, Step 1 implies that the right hand side of Equation (33) is decreasing in $w_{f^*,o}$ whereas Expression (32) implies that the right hand side of Equation (33) increases when $\mathbf{F}_o^{\text{migrant}}$ expands from $\mathbf{F}_o^{\text{migrant},0}$ to $\mathbf{F}_o$. By Lemma A.4, for any $w_{-f^*,o}$:

$$w_{f^*,o}\left(w_{-f^*,o}; \mathbf{F}_o^{\text{migrant},0}\right) < w_{f^*,o}\left(w_{-f^*,o}; \mathbf{F}\right).$$

85

*Step 5: Allowing migrants to work at any firm leaves unchanged the best response schedules of firms which could not initially employ migrants.*

Fix a firm $f^* \notin \mathbf{F}_o^{\text{migrant},0}$. For such a firm, $\eta_{f^*,o}\left(w_{f^*,o}, w_{-f^*,o}, \mathbf{F}_o^{\text{migrant},0}\right) = \eta_{f^*,o}^{\text{resident}}\left(w_{f^*,o}, w_{-f^*,o}\right)$. By Step 2, $\eta_{f^*,o}\left(w_{f^*,o}, w_{-f^*,o}, \mathbf{F}_o\right) = \eta_{f^*,o}^{\text{resident}}\left(w_{f^*,o}, w_{-f^*,o}\right)$. Thus:

$$\eta_{f^*}\left(w_{f^*}, w_{-f^*}, \mathbf{F}_o^{\text{migrant},0}\right) = \eta_{f^*}\left(w_{f^*}, w_{-f^*}, \mathbf{F}_o\right). \tag{34}$$

By Lemma 3, each firm $f$'s best response schedule solves the equation

$$w_{f,o} = \left(\frac{1}{1 + \frac{1}{\eta_f\left(w_{f,o}, w_{-f,o}, \mathbf{F}_o^{\text{migrant}}\right)}}\right) y'_{f,o},$$

given $w_{-f,o}$. By Equation (34) this best response schedule will be invariant over $\mathbf{F}_o^{\text{migrant}} \in \left\{\mathbf{F}_o^{\text{migrant},0}, \mathbf{F}_o\right\}$.

*Step 6: Allowing migrants to work at any firm will increase wages at every firm.*

Let $\left(w_{g,o}^0\right)_{g \in \mathbf{F}_o}$ denote the equilibrium wages when migrants can only work at firms in $\mathbf{F}_o^{\text{migrant},0}$, and let $\left(w_{g,o}^*\right)_{g \in \mathbf{F}_o}$ denote the equilibrium wages when migrants can work at any firm in $\mathbf{F}_o$. Let $BR\left(\left(w_{g,o}\right)_{g \in \mathbf{F}_o}, \mathbf{F}_o^{\text{migrant}}\right)$ denote the best-response schedule which returns the wage that each firm would choose were other firms to choose wage $\left(w_{g,o}\right)_{g \in \mathbf{F}_o}$ when migrants can work at firms $\mathbf{F}_o^{\text{migrant}}$. By steps 4 and 5:

$$\left(w_{g,o}^0\right)_{g \in \mathbf{F}_o} < BR\left(\left(w_{g,o}^0\right)_{g \in \mathbf{F}_o}, \mathbf{F}_o\right).$$

Let $\left(w_{g,o}^1\right)_{g \in \mathbf{F}_o} \equiv BR\left(\left(w_{g,o}^0\right)_{g \in \mathbf{F}_o}, \mathbf{F}_o\right)$, let $\left(w_{g,o}^2\right)_{g \in \mathbf{F}_o} \equiv BR\left(\left(w_{g,o}^1\right)_{g \in \mathbf{F}_o}, \mathbf{F}_o\right)$, etc. By Step 4, the sequence $\left(\left(w_{g,o}^k\right)_{g \in \mathbf{F}_o}\right)_{k=0}^{\infty}$ is monotonically increasing. By Lemma A.2 the sequence is bounded above by firms' marginal products, and thus by the monotone convergence theorem the sequence converges. Given that best responses converge (and that the best response schedule is continuous), they converge to the equilibrium. Thus:

$$\left(w_{g,o}^0\right)_{g \in \mathbf{F}_o} < \left(w_{g,o}^1\right)_{g \in \mathbf{F}_o} < \left(w_{g,o}^2\right)_{g \in \mathbf{F}_o} < ... < \lim_{k \to \infty}\left(w_{g,o}^k\right)_{g \in \mathbf{F}_o} = \left(w_{g,o}^*\right)_{g \in \mathbf{F}_o},$$

completing the proof of Step 6 and thus of Proposition A.2. □

# B   Identification of the Stayers Average Treatment Effect

This appendix formalizes the identification argument made in Subsection 5.3. We are interested in how winning a resident visa lottery — which increases workers' outside job options —

affects the earnings of those workers who remain at their pre-lottery firm. In this appendix, we consider a stylized setup under which this conditional average treatment effect is nonpara-metrically identified. We hope that this clarifies the role played by the parametric conditions imposed in Subsection 5.3.

Consider a population $\Omega$ of workers, who are all observed in two periods $t \in \{0, 1\}$. Timing is as follows:

0.1 Each worker has an initial firm.

0.2 Each worker receives earnings from their initial firm.

0.3 The lottery is held, and workers learn whether they have become residents.

1.1 Workers optionally move to a new firm.

1.2 Each worker receives earnings from their current firm.

We use the potential outcomes framework to represent workers' counterfactual outcomes: let $Y_{i,t}(W, M)$ denote the potential log earnings of worker $i \in \Omega$ in period $t \in 0, 1$; log earnings depend on whether they won their lottery $W$ and whether they moved firms $M$. Whether the worker moves firms will itself depend on whether they won their lottery; we represent this dependence with an additional potential outcome $M_i(W)$. As is standard in the potential outcomes framework, we abuse notation by also letting $Y_{i,t}$ and $M_i$ represent *realized* outcomes; we thus have that

$$Y_{i,t} = Y_{i,t}(W_i, M_i) = Y_{i,t}(W_i, M_i(W_i)),$$

where $W_i$ indicates whether $i$ won their lottery.

We hope to identify the *stayers average treatment effect*:

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

In words: $\text{ATE}_{\text{stayers}}$ measures the average effect of winning a resident visa lottery on workers' log earnings, among those workers who do not switch jobs.

We will show that $\text{ATE}_{\text{stayers}}$ can be identified under the following conditions:

**Assumption B.1 (random lottery).** *The lottery is independent of workers' potential outcomes:*

$$W_i \perp\!\!\!\perp \left(M_i(W)\right)_{W \in 0,1}, \left(Y_{i,t}(W, M)\right)_{W,M,t \in 0,1}.$$

In our application, winning the lottery is only random conditional on the lottery a worker has entered. With Assumption B.1, we consider the simpler case in which the lottery is unconditionally random. In our empirical analysis we relax Assumption B.1 by allowing for selection into different lotteries.

**Assumption B.2 (losers stay).** *Lottery losers never switch jobs:* $\forall i \in \Omega : M_i(0) = 0$.

As discussed in Subsection 5.3, we rely on Assumption B.2 to prove *nonparametric* identification. In our empirical analysis we relax Assumption B.2 at the cost of additional parametric structure.

**Assumption B.3 (Markovian moves).** *The decision to move firms is Markovian in counterfactual earnings:*

$$M_i(1) \perp\!\!\!\perp Y_{i,0}(0,0) \mid Y_{i,1}(0,0).$$

Assumption B.3 requires that a worker's decision to move firms is independent of historic earnings, given what the worker would earn were they not to move firms. We view Assumption B.3 as plausible in contexts in which historic earnings are uninformative about the benefit of staying at a job, given current earnings. Assumption B.3 might fail if jobs differ in their earnings trajectories, or when workers' decisions to leave a job depends on their accumulated wealth.

**Assumption B.4 (arrow of time).** $Y_{i,0}(0,0) = Y_{i,0}(1,0) = Y_{i,0}(0,1) = Y_{i,0}(1,1)$.

Assumption B.4 requires that winning the lottery or moving firms in period 1 has no effect on period 0 outcomes.

Let both $Y_{i,0}(0,0)$ and $Y_{i,1}(0,0)$ have support $\mathcal{Y}$. We require that probability of switching given either $Y_{i,0}(0,0)$ objects are square-integrable on $\mathcal{Y}$:

**Assumption B.5 (regularity).** *Both the function* $\mathbb{P}\left[M_i(1) = 1 \big| Y_{i,0}(0,0) = y_0\right]$ *and the function* $\mathbb{P}\left[M_i(1) = 1 \big| Y_{i,1}(0,0) = y_1\right]$ *lie within* $\mathcal{H}$, *a known subset of square-integrable functions on* $\mathcal{Y}$*:*

$$\left\{\mathbb{P}\left[M_i(1) = 1 \big| Y_{i,0}(0,0) = y_0\right], \mathbb{P}\left[M_i(1) = 1 \big| Y_{i,1}(0,0) = y_1\right]\right\} \subset \mathcal{H} \subset \mathcal{L}^2(\mathcal{Y}),$$

*while the function* $d\mathbb{P}\left[Y_{i,1}(0,0) \le y_1 \mid Y_{i,0}(0,0) = y_0\right]$ *is square-integrable on* $\mathcal{Y}^2$.

Finally, we require that the data generating process for counterfactual earnings be sufficiently non-degenerate:

**Assumption B.6 (completeness).** *The null space of the kernel $d\mathbb{P}\left[Y_{i,1}(0,0) \leq y_1 \mid Y_{i,0}(0,0) = y_0\right]$ is 0:*

$$\forall f \in \mathcal{H}: \text{ if } \int_{y_1 \in \mathcal{Y}} f\left(y_1\right) dF_{Y_{i1}(0,0)}\left(y_1 \mid Y_{i,0}(0,0) = y_0\right) = 0, \text{ then for all } y_1 : f\left(y_1\right) = 0,$$

*where $\mathcal{H}$ is the function space assumed by Assumption B.5.*

If earnings have discrete support, Assumption B.6 requires that its transition matrix be invertible. Assumption B.6 will also be satisfied whenever $Y_{i,1}(0,0)$ is increasing in $Y_{i,0}(0,0)$ (in the sense of first order stochastic dominance), as would be the case if they were positively correlated normals. Assumption B.6 is similar to the completeness condition required by the nonparametric instrumental variables literature (D'Haultfoeuille, 2011).

**Proposition B.1.** *Given Assumptions B.1–B.6, the average treatment effect among stayers is identified from the joint distribution of earnings, moving indicators and lottery-winning indicators $\left(Y_{i,0}, Y_{i,1}, M_i, W_i\right)_{i \in \Omega}$.*

*Proof.* First, note that, because the lottery is random (Assumption B.1), we can infer use lottery-winning job-stayers to infer $\mathbb{E}\left[Y_{i,1}(1,0) \mid M_i(1) = 0\right]$:

$$\begin{aligned}
\mathbb{E}\left[Y_{i,1}(1,0) \mid M_i(1) = 0\right] &= \mathbb{E}\left[Y_{i,1}(1,0) \big| M_i(1) = 0, W_i = 1\right] \\
&= \mathbb{E}\left[Y_{i,1} \big| M_i = 0, W_i = 1\right],
\end{aligned}$$

which is observed. It thus remains to identify $\mathbb{E}\left[Y_{i,1}(0,0) \mid M_i(1) = 0\right]$.

We will next show that we can infer how a worker's decision to move depends on her initial earnings by only looking at lottery winners. Given that the lottery is random (Assumption B.1), we can condition on lottery winners:

$$\mathbb{P}\left[M_i(1) = 1 \big| Y_{i,0}(0,0) = y_0\right] = \mathbb{P}\left[M_i(1) = 1 \big| Y_{i,0}(0,0) = y_0, W_i = 1\right].$$

Given our timing assumption (Assumption B.4), $Y_{i,0} = Y_{i,0}(0,0)$, and so:

$$\mathbb{P}\left[M_i(1) = 1 \big| Y_{i,0}(0,0) = y_0, W_i = 1\right] = \mathbb{P}\left[M_i(1) = 1 \big| Y_{i,0} = y_0, W_i = 1\right].$$

Finally, among the population with $W_i = 1$, $M_i(1) = M_i$. Thus

$$\mathbb{P}\left[M_i(1) = 1 \big| Y_{i,0} = y_0, W_i = 1\right] = \mathbb{P}\left[M_i = 1 \big| Y_{i,0} = y_0, W_i = 1\right].$$

Combining equalities, we have

$$\mathbb{P}\left[M_i(1) = 1 \big| Y_{i,0}(0,0) = y_0\right] = \mathbb{P}\left[M_i = 1 \big| Y_{i,0} = y_0, W_i = 1\right], \tag{35}$$

the right hand side of which is observed.

Similarly, we will now show that we can identify the joint distribution of $\left(Y_{i,0}(0,0), Y_{i,1}(0,0)\right)$ from lottery losers. Given that the lottery is random (Assumption B.1):

$$\mathbb{P}\left[Y_{i,1}(0,0) \leq y_1 \mid Y_{i,0}(0,0) = y_0\right] = \mathbb{P}\left[Y_{i,1}(0,0) \leq y_1 \mid Y_{i,0}(0,0) = y_0, W_i = 0\right].$$

Assumption B.2 required that lottery losers never switch firms, and so having already conditioned on $W_i = 0$ we can additionally condition on $M_i = 0$:

$$\mathbb{P}\left[Y_{i,1}(0,0) \leq y_1 \mid Y_{i,0}(0,0) = y_0, W_i = 0\right] = \mathbb{P}\left[Y_{i,1}(0,0) \leq y_1 \mid Y_{i,0}(0,0) = y_0, W_i = 0, M_i = 0\right].$$

By our timing assumption (Assumption B.4) $Y_{i,0} = Y_{i,0}(0,0)$, and so:

$$\mathbb{P}\left[Y_{i,1}(0,0) \leq y_1 \mid Y_{i,0}(0,0) = y_0, W_i = 0, M_i = 0\right] = \mathbb{P}\left[Y_{i,1}(0,0) \leq y_1 \mid Y_{i,0} = y_0, W_i = 0, M_i = 0\right].$$

Finally, among with population with $W_i = 0$ and $M_i = 0$: $Y_{i,1}(0,0) = Y_{i,1}$. As such:

$$\mathbb{P}\left[Y_{i,1}(0,0) \leq y_1 \mid Y_{i,0} = y_0, W_i = 0, M_i = 0\right] = \mathbb{P}\left[Y_{i,1} \leq y_1 \mid Y_{i,0} = y_0, W_i = 0, M_i = 0\right].$$

Combining equalities, we have that

$$\mathbb{P}\left[Y_{i,1}(0,0) \leq y_1 \mid Y_{i,0}(0,0) = y_0\right] = \mathbb{P}\left[Y_{i,1} \leq y_1 \mid Y_{i,0} = y_0, W_i = 0, M_i = 0\right], \tag{36}$$

the right hand side of which is observed.

By the law of total probability:

$$\mathbb{P}\left[M_i(1) = 1 \mid Y_{i,0}(0,0) = y_0\right]$$
$$= \int_{y_1 \in \mathcal{Y}} \mathbb{P}\left[M_i(1) = 1 \mid Y_{i,0}(0,0) = y_0, Y_{i,1}(0,0) = y_1\right] d\mathbb{P}\left[Y_{i,1}(0,0) \leq y_1 \mid Y_{i,0}(0,0) = y_0\right]. \tag{37}$$

By Assumption B.3:

$$\mathbb{P}\left[M_i(1) = 1 \mid Y_{i,0}(0,0) = y_0, Y_{i,1}(0,0) = y_1\right] = \mathbb{P}\left[M_i(1) = 1 \mid Y_{i,1} = y_1\right]. \tag{38}$$

Substituting equations (35), (36) and (38) into Equation (37) yields the equation

$$\mathbb{P}\left[M_i = 1 \mid Y_{i,0} = y_0, W_i = 1\right]$$
$$= \int_{y_1 \in \mathcal{Y}} \mathbb{P}\left[M_i(1) = 1 \mid Y_{i,1}(0,0) = y_1\right] d\mathbb{P}\left[Y_{i,1} \leq y_1 \mid Y_{i,0} = y_0, W_i = 0, M_i = 0\right]. \tag{39}$$

Equation (39) is a Fredholm integral equation of the first kind. Given assumptions B.5 and B.6, $\mathcal{H}$ contains at most one solution for $\mathbb{P}\left[M_i(1) = 1 \mid Y_{i,1}(0,0) = y_1\right]$ in terms of $\mathbb{P}\left[M_i = 1 \mid Y_{i,0} = y_0, W_i = 1\right]$ and $d\mathbb{P}\left[Y_{i,1} \leq y_1 \mid Y_{i,0} = y_0, W_i = 0, M_i = 0\right]$ (Vangel, 1992; Groetsch, 2007). Given that both the

function $\mathbb{P}\left[M_i = 1 \middle| Y_{i,0} = y_0, W_i = 1\right]$ and the function $d\mathbb{P}\left[Y_{i,1} \le y_1 \middle| Y_{i,0} = y_0, W_i = 0, M_i = 0\right]$ are observed, it follows that we can identify $\mathbb{P}\left[M_i(1) = 1 \middle| Y_{i,1} = y_1\right]$.

We will now use $\mathbb{P}\left[M_i(1) = 1 \middle| Y_{i,1}(0,0) = y_1\right]$ to identify $\mathbb{E}\left[Y_{i,1}(0,0) \mid M_i(1) = 0\right]$. By Assumption B.1:

$$\mathbb{P}\left[M_i(1) = 1\right] = \mathbb{P}\left[M_i(1) = 1 | W_i = 1\right] = \mathbb{P}\left[M_i = 1 | W_i = 1\right]. \tag{40}$$

Invoking both Assumption B.1 and Assumption B.2:

$$\mathbb{P}\left[Y_{i,1}(0,0) \le y_1\right] = \mathbb{P}\left[Y_{i,1}(0,0) \le y_1 \middle| W_i = 0\right] = \mathbb{P}\left[Y_{i,1}(0,0) \le y_1 \middle| W_i = 0, M_i = 0\right]$$
$$= \mathbb{P}\left[Y_{i,1} \le y_1 \middle| W_i = 0, M_i = 0\right]. \tag{41}$$

By Bayes' rule:

$$d\mathbb{P}\left[Y_{i,1}(0,0) \le y_1 \middle| M_i(1) = 1\right] = \mathbb{P}\left[M_i(1) = 1 \middle| Y_{i,1}(0,0) = y_1\right] \frac{d\mathbb{P}\left[Y_{i,1}(0,0) \le y_1\right]}{\mathbb{P}\left[M_i(1) = 1\right]}. \tag{42}$$

Substituting equations (40) and (41) into Equation (42) yields the equation

$$d\mathbb{P}\left[Y_{i,1}(0,0) \le y_1 \middle| M_i(1) = 1\right] = \mathbb{P}\left[M_i(1) = 1 \middle| Y_{i,1}(0,0) = y_1\right] \frac{d\mathbb{P}\left[Y_{i,1} \le y_1 \middle| W_i = 0, M_i = 0\right]}{\mathbb{P}\left[M_i = 1 | W_i = 1\right]}. \tag{43}$$

Each term on the right hand side of Equation (43) is identified, and thus its left hand side is as well. Integrating over $d\mathbb{P}\left[Y_{i,1}(0,0) \le y_1 \middle| M_i(1) = 1\right]$ yields $\mathbb{E}\left[Y_{i,1}(0,0) \mid M_i(1) = 0\right]$. We have thus identified both $\mathbb{E}\left[Y_{i,1}(1,0) \mid M_i(1) = 0\right]$ and $\mathbb{E}\left[Y_{i,1}(0,0) \mid M_i(1) = 0\right]$. Differencing these two expectations yields the stayers average treatment effect $\text{ATE}_{\text{stayers}}$.

$\square$

# C  Estimation algorithm for the stayers average treatment effect

In this appendix we specify the algorithm with which we estimate the parametric model discussed in Subsection 5.3. The algorithm imposes Bayesian priors on the model parameters, and then calculates the posterior using a Gibbs sampler.

**Model.** For the reader's convenience, we here repeat the model from Subsection 5.3.

Associate each worker $i$ with a lottery $l(i)$. Consider a worker $i$ and time $t$, where time is measured relative to the date of the worker's lottery (i.e. $t = 0$ is the quarter in which the lottery was held). Let $Y_{i,t}(W, M)$ indicate the worker's potential log earnings, where $W$ indicates that the worker won their lottery and $M$ indicates that the worker has moved firms between quarter $0$ and quarter $t$. The worker's decision to move firms also depends on whether she won the lottery, which we represent with another potential outcome $M_{i,t}(W)$. Letting $W_i$ indicate whether the worker won their lottery, a worker's realized log earnings are thus $Y_{i,t} = Y_{i,t}(W_i, M_{i,t}) =$

$Y_{i,t}\left(W_i, M_{i,t}(W_i)\right)$. Our target estimand is the average effect of winning the lottery, among workers who are do not move firms as a result, 1–2 years after the lottery is held:

$$\text{ATE}_{\text{stayers}} \equiv \mathbb{E}\left[ Y_{i,t}(1,0) - Y_{i,t}(0,0) \,\middle|\, M_{i,t}(1) = M_{i,t}(0) = 0; t \in 4, ..., 11 \right].$$

We impose the following assumptions:

1. $M_{i,t}(1) \geq M_{i,t}(0)$.

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

3. $\mathbb{P}\left[M_{i,t} = 1 \mid W_i, \left(Y_{i,s}(0,0)\right)_{s\leq t}, M_{i,t-1} = 0\right] = \Phi\left(\beta_0 + \beta_1 W_i + \beta_2 Y_{i,t}(0,0) + \beta_3 W_i Y_{i,t}(0,0) + \delta_{l(i),t}\right)$;

4. $Y_{i,t}(0,0) = \alpha_0 + \alpha_1 Y_{i,t-1}(0,0) + \gamma_{l(i),t} + \epsilon_{i,t};\quad \epsilon_{i,t} \sim N(0, \sigma_\epsilon)$;

5. $\left(\delta_{l,t}, \gamma_{l,t}\right) \sim N\left(0, \Sigma_{\delta\gamma}\right)$.

We condition on the population who have a stable firm in the quarter prior to the lottery: $M_{i,-1} = 0$. The model treats baseline counterfactual earnings $Y_{i,-1}(0,0)$ as fixed. Given that $Y_{i,-1}(1,0) = Y_{i,-1}(0,0)$ and that $M_{i,-1} = 0$ we can infer $Y_{i,-1}(0,0)$ from realized baseline earnings $Y_{i,-1}$. We estimate the model for 12 periods after the lottery (i.e. $t = 0, 1, ..., 11$).

**Priors.** We impose the following uninformative priors:

$\beta \sim N(0, 1000 I_4)$;

$\alpha \sim N(0, 1000 I_2)$;

$\sigma_\epsilon^2 \sim \text{inverse-gamma}(0.01, 0.01)$;

$\Sigma_{\delta\gamma} \sim \text{inverse-Wishard}(2, 0.01 I_2)$.

**Gibbs sampler.** We construct a joint posterior for $\left(M_{i,t}, Y_{i,t}(0,0)\right)$ using a Gibbs sampler.[37] Following McCulloch and Rossi (1994) we model the probit 'selection equation' using a latent variable:

$$M_{i,t} = \max\left\{M_{i,t-1}, 1\left\{m_{i,t} \geq 0\right\}\right\};$$
$$m_{i,t} \sim N\left(\beta_0 + \beta_1 W_i + \beta_2 Y_{i,t}(0,0) + \beta_3 W_i Y_{i,t}(0,0) + \delta_{l(i),t},\ 1\right).$$

The state of the Gibbs sampler is the vector

$$\theta^r \equiv \left(\left\{m_{i,t}^r\right\}, \left\{Y_{i,t}^r(0,0)\right\}, \beta^r, \alpha^r, \left\{\delta_{l,t}^r\right\}, \left\{\gamma_{l,t}^r\right\}, \Sigma_{\delta\gamma}^r, \sigma_\epsilon^r\right).$$

In each iteration of the sampler $r$, each component of $\theta^r$ is drawn conditional on the other components of $\theta^r$. Conditional posteriors for each component of $\theta^r$ are as follows:

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[37] For an overview of Gibbs sampler algorithms, including theoretical results on convergence, see Chib (2001).

- The posterior distribution of $m_{i,t}$ is truncated normal:

$$m_{i,t}^r \sim \begin{cases} N\left(\beta_0^r + \beta_1^r W_i + \beta_2^r Y_{i,t}^r(0,0) + \beta_3^r W_i Y_{i,t}^r(0,0) + \delta_{l(i),t}^r, 1\right) & \text{if } M_{i,t-1} = 1; \\ TN\left(\beta_0^r + \beta_1^r W_i + \beta_2^r Y_{i,t}^r(0,0) + \beta_3^r W_i Y_{i,t}^r(0,0) + \delta_{l(i),t}^r, 1, -\infty, 0\right) & \text{if } M_{i,t-1} = 0, M_{i,t} = 0; \\ TN\left(\beta_0^r + \beta_1^r W_i + \beta_2^r Y_{i,t}^r(0,0) + \beta_3^r W_i Y_{i,t}^r(0,0) + \delta_{l(i),t}^r, 1, 0, \infty\right) & \text{if } M_{i,t-1} = 0, M_{i,t} = 1, \end{cases}$$

where $TN(a,b,c,d)$ is the truncated normal distribution with location parameter $a$, scale parameter $b$, lower bound $c$ and upper bound $d$.

- Some values of potential log earnings $Y_{i,t}(0,0)$ are known. Others are not: because the worker is a lottery winner, because the worker has moved firms, or because log earnings for the worker are unobserved (e.g. because she is not working). For each worker $i$, let $z_i^r \equiv \left(\left\{Y_{i,t}^r(0,0)\right\}, \left\{m_{i,t}^r\right\}\right)$ concatenate both potential earnings $Y_{i,t}^r(0,0)$ and the latent variable $m_{i,t}^r$ across all periods excluding the baseline period (which we treat as fixed). Let $known(i)$ denote the components of $z_i$ which are known and let $unknown(i)$ denote the components of $z_i$ which are unknown.

Let $E\left[Y_{i,t}^r(0,0)\right]$ denote the marginal expectation of $Y_{i,t}^r(0,0)$:

$$E\left[Y_{i,t}^r(0,0)\right]_s = \alpha_1^{s+1} Y_{i,-1}(0,0) + \sum_{s'=0}^s \alpha_1^{s-s'}(\gamma_{l(i),s'} + \alpha_0).$$

Let $E\left[m_{i,t}^r\right]$ denote the marginal expectation of $m_{i,t}^r$:

$$E\left[m_{i,t}^r\right]_s = \beta_0 + \beta_1 W_i + (\beta_2 + \beta_3 W_i) E\left[Y_{i,t}^r(0,0)\right]_s + \delta_{l(i),s}.$$

Let $E\left[z_i^r\right]$ concatenate both $E\left[Y_{i,t}^r(0,0)\right]$ and $E\left[m_{i,t}^r\right]$. Let $V\left[Y_{i,t}^r(0,0)\right]$ denote the auto-covariance of $Y_{i,t}^r(0,0)$:

$$V\left[Y_{i,t}^r(0,0)\right]_{s,s} = \sigma_\epsilon^2 \sum_{s'=0}^s \alpha_1^{2(s-s')};$$

$$\forall s \neq s' : V\left[Y_{i,t}^r(0,0)\right]_{s,s'} = \alpha_1^{|s-s'|} V\left[Y_{i,t}^r(0,0)\right]_{\min\{s,s'\},\min\{s,s'\}}.$$

Let $V\left[z_i^r\right]$ denote the covariance of $z_i^r$:

$$V\left[z_i^r\right] = \begin{bmatrix} V\left[Y_{i,t}^r(0,0)\right] & (\beta_2 + \beta_3 W_i) V\left[Y_{i,t}^r(0,0)\right] \\ (\beta_2 + \beta_3 W_i) V\left[Y_{i,t}^r(0,0)\right] & (\beta_2 + \beta_3 W_i)^2 V\left[Y_{i,t}^r(0,0)\right] + I_{11}. \end{bmatrix}$$

The posterior distribution of unknown potential log earnings is normal, with mean

$$E\left[z_i^r\right]_{unknown(i)} + V\left[z_i^r\right]_{unknown(i),known(i)} \left(V\left[z_i^r\right]_{known(i),known(i)}\right)^{-1} \left((z_i)_{known(i)} - E\left[z_i^r\right]_{known(i)}\right)$$

and covariance

$$V\left[z_i^r\right]_{unknown(i),unknown(i)} - V\left[z_i^r\right]_{unknown(i),known(i)} \left(V\left[z_i^r\right]_{known(i),known(i)}\right)^{-1} V\left[z_i^r\right]_{known(i),unknown(i)}.$$

- Let $\text{RHS}^r_\beta$ be a matrix in which different rows correspond to different $i, t$ observations (for $t \geq 0$):

$$\left[\text{RHS}^r_\beta\right]_{(i,t),:} = \left[1, W_i, Y^r_{i,t}(0,0), W_i Y^r_{i,t}(0,0)\right].$$

Let $\text{LHS}^r_\beta$ be a vector comprising elements $m^r_{i,t} - \delta^r_{l(i),t}$. The posterior distribution of $\beta^r$ is normal with variance

$$\left(\text{RHS}^{r\,\prime}_\beta \text{RHS}^r_\beta + \frac{1}{1000} I_4\right)^{-1}$$

and mean

$$\left(\text{RHS}^{r\,\prime}_\beta \text{RHS}^r_\beta + \frac{1}{1000} I_4\right)^{-1} \text{RHS}^{r\,\prime}_\beta \text{LHS}^r_\beta.$$

- Let $\text{RHS}^r_\alpha$ be a matrix in which different rows correspond to different $i, t$ observations (for $t \geq 0$):

$$[\text{RHS}^r_\alpha]_{(i,t),:} = \left[1, Y^r_{i,t-1}(0,0)\right].$$

Let $\text{LHS}^r_\alpha$ be a vector comprising elements $Y^r_{i,t}(0,0) - \gamma^r_{l(i),t}$. The posterior distribution of $\alpha^r$ is normal with variance

$$\left(\text{RHS}^{r\,\prime}_\alpha \text{RHS}^r_\alpha \frac{1}{(\sigma^r_\epsilon)^2} + \frac{1}{1000} I_2\right)^{-1}$$

and mean

$$\left(\text{RHS}^{r\,\prime}_\alpha \text{RHS}^r_\alpha \frac{1}{(\sigma^r_\epsilon)^2} + \frac{1}{1000} I_2\right)^{-1} \text{RHS}^{r\,\prime}_\alpha \text{LHS}^r_\alpha \frac{1}{(\sigma^r_\epsilon)^2}.$$

- Let $N_l$ denote the number of workers in lottery $l$, let $\bar{\delta}^r_{l,t}$ be given by

$$\bar{\delta}^r_{l,t} = \frac{1}{N_l} \sum_{i:l(i)=l} \left[m^r_{i,t} - \beta_0 - \beta_1 W_i - (\beta_2 + \beta_3 W_i) Y^r_{i,t}(0,0)\right],$$

let $\tilde{\delta}^r_{l,t}$ be the expectation of $\delta_{l,t}$ conditional on $\gamma_{l,t}$:

$$\tilde{\delta}^r_{l,t} = \frac{\Sigma^r_{\delta\gamma_{1,2}}}{\Sigma^r_{\delta\gamma_{2,2}}} \gamma^r_{l,t}$$

and let $\tau^r_\delta$ denote the precision of $\delta_{l,t}$ conditional on $\gamma_{l,t}$:

$$\tau^r_\delta = \frac{1}{\Sigma^r_{\delta\gamma_{1,1}} - \frac{\Sigma^{r\,2}_{\delta\gamma_{1,2}}}{\Sigma^r_{\delta\gamma_{2,2}}}}.$$

The posterior distribution of each $\delta^r_{l,t}$ is normal, with mean

$$\frac{\bar{\delta}^r_{l,t} N_l + \tau^r_\delta \tilde{\delta}^r_{l,t}}{N_l + \tau^r_\delta}$$

and variance

$$\frac{1}{N_l + \tau^r_\delta}.$$

- Let $\bar{\gamma}^r_{l,t}$ be given by

$$\bar{\gamma}^r_{l,t} = \frac{1}{N_l} \sum_{i:l(i)=l} \left[ Y^r_{i,t}(0,0) - \alpha_0 - \alpha_1 Y^r_{i,t-1}(0,0) \right],$$

let $\tilde{\gamma}^r_{l,t}$ be the expectation of $\gamma_{l,t}$ conditional on $\delta_{l,t}$:

$$\tilde{\gamma}^r_{l,t} = \frac{\Sigma^r_{\delta\gamma 1,2}}{\Sigma^r_{\delta\gamma 1,1}} \delta^r_{l,t}$$

and let $\tau^r_\gamma$ denote the precision of $\gamma_{l,t}$ conditional on $\delta_{l,t}$:

$$\tau^r_\gamma = \frac{1}{\Sigma^r_{\delta\gamma 2,2} - \frac{\Sigma^{r\,2}_{\delta\gamma 1,2}}{\Sigma^r_{\delta\gamma 1,1}}}.$$

The posterior distribution of each $\gamma^r_{l,t}$ is normal, with mean

$$\frac{\bar{\gamma}^r_{l,t} N_l \left(\sigma^r_\epsilon\right)^{-2} + \tau^r_\gamma \tilde{\gamma}^r_{l,t}}{N_l \left(\sigma^r_\epsilon\right)^{-2} + \tau^r_\gamma}$$

and variance

$$\frac{1}{N_l \left(\sigma^r_\epsilon\right)^{-2} + \tau^r_\gamma}.$$

- Let there be $L$ lotteries and note that we model $\delta_{l,t}$ for 12 periods (including period 0 but excluding period -1). Let $[\delta\gamma]^r$ be an $12L \times 2$ matrix with first column $\left(\delta^r_{l,t}\right)$ and second column $\left(\gamma^r_{l,t}\right)$. The posterior distribution of $\Sigma^r_{\delta\gamma}$ is inverse Wishart, with degrees of freedom $2 + 12B$ and scale matrix $(0.01 I_2 + [\delta\gamma]^{r\prime}[\delta\gamma]^r)^{-1}$.
- Let there be $N$ worker-by-quarter observations. Let $\epsilon^r \equiv \left( Y^r_{i,t}(0,0) - \alpha^r_0 - \alpha^r_1 Y^r_{i,t-1}(0,0) - \gamma^r_{l(i),t} \right)$. The posterior distribution of $\sigma^{2\,r}_\epsilon$ is inverse gamma, with shape parameter $0.01 + \frac{N}{2}$ and scale parameter $0.01 + \frac{\epsilon^{r\prime}\epsilon^r}{2}$.

We iterate the Gibbs sampler over 2000 iterations, discarding the first 200 iterations as a burn-in period. In each iteration we additionally calculate $\text{ATE}_{\text{stayers}}$ given the observed $Y_{i,t}(1,0)$ and the state $Y^r_{i,t}(0,0)$.

**Convergence.** Trace plots for the hyper-parameters are depicted in Appendix Figure A3. Evidently the sampler quickly converges to its equilibrium distribution, and the choice of a 200-iteration burn-in is sufficient.

# D   Estimating an Average Effect of Including an Occupation on an Essential Skills in Demand List

In this appendix, we present the estimator used in Section 6, which recovers an average effect of including an occupation on an Essential Skills in Demand list. To allow other research to use our estimator we will keep the exposition general; we work with a potential outcomes model similar to those used elsewhere in the difference-in-difference literature. After presenting this model, in this appendix we define our estimator and show that the estimator is unbiased for an average treatment effect.

Our approach is very similar to those proposed by De Chaisemartin and d'Haultfoeuille (2020) and De Chaisemartin and d'Haultfoeuille (2024). Our approach differs from De Chaisemartin and d'Haultfoeuille (2024) in that it exploits each event in which a unit's treatment changes, not just each unit's first such event.[38] Our approach differs from De Chaisemartin and d'Haultfoeuille (2020) in that it allows for dynamic treatment effects: we allow the outcome to depend not only whether the unit's current treatment status but also on its historic treatment status, up to a certain *a priori* lag.

**The statistical model**. Consider a balanced panel comprising a cross-section of units $g \in G$ and periods $t \in \mathcal{T} \subset \mathbb{N}$. Units are drawn independently from a population $\mathcal{G}$. The econometrician observes an outcome $Y_{g,t} \in \mathbb{R}$ and treatment status $Z_{g,t} \in \{0,1\}$ for each $(g,t) \in G \times \mathcal{T}$. With three assumptions —

**Assumption D.1 (SUTVA).** *A unit's outcome depends only on their own treatment.*

**Assumption D.2 (no anticipation).** *A unit's outcome depends only on their current and lagged, not on their future treatments.*

**Assumption D.3 (finite relevant history).** *A unit's outcome depends only on their current treatment and up to L lags of their treatment.*

— we can define unit $g$'s potential outcome as $Y_{g,t}(\mathbf{Z}_{g,t})$, where $\mathbf{Z}_{g,t}$ is the vector $\mathbf{Z}_{g,t} \equiv (Z_{g,s})_{t-L \leq s \leq t}$. We impose the parallel trends assumption as:

**Assumption D.4 (parallel trends).** *Conditional on a treatment history $\mathbf{Z}_{g,t_0}$, changes in potential outcomes are mean independent of changes to treatments:*

$$\forall t_0 < s, \mathbf{Z} \in \{0,1\}^{L+1} : E\left[Y_{g,s}(\mathbf{Z}) - Y_{g,t_0}(\mathbf{Z}) \middle| \mathbf{Z}_{g,t_0}, \mathbf{Z}_{g,s}\right] = E\left[Y_{g,s}(\mathbf{Z}) - Y_{g,t_0}(\mathbf{Z}) \middle| \mathbf{Z}_{g,t_0}\right].$$

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[38] Repeated switching is relatively common in our context. Among the 280 occupations ever included on an Essential Skills in Demand list during the period we study: 81 were always included, 142 experienced one switch, and the remaining 57 experienced at least two switches. For one example, 'Forest Scientist' was added to the Long Term Skill Shortage list in September 2010 and then removed in February 2018.

**The estimator**. Let treated$_t \equiv \{g \in G : Z_{g,t} = 1\}$. denote the set of units treated during period $t$. Let untreated$_t \equiv \{g \in G : Z_{g,t} = 0\}$ denote the set of units untreated during period $t$. Let unchanged$_{t_1,t_2}$ be the set of units with unchanged treatment status between period $t_1$ and month $t_2$:

$$\text{unchanged}_{t_1,t_2} = \left( \bigcap_{s=t_1}^{t_2} \text{treated}_s \right) \bigcup \left( \bigcap_{s=t_1}^{t_2} \text{untreated}_s \right).$$

We study both treating events, in which a unit is treated after being untreated for at least $L$ periods:

$$\text{treating\_events}_t \equiv \text{treated}_t \bigcap \text{untreated}_{t-1} \bigcap \text{unchanged}_{t-L,t-1},$$

and untreating events, in which an event is untreated after being treated for at least $L$ periods:

$$\text{untreating\_events}_t \equiv \text{untreated}_t \bigcap \text{treated}_{t-1} \bigcap \text{unchanged}_{t-L,t-1}.$$

For treating events in period $t$, the controls available to study outcomes in some later period $s \geq t$ are those units which were untreated in the $L$ periods prior to $t$, and remained untreated in $s$:

$$\text{treating\_controls}_{t,s} \equiv \text{untreated}_s \bigcap \text{unchanged}_{t-L,s}.$$

For untreating events in period $t$, the controls available to study outcomes in some later period $s \geq t$ are those units which were treated in the $L$ periods prior to $t$, and remained treated in $s$:

$$\text{untreating\_controls}_{t,s} \equiv \text{treated}_s \bigcap \text{unchanged}_{t-L,s}.$$

For each treating event, we can calculate the difference-in-difference estimate of that event using an appropriate control

$$\forall s \geq t,\, g \in \text{treating\_events}_t,\, c \in \text{treating\_controls}_{t,s} : \beta_{g,t,s,c} \equiv \left( Y_{g,s} - Y_{g,t-1} \right) - \left( Y_{c,s} - Y_{c,t-1} \right).$$

Estimates for each untreating event are similar, although we multiply them by $-1$ to preserve the convention that they represent the effect of treatment vs. no treatment:

$$\forall s \geq t,\, g \in \text{untreating\_events}_t,\, c \in \text{untreating\_controls}_{t,s} : \beta_{g,t,s,c} \equiv \left( Y_{c,s} - Y_{c,t-1} \right) - \left( Y_{g,s} - Y_{g,t-1} \right).$$

In aggregating these treatment-by-month-by-control estimates, we average first across all available controls, for each event and outcome periods

$$\forall s \geq t,\, g \in \text{treating\_events}_t : \beta_{g,t,s} \equiv \frac{1}{\left| \text{treating\_controls}_{t,s} \right|} \sum_{c \in \text{treating\_controls}_{t,s}} \beta_{g,t,s,c};$$

$$\forall s \geq t,\, g \in \text{untreating\_events}_t : \beta_{g,t,s} \equiv \frac{1}{\left| \text{untreating\_controls}_{t,s} \right|} \sum_{c \in \text{untreating\_controls}_{t,s}} \beta_{g,t,s,c}.$$

We next form an estimate for each event, averaging up to $T$ periods after the event (we use fewer months if the unit switched back to its prior status within $T$ periods):

$$\forall g \in \text{treating\_events}_t : \beta_{g,t} \equiv \frac{1}{S_{g,t}} \sum_{s=0}^{S_{g,t}} \beta_{g,t,s}; \ S_{g,t} \equiv \min\left\{t + T, \min\{s > t : g \in \text{untreated}_s\}\right\};$$

$$\forall g \in \text{untreating\_events}_t : \beta_{g,t} \equiv \frac{1}{S_{g,t}} \sum_{s=0}^{S_{g,t}} \beta_{g,t,s}; \ S_{g,t} \equiv \min\left\{t + T, \min\{s > t : g \in \text{treated}_s\}\right\}.$$

Finally, our point estimate for the average treatment effect averages across event-specific estimates:

$$\beta^{\text{ATE}} \equiv \frac{\left(\sum_t \sum_{g \in \text{treating\_events}_t} \beta_{g,t}\right) + \left(\sum_t \sum_{g \in \text{untreating\_events}_t} \beta_{g,t}\right)}{\left|\left(\bigcup_t \text{treating\_events}_t\right) \cup \left(\bigcup_t \text{untreating\_events}_t\right)\right|}.$$

**Unbiasedness.** An estimator $\beta$ is an unbiased estimator of an average treatment effect if there exists hypothetical treatments $\left(\mathbf{z}_{g,t}\right)_{g \in \mathcal{G}, t \in \mathcal{T}}$ and $\left(\mathbf{z}'_{g,t}\right)_{g \in \mathcal{G}, t \in \mathcal{T}}$ such that $\mathbf{z}_{g,t} > \mathbf{z}'_{g,t}$ and that

$$E[\beta] = E_\mu \left[Y_{g,t}\left(\mathbf{z}_{g,t}\right) - Y_{g,t}\left(\mathbf{z}'_{g,t}\right)\right],$$

where $>$ is the strict partial order on vectors,[39] and $\mu$ is a probability measure on $\mathcal{G} \times \mathcal{T}$.

**Proposition D.1.** *The estimator $\beta^{ATE}$ is an unbiased estimator of an average treatment effect.*

*Proof.* For some periods $t, s$ with $t < s$: consider a treated unit $g \in \text{treating\_events}_t$ and a control unit $c \in \text{treating\_controls}_{t,s}$. The event-, control- and period-specific estimate $\beta_{g,t,s,c}$ can be decomposed as

$$\begin{aligned}
\beta_{g,t,s,c} &\equiv \left(Y_{g,s} - Y_{o,t-1}\right) - \left(Y_{c,s} - Y_{c,t-1}\right) \\
&= \left(Y_{g,s}\left(\mathbf{z}_{g,s}\right) - Y_{g,t-1}\left(\mathbf{z}_{g,t-1}\right)\right) - \left(Y_{c,s}\left(\mathbf{z}_{c,s}\right) - Y_{c,t-1}\left(\mathbf{z}_{c,t-1}\right)\right) \\
&= \left(Y_{g,s}\left(\mathbf{z}_{g,s}\right) - Y_{g,t-1}\left(\mathbf{z}_{g,t-1}\right)\right) - \left(Y_{c,s}\left(\mathbf{z}_{c,s}\right) - Y_{c,t-1}\left(\mathbf{z}_{c,t-1}\right)\right) - Y_{g,s}\left(\mathbf{z}_{c,s}\right) + Y_{g,s}\left(\mathbf{z}_{c,s}\right) \\
&= \left(Y_{g,s}\left(\mathbf{z}_{g,s}\right) - Y_{g,s}\left(\mathbf{z}_{c,s}\right)\right) + \left(Y_{g,s}\left(\mathbf{z}_{c,s}\right) - Y_{g,t-1}\left(\mathbf{z}_{g,t-1}\right)\right) - \left(Y_{c,s}\left(\mathbf{z}_{c,s}\right) - Y_{c,t-1}\left(\mathbf{z}_{c,t-1}\right)\right).
\end{aligned}$$

By the definition of the sets $\text{treating\_events}_t$ and $\text{treating\_controls}_{t,s}$: $\mathbf{z}_{c,s} = \mathbf{z}_{c,t-1} = \mathbf{z}_{g,t-1} = \mathbf{0} \equiv (0, 0, ..., 0)$. Thus:

$$\beta_{g,t,s,c} = \left(Y_{g,s}\left(\mathbf{z}_{g,s}\right) - Y_{g,s}\left(\mathbf{z}_{c,s}\right)\right) + \left(Y_{g,s}\left(\mathbf{0}\right) - Y_{g,t-1}\left(\mathbf{0}\right)\right) - \left(Y_{c,s}\left(\mathbf{0}\right) - Y_{c,t-1}\left(\mathbf{0}\right)\right). \tag{44}$$

Taking an expectation over both sides of Equation (44), conditioning on $g \in \text{treating\_events}_t$

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[39]I.e. $\mathbf{x} > \mathbf{x}'$ iff $\mathbf{x} \neq \mathbf{x}'$ and $\forall k : \mathbf{x}_k \geq \mathbf{x}'_k$.

and $c \in$ treating_controls$_{t,s}$, yields

$$E\left[\beta_{g,t,s,c} \big| g \in \text{treating\_events}_t, c \in \text{treating\_controls}_{t,s}\right]$$

$$=E\Big[\left(Y_{g,s}\left(\mathbf{z}_{g,s}\right) - Y_{g,s}\left(\mathbf{z}_{c,s}\right)\right) + \left(Y_{g,s}\left(\mathbf{0}\right) - Y_{g,t-1}\left(\mathbf{0}\right)\right) - \left(Y_{c,s}\left(\mathbf{0}\right) - Y_{c,t-1}\left(\mathbf{0}\right)\right)$$

$$\Big| g \in \text{treating\_events}_t, c \in \text{treating\_controls}_{t,s}\Big]$$

$$=E\left[Y_{g,s}\left(\mathbf{z}_{g,s}\right) - Y_{g,s}\left(\mathbf{z}_{c,s}\right)\big| g \in \text{treating\_events}_t, c \in \text{treating\_controls}_{t,s}\right]$$

$$+E\left[Y_{g,s}\left(\mathbf{0}\right) - Y_{g,t-1}\left(\mathbf{0}\right)\big| g \in \text{treating\_events}_t, c \in \text{treating\_controls}_{t,s}\right]$$

$$-E\left[Y_{c,s}\left(\mathbf{0}\right) - Y_{c,t-1}\left(\mathbf{0}\right)\big| g \in \text{treating\_events}_t, c \in \text{treating\_controls}_{t,s}\right]. \tag{45}$$

By the assumption that units are IID:

$$E\left[Y_{g,s}\left(\mathbf{0}\right) - Y_{g,t-1}\left(\mathbf{0}\right)\big| g \in \text{treating\_events}_t, c \in \text{treating\_controls}_{t,s}\right]$$

$$=E\left[Y_{g,s}\left(\mathbf{0}\right) - Y_{g,t-1}\left(\mathbf{0}\right)\big| g \in \text{treating\_events}_t\right]. \tag{46}$$

(Note the expectation on the left hand side is properly understood as an expectation over pairs, whereas the expectation on the right hand side is an expectation over units.) Note that the set treating_events$_t$ is equal to

$$\text{treating\_events}_t = \left\{ g \in G : \mathbf{Z}_{g,t-1} = \mathbf{0}, Z_{g,t} = 1 \right\}.$$

It follows from Assumption D.4 that

$$E\left[Y_{g,s}\left(\mathbf{0}\right) - Y_{g,t-1}\left(\mathbf{0}\right)\big| g \in \text{treating\_events}_t\right] = E\left[Y_{g,s}\left(\mathbf{0}\right) - Y_{g,t-1}\left(\mathbf{0}\right)\big| \mathbf{Z}_{g,t-1} = \mathbf{0}\right]. \tag{47}$$

Combining equations (46) and (47) yields

$$E\left[Y_{g,s}\left(\mathbf{0}\right) - Y_{g,t-1}\left(\mathbf{0}\right)\big| g \in \text{treating\_events}_t, c \in \text{treating\_controls}_{t,s}\right] = E\left[Y_{g,s}\left(\mathbf{0}\right) - Y_{g,t-1}\left(\mathbf{0}\right)\big| \mathbf{Z}_{g,t-1} = \mathbf{0}\right].$$

Similarly, one can show that

$$E\left[Y_{c,s}\left(\mathbf{0}\right) - Y_{c,t-1}\left(\mathbf{0}\right)\big| g \in \text{treating\_events}_t, c \in \text{treating\_controls}_{t,s}\right] = E\left[Y_{c,s}\left(\mathbf{0}\right) - Y_{c,t-1}\left(\mathbf{0}\right)\big| \mathbf{Z}_{c,t-1} = \mathbf{0}\right].$$

Returning to Equation (45), we see that these terms cancel and are left with

$$E\left[\beta_{g,t,s,c} \big| g \in \text{treating\_events}_t, c \in \text{treating\_controls}_{t,s}\right]$$

$$= E\left[Y_{g,s}\left(\mathbf{z}_{g,s}\right) - Y_{g,s}\left(\mathbf{z}_{c,s}\right)\big| g \in \text{treating\_events}_t, c \in \text{treating\_controls}_{t,s}\right].$$

One can prove a similar result for untreating events. Proposition D.1 then follows from the linearity of unbiasedness and of sample averages. $\square$

# E   Additional Details for Structural Estimation

**Calculating the amenity value of employment.** We infer the within-market amenity terms $\xi_{f,o,x,t}$ using the labor supply of residents. Specifically, combining equations (13) and (15) implies that

$$\xi_{f,o,x,t} = \log \sigma_{f,o,x,t|c_f}^{resident} - \tau \log(w_{f,o,t}) + D_{c_f,o,x,t}, \tag{48}$$

where $D_{c,o,x,t}$ is a location-by-occupation constant.

Imposing the constraint that $\log \sum_{f \in \mathbf{F}_{c,o,t}} \exp \xi_{f,o,x,t} = 0$ on Equation (48) implies that

$$\xi_{f,o,x,t} = \log \sigma_{f,o,x,t|c_f}^{resident} - \tau \log(w_{f,o,t}) - \log \sum_{g \in \mathbf{F}_{c_f,o,t}} \exp \left( \log \sigma_{g,o,x,t|c_f}^{resident} - \tau \log(w_{g,o,t}) \right).$$

We also infer the between-market terms $\bar{\xi}_{c,o,x,t}$ using the market-level labor supply of residents. From equations (14) and (16):

$$\bar{\xi}_{c,o,x,t} = \frac{1}{\lambda} \log \sigma_{c,o,x,t}^{resident} - \log \left( \sum_{f \in \mathbf{F}_{c,o,t}} \exp \left( \tau \log(w_{f,o,t}) + \xi_{f,o,x,t} \right) \right) + D_{o,x,t}, \tag{49}$$

where $D_{o,x,t}$ is an occupation-level constant.

Imposing the constraint that $\log \sum_{c \in \mathbf{C}} \exp \bar{\xi}_{c,o,x,t} = 0$ on Equation (49) implies that

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

$$- \log \sum_{c' \in \mathbf{C}} \exp \left( \frac{1}{\lambda} \log \sigma_{c',o,x,t}^{resident} - \log \left( \sum_{f \in \mathbf{F}_{c',o,t}} \exp \left( \tau \log(w_{f,o,t}) + \xi_{f,o,x,t} \right) \right) \right).$$

**Calculating labor-augmenting productivity.** Combining equations (11) and (12) and taking logs yields the wage equation

$$\log w_{f,o,t} = \log v + \phi_{f,o,t}$$

$$+ \left( \frac{v - \rho}{\rho} \right) \log \left( \sum_{o' \in \mathbf{O}_{f,t}} \exp \left( \phi_{f,o',t} \right) L_{f,o',t}^{\rho} \right) + (\rho - 1) \log l_{f,o,t} - \log \left( 1 + \frac{1}{\eta_{f,o,t}} \right). \tag{50}$$

Rearranging Equation (50) yields:

$$\phi_{f,o,t} = \log w_{f,o,t} + \log \left( 1 + \frac{1}{\eta_{f,o,t}} \right) + (1 - \rho) \log L_{o,f,t} - \log v + C_{f,t}, \tag{51}$$

where the firm-year term $C_{f,t}$ is given by

$$C_{f,t} \equiv \left( \frac{\rho - v}{\rho} \right) \log \left( \sum_{o' \in \mathbf{O}_{f,t}} \exp \left( \phi_{f,o',t} \right) L_{f,o',t}^{\rho} \right). \tag{52}$$

Substituting Equation (51) into Equation (52) and solving for $C_{f,t}$ yields the equation

$$C_{f,t} = \left(\frac{\rho - \nu}{\nu}\right) \log\left(\sum_{o' \in \mathbf{O}_{f,t}} \exp\left(\log w_{f,o',t} + \log\left(1 + \frac{1}{\eta_{f,o',t}}\right) + \log L_{o',f,t} - \log\nu\right)\right). \quad (53)$$

Combining equations (51) and (53) (and combining the $\log\nu$ terms) yields

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

$$+ \left(\frac{\rho - \nu}{\nu}\right)\log\left(\sum_{o' \in \mathbf{O}_{f,t}} \exp\left(\log w_{f,o',t} + \log\left(1 + \frac{1}{\eta_{f,o',t}}\right) + \log L_{o',f,t}\right)\right). \quad (54)$$

# F   Additional Details for Calculation of Counterfactuals

## F.1   Imputation of amenities when no types are observed at a firm

When no type-$x$ residents are observed at an occupation, amenities must be imputed. We impute these amenities by approximating the posterior mode under the assumption that amenities are joint-normally distributed across types.

Specifically, we first calculate the empirical covariance of type-$NZ$ and type-$abroad$ amenities across firm-by-occupations at which both are observed. We then use this covariance and the observed amenities to form a normal prior for unobserved amenities; let $\mu^{\xi}_{f,o,x,t}$ and $s^{\xi}_{f,o,x,t}$ denote the mean and standard deviation of this prior. Equations (15) and (7.2) imply that, given the vector of amenities $\tilde{\xi}_{f,o,x,t}$, the distribution of occupation-$o$ type-$x$ residents across firms in location $c$ will be multinomial with assignment probability $\frac{\exp(\tau\log(w_{f,o,t}) + \tilde{\xi}_{f,o,x,t})}{\sum_{f' \in \mathbf{F}_{c,o,t}} \exp(\tau\log(w_{f',o,t}) + \tilde{\xi}_{f',o,x,t})}$. The log posterior for $\tilde{\xi}_{f,o,x,t}$, given that no type-$x$ occupation-$o$ residents are employed at firm $f$, is thus equal to

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

where the constant $C$ does not depend on the amenities and $n_{x,c,t}$ is the number of type-$x$ workers in location $c$ during period $t$. Taking a first-order condition for $\tilde{\xi}_{f,o,x,t}$ implies that the posterior mode solves the vector equation

$$-n_{x,c,t}\left(\frac{\exp(\tau\log(w_{f,o,t}) + \tilde{\xi}_{f,o,x,t})}{\sum_{f' \in \mathbf{F}_{c,o,t}} \exp(\tau\log(w_{f',o,t}) + \tilde{\xi}_{f',o,x,t})}\right) - \frac{\left(\tilde{\xi}_{f,o,x,t} - \mu^{\xi}_{f,o,x,t}\right)}{s^{\xi}_{f,o,x,t}{}^2} = 0. \quad (55)$$

This equation lacks a closed-form solution. We find an approximate solution by replacing the term $\left(\frac{\exp\left(\tau\log(w_{f,o,t})+\tilde{\xi}_{f,o,x,t}\right)}{\sum_{f'\in\mathbf{F}_{c,o,t}}\exp\left(\tau\log(w_{f',o,t})+\tilde{\xi}_{f',o,x,t}\right)}\right)$ with its evaluation at the prior $\tilde{\xi}_{f',o,x,t}\approx\mu^{\xi}_{f',o,x,t}$. This approximation simplifies Equation (55) to a linear equation, yielding our imputed value of $\tilde{\xi}_{f,o,x,t}$ as

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

We impute amenities for occupation-by-location markets at which no type-$x$ workers are observed similarly.

## F.2 A novel algorithm for drawing nested extreme value random variables

We are interested in drawing nested extreme value random variables random variables — i.e. those which follow this CDF:

$$\mathbb{P}\left[\left(X_j\right)_{j\in\mathbf{J}}\le\left(x_j\right)_{j\in\mathbf{J}}\right]=\exp\left(\sum_{C\in\mathbf{C}}\left(\sum_{j\in C}\exp\left(\frac{-x_j}{1-\sigma}\right)\right)^{1-\sigma}\right),$$

where $\mathbf{C}$ is a partition on $\mathbf{J}$ and the parameter $\sigma$ measures within-group correlation.[40] We are particularly interested in contexts in which both the set of alternatives $\mathbf{J}$ and the set of nests $\mathbf{C}$ may be large. In that context, existing algorithms (like that implemented by Stephenson (2002)) seem to be computationally infeasible.

Cardell (1997) shows that nested-logit random variables can be characterized as

$$X_j=\zeta_{C(j)}+(1-\sigma)\epsilon_j, \tag{56}$$

where $C(j)\equiv C\in\mathbf{C}: j\in C$ is the nest containing $j$, and both $X_j$ and $\epsilon_j$ have marginal standard-Gumbel distributions. The requisite distribution of $\zeta_C$ is unique but lacks a closed form; by the Convolution Theorem its characteristic function $\phi_\zeta(t)$ is given by

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

where $\Gamma(1-it)$ is the characteristic function of $X_j$, $\Gamma(1-i(1-\sigma)t)$ is the characteristic function of $(1-\sigma)\epsilon_j$, and $\Gamma$ is the gamma function. By the Fourier inversion theorem, the PDF of $\zeta$ is given by

$$f_\zeta(x)=\frac{1}{2\pi}\int_0^\infty e^{-tx}\phi_\zeta(t)dt.$$

---

[40]To allow the algorithm to be used by others, we adopt the more standard convention using the parameter $\sigma$; in our model we instead use a convention with $\lambda=1-\sigma$. Note this distribution is rarely called the 'nested extreme value distribution'; more often, it is called something like 'the generalized extreme value distribution which yields the nested logit model'.

We approximate $f_\zeta(x)$ using the Basulto-Elias (2023) R package. We then draw $\zeta_C$ using inverse transform sampling. We independently draw $\epsilon_j$ from a standard Gumbel distribution and so form $X_j$ using Equation (56).

Figure A1: How employment, visa status, hours of work and firm size change when a migrant receives a resident visa
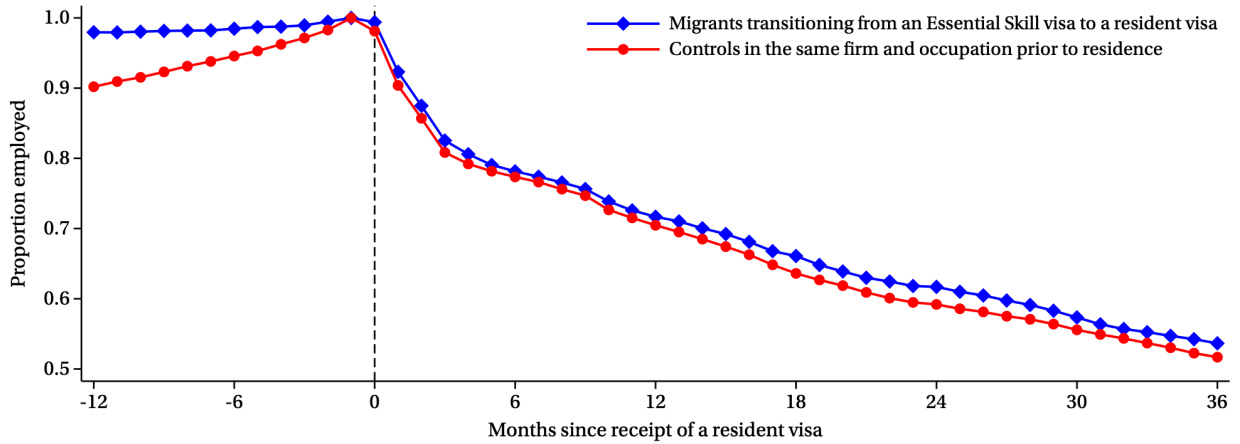


Panel A: Employment
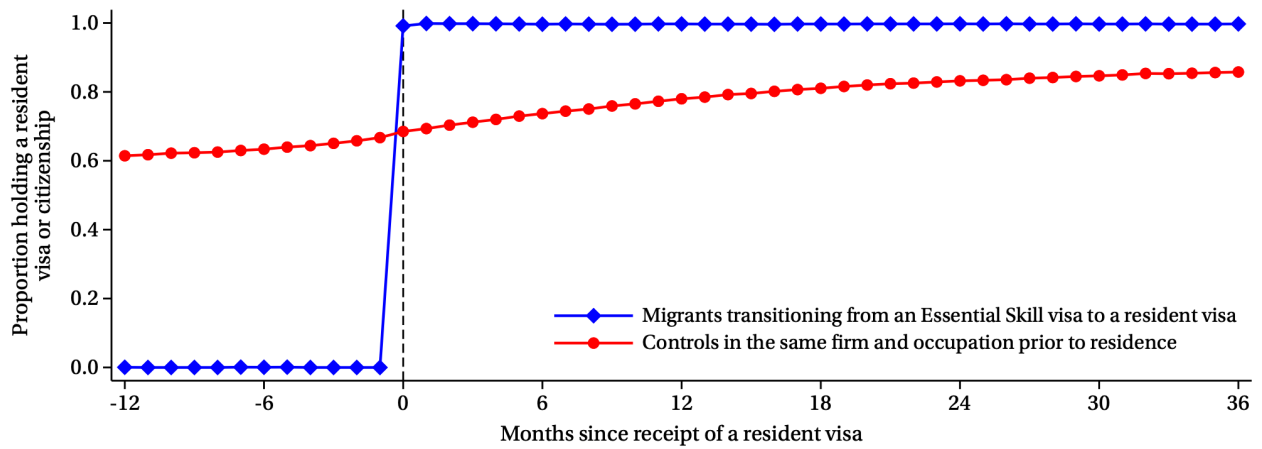


Panel B: Visa status
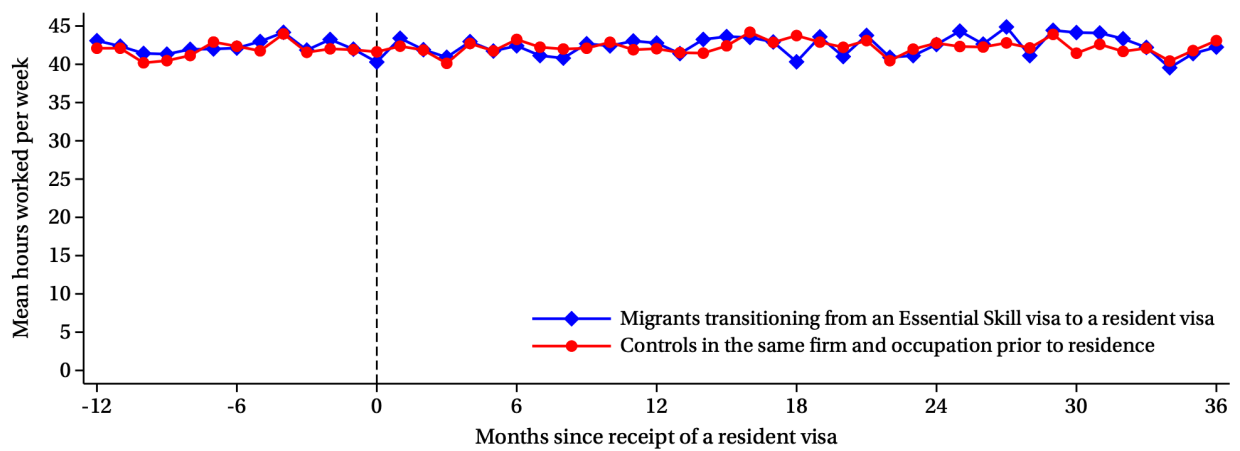


Panel C: Hours of work

Figure A1 (continued): How employment, visa status, hours of work and firm size change when a migrant receives a resident visa
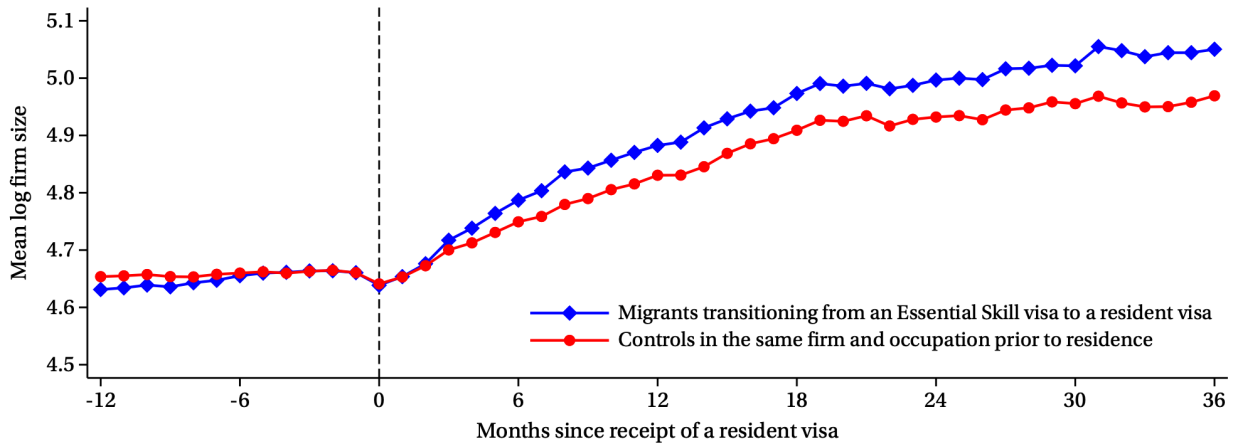


Panel D: Firm size of work

This figure depicts how employment (Panel A), visa status (Panel B), hours of work (Panel C) and firm size (Panel D) change around the time that a migrant transitions from an Essential Skills visa to a resident visa. The dependent variable in Panel A indicates a worker has positive earnings. The dependent variable in Panel B indicates that the worker held either a resident visa or citizenship at the start of the month. The dependent variable in Panel C is a worker's self-reported usual weekly hours of work. The dependent variable in Panel D is the mean log number of employees, where the mean is taken across all firms in which a worker is employed in a given month. The blue series comprise only workers who held an Essential Skills visa for at least 18 months prior to receiving a resident visa. The red series comprises workers who worked in the same firm and occupation as the modal migrant in the month prior to the modal migrants receiving a resident visa. See Section 3 for data sources and Subsection 5.1 for details on the analytic sample.

Figure A2: How including an occupation on an Essential Skills in Demand list affects earnings, by the proportion of that occupation who hold an Essential Skills visa
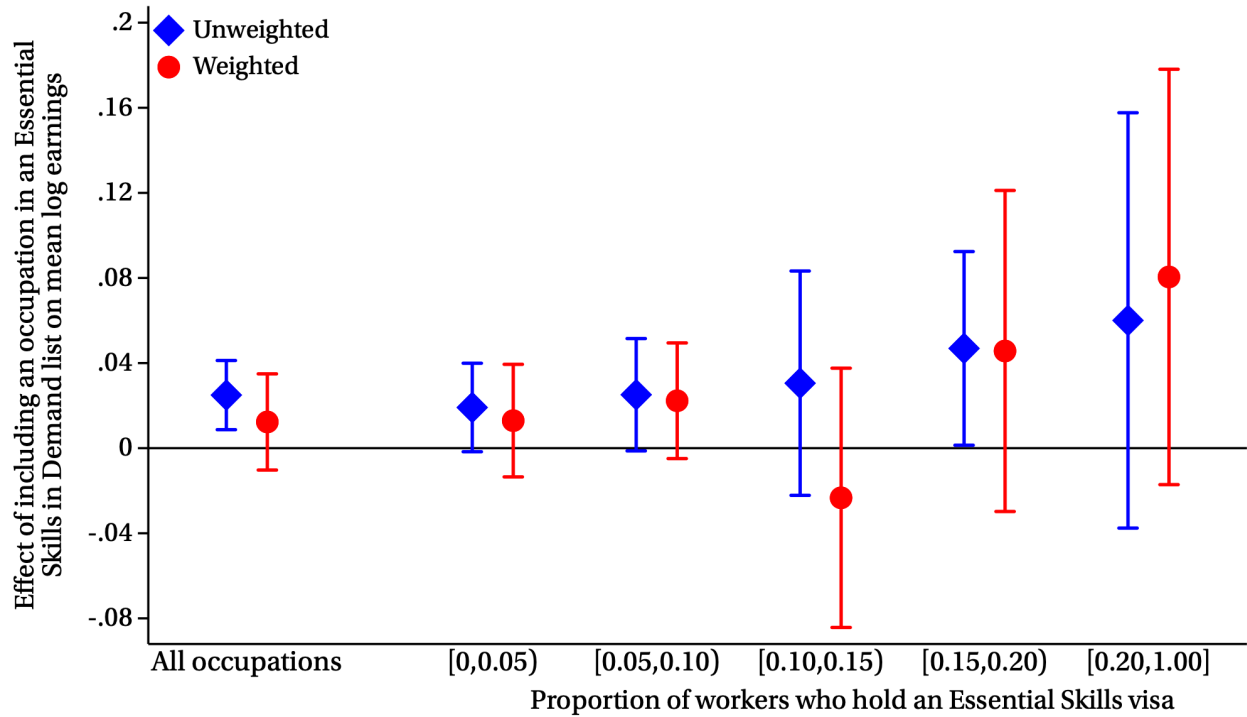


This figure depicts the conditional average effect of including an occupation on an Essential Skills in Demand list, by the proportion of that occupation who hold an Essential Skills visa. The proportion who hold an Essential Skills visa is a time-invariant variable, calculated by taking the mean across all monthly observations for each occupation. Occupation-specific effects are calculated using the estimator presented in Appendix D. In the blue series, these effects are average without weighting; in the red series, these effects are weighted by the number of workers in the occupation during the month it was added to or removed from an Essential Skills in Demand list. Bars represent 95% confidence intervals. See Section 6 for details on the analytic sample.

# Figure A3: Trace plots for the Stayers Average Treatment Effect



Panel A: $\beta_0$

Panel B: $\beta_1$

Panel C: $\beta_2$

Panel D: $\beta_3$

Panel E: $\alpha_0$

Panel F: $\alpha_1$

Panel G: $\text{var}(\delta)$

Panel H: $\text{var}(\gamma)$

Panel I: $\text{cov}(\delta, \gamma)$

Panel J: $\text{var}(\epsilon)$
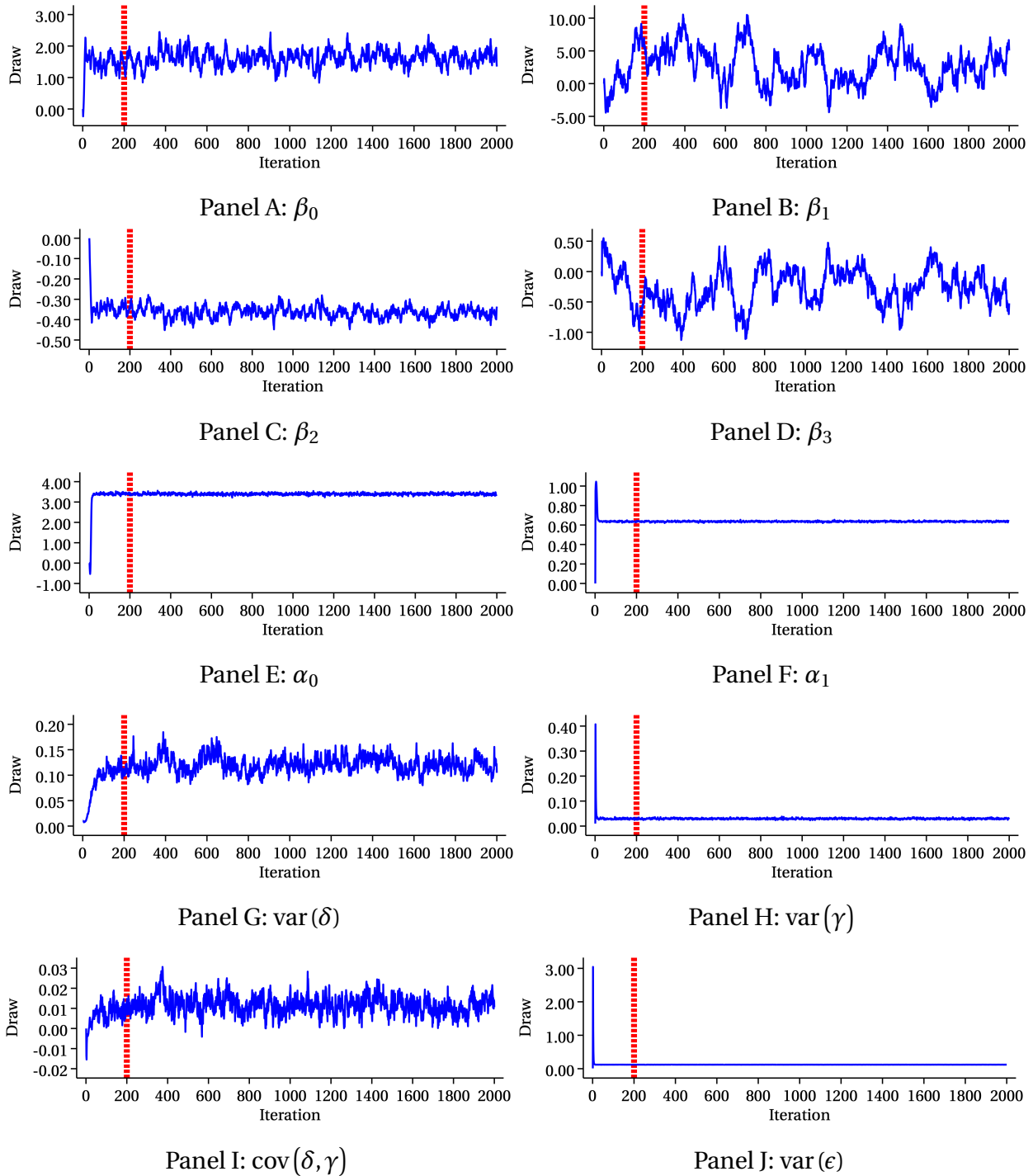
This figure depicts trace plots for the Gibbs sampler used to calculate the posterior distribution of the Stayers Average Treatment Effect. Each panel depicts the path of one hyperparameter. See Appendix C for details on the estimation algorithm. The area left of the red dashed line is the burn-in period, which is discarded when forming the posterior distribution described in Table 6.

# Table A1: Cross-sectional wage regressions

Panel A: 2013 Census; those with 12 months of earnings at a unique employer

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Fixed effects: | None | None | Occupation | Firm | Occ. × firm | Occ. × firm |
| Holds an Essential Skills visa | -0.194 | -0.184 | -0.048 | -0.025 | -0.010 | -0.032 |
| | [0.006] | [0.005] | [0.004] | [0.005] | [0.006] | [0.006] |
| Log hours of work | — | 0.974 | 0.829 | 0.965 | 0.641 | — |
| | | [0.004] | [0.004] | [0.004] | [0.006] | |
| Age: | | | | | | |
| 30-39 | — | 0.280 | 0.221 | 0.239 | 0.196 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| 40-49 | — | 0.385 | 0.311 | 0.344 | 0.282 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| 50-59 | — | 0.367 | 0.310 | 0.343 | 0.293 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| 60+ | — | 0.329 | 0.283 | 0.324 | 0.277 | — |
| | | [0.002] | [0.002] | [0.002] | [0.002] | |
| Highest qualification: | | | | | | |
| High school | — | 0.167 | 0.065 | 0.100 | 0.036 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| Trade certificate or diploma | — | 0.290 | 0.136 | 0.200 | 0.084 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| Bachelor's degree | — | 0.463 | 0.227 | 0.330 | 0.135 | — |
| | | [0.002] | [0.002] | [0.002] | [0.002] | |
| Postgraduate degree | — | 0.590 | 0.304 | 0.430 | 0.192 | — |
| | | [0.002] | [0.002] | [0.002] | [0.003] | |
| $R^2$ | 0.001 | 0.333 | 0.547 | 0.609 | 0.835 | 0.790 |
| Number of fixed effects | 0 | 0 | 1005 | 78219 | 274665 | 279885 |
| Number of workers | 714915 | 696870 | 679533 | 696870 | 679533 | 696648 |

Panel B: 2013 Census; those with 6 months of earnings at a unique employer

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Fixed effects: | None | None | Occupation | Firm | Occ. × firm | Occ. × firm |
| Holds an Essential Skills visa | -0.157 | -0.156 | -0.043 | -0.003 | -0.015 | -0.034 |
| | [0.005] | [0.005] | [0.003] | [0.005] | [0.005] | [0.005] |
| Log hours of work | — | 0.964 | 0.826 | 0.952 | 0.645 | — |
| | | [0.004] | [0.004] | [0.004] | [0.005] | |
| Age: | | | | | | |
| 30-39 | — | 0.279 | 0.216 | 0.235 | 0.188 | — |
| | | [0.001] | [0.001] | [0.001] | [0.001] | |
| 40-49 | — | 0.386 | 0.305 | 0.337 | 0.272 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| 50-59 | — | 0.368 | 0.303 | 0.336 | 0.281 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| 60+ | — | 0.329 | 0.275 | 0.313 | 0.262 | — |
| | | [0.002] | [0.001] | [0.002] | [0.002] | |
| Highest qualification: | | | | | | |
| High school | — | 0.160 | 0.061 | 0.095 | 0.034 | — |
| | | [0.001] | [0.001] | [0.001] | [0.001] | |
| Trade certificate or diploma | — | 0.281 | 0.131 | 0.192 | 0.082 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| Bachelor's degree | — | 0.457 | 0.220 | 0.320 | 0.132 | — |
| | | [0.002] | [0.002] | [0.002] | [0.002] | |
| Postgraduate degree | — | 0.589 | 0.297 | 0.420 | 0.188 | — |
| | | [0.002] | [0.002] | [0.002] | [0.003] | |
| $R^2$ | 0.001 | 0.333 | 0.542 | 0.609 | 0.830 | 0.785 |
| Number of fixed effects | 0 | 0 | 1008 | 88098 | 314133 | 320070 |
| Number of workers | 833061 | 811881 | 792060 | 811881 | 792060 | 812175 |

Panel C: 2018 Census; those with 12 months of earnings at a unique employer

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Fixed effects: | None | None | Occupation | Firm | Occ. × firm | Occ. × firm |
| Holds an Essential Skills visa | -0.222 | -0.189 | -0.049 | -0.048 | -0.004 | -0.026 |
| | [0.003] | [0.003] | [0.003] | [0.004] | [0.005] | [0.005] |
| Log hours of work | — | 0.980 | 0.806 | 0.940 | 0.623 | — |
| | | [0.004] | [0.004] | [0.004] | [0.005] | |
| Age: | | | | | | |
| 30-39 | — | 0.265 | 0.209 | 0.232 | 0.194 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| 40-49 | — | 0.379 | 0.308 | 0.350 | 0.288 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| 50-59 | — | 0.372 | 0.314 | 0.356 | 0.303 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| 60+ | — | 0.323 | 0.285 | 0.330 | 0.287 | — |
| | | [0.002] | [0.001] | [0.002] | [0.002] | |
| Highest qualification: | | | | | | |
| High school | — | 0.155 | 0.061 | 0.095 | 0.035 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| Trade certificate or diploma | — | 0.267 | 0.121 | 0.185 | 0.076 | — |
| | | [0.002] | [0.001] | [0.001] | [0.002] | |
| Bachelor's degree | — | 0.408 | 0.196 | 0.306 | 0.119 | — |
| | | [0.002] | [0.002] | [0.002] | [0.002] | |
| Postgraduate degree | — | 0.545 | 0.280 | 0.416 | 0.176 | — |
| | | [0.002] | [0.002] | [0.002] | [0.002] | |
| $R^2$ | 0.003 | 0.314 | 0.553 | 0.592 | 0.832 | 0.786 |
| Number of fixed effects | 0 | 0 | 1017 | 84003 | 295482 | 296244 |
| Number of workers | 772842 | 770367 | 750789 | 770367 | 750789 | 753039 |

Panel D: 2018 Census; those with 6 months of earnings at a unique employer

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Fixed effects: | None | None | Occupation | Firm | Occ. × firm | Occ. × firm |
| Holds an Essential Skills visa | -0.180 | -0.161 | -0.039 | -0.027 | 0.002 | -0.012 |
| | [0.003] | [0.003] | [0.002] | [0.003] | [0.004] | [0.004] |
| Log hours of work | — | 0.979 | 0.809 | 0.933 | 0.629 | — |
| | | [0.004] | [0.004] | [0.004] | [0.005] | |
| Age: | | | | | | |
| 30-39 | — | 0.263 | 0.202 | 0.228 | 0.184 | — |
| | | [0.001] | [0.001] | [0.001] | [0.001] | |
| 40-49 | — | 0.376 | 0.298 | 0.343 | 0.275 | — |
| | | [0.001] | [0.001] | [0.001] | [0.001] | |
| 50-59 | — | 0.369 | 0.303 | 0.347 | 0.289 | — |
| | | [0.001] | [0.001] | [0.001] | [0.001] | |
| 60+ | — | 0.320 | 0.273 | 0.319 | 0.270 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| Highest qualification: | | | | | | |
| High school | — | 0.148 | 0.058 | 0.091 | 0.034 | — |
| | | [0.001] | [0.001] | [0.001] | [0.001] | |
| Trade certificate or diploma | — | 0.258 | 0.117 | 0.178 | 0.076 | — |
| | | [0.001] | [0.001] | [0.001] | [0.002] | |
| Bachelor's degree | — | 0.400 | 0.187 | 0.294 | 0.114 | — |
| | | [0.002] | [0.002] | [0.002] | [0.002] | |
| Postgraduate degree | — | 0.539 | 0.271 | 0.403 | 0.170 | — |
| | | [0.002] | [0.002] | [0.002] | [0.002] | |
| $R^2$ | 0.002 | 0.318 | 0.546 | 0.590 | 0.826 | 0.779 |
| Number of fixed effects | 0 | 0 | 1020 | 94686 | 341199 | 342120 |
| Number of workers | 909108 | 906093 | 883395 | 906093 | 883395 | 886146 |

Table A1 reports cross-sectional regressions in which the dependent variable is an employee's log earnings across either the 6 months or 12 months prior to either the 2013 Population Census or the 2018 Population Census. These regressions are estimated using full-time paid employees with a unique employer. See Section 3 for data sources and see Section 4 for a detailed description of the sample.

## Table A2: How receiving a resident visa affects earnings

| | (1) All occupations | (2) On a skill list | (3) Not on a skill list | (4) Managers | (5) Professionals | (6) Technicians & trades | (7) Community & personal services | (8) Clerical & admin. | (9) Sales | (10) Machinery & drivers | (11) Laborers |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Dependent variable is log earnings | | | | | | | | | | | |
| Effect of a resident visa $\beta$ | 0.002 | -0.001 | 0.004 | 0.001 | -0.003 | -0.005 | 0.042 | 0.009 | 0.007 | 0.030 | 0.011 |
| | [0.003] | [0.004] | [0.005] | [0.009] | [0.005] | [0.004] | [0.011] | [0.019] | [0.031] | [0.023] | [0.019] |
| Coefficient on baseline $\delta$ | 0.433 | 0.377 | 0.496 | 0.544 | 0.455 | 0.339 | 0.431 | 0.508 | 0.545 | 0.597 | 0.322 |
| | [0.020] | [0.029] | [0.023] | [0.037] | [0.050] | [0.025] | [0.047] | [0.151] | [0.114] | [0.097] | [0.058] |
| Number of observations | 275550 | 160176 | 115377 | 36399 | 84495 | 113193 | 22650 | 4731 | 4128 | 4389 | 5568 |
| Number of new residents | 11292 | 6168 | 5124 | 1506 | 3378 | 4476 | 1188 | 219 | 174 | 147 | 201 |
| Number of baseline firms | 5769 | 3465 | 2907 | 1197 | 1605 | 2757 | 453 | 189 | 123 | 120 | 138 |
| Panel B: Dependent variable is colleagues' mean log earnings | | | | | | | | | | | |
| Effect of a resident visa $\beta$ | 0.008 | 0.004 | 0.014 | 0.019 | 0.001 | 0.004 | 0.036 | 0.036 | 0.014 | 0.033 | 0.008 |
| | [0.002] | [0.002] | [0.003] | [0.006] | [0.003] | [0.003] | [0.007] | [0.010] | [0.023] | [0.014] | [0.012] |
| Coefficient on baseline $\delta$ | 0.327 | 0.282 | 0.395 | 0.414 | 0.346 | 0.281 | 0.450 | 0.559 | 1.180 | -2.271 | 0.448 |
| | [0.054] | [0.066] | [0.083] | [0.091] | [0.155] | [0.078] | [0.149] | [0.153] | [1.324] | [0.739] | [0.179] |
| Number of observations | 218892 | 128655 | 90240 | 27639 | 69621 | 89781 | 16911 | 3867 | 3072 | 3675 | 4323 |
| Number of new residents | 9555 | 5397 | 4158 | 1287 | 2874 | 3891 | 858 | 183 | 156 | 132 | 180 |
| Number of baseline firms | 5001 | 3021 | 2484 | 1020 | 1392 | 2397 | 366 | 156 | 108 | 108 | 123 |

Table A2 reports estimates of the effect of receiving a resident visa using the doubly-robust matching estimator in Equation (2). Column (1) is estimated using all workers, while later columns are estimated on subsets of workers based on their occupation in the month prior to them receiving a resident visa. Columns (2) and (3) distinguish occupations by whether they were on an Essential Skills in Demand list during the month prior to the receipt of the resident visa. The dependent variable in Panel A is log earnings, and the dependent variable in Panel B is the mean log earnings of contemporaneous colleagues (among worker-month observations with a unique employer, excluding spell starts and ends).Standard errors are clustered at the level of the baseline firm. See Section 3 for data sources and see Subsection 5.1 for details on the analytic sample and estimator.

## Table A3: Lottery sample summary statistics

|  | All entrants | Successful entrants | Unsuccessful entrants |
|---|---|---|---|
| Percentage from: |  |  |  |
|   Fiji | 0.684 | 0.403 | 0.693 |
|   Samoa | 0.160 | 0.290 | 0.156 |
|   Tonga | 0.128 | 0.226 | 0.125 |
|   Tuvalu or Kiribati | 0.027 | 0.079 | 0.026 |
| Average age | 34.8 | 34.3 | 34.8 |
| Average number of dependants | 1.9 | 2.0 | 1.9 |
| Average months in New Zealand | 44.5 | 47.3 | 44.4 |
| Percentage men | 0.791 | 0.746 | 0.793 |
| Percentage in Auckland | 0.456 | 0.444 | 0.456 |
| Percentage urban | 0.665 | 0.660 | 0.665 |
| In the six months prior to the lottery: |  |  |  |
|   Percentage employed in NZ | 0.953 | 0.968 | 0.952 |
|   Average monthly NZ earnings | 3927.9 | 3811.8 | 3931.6 |
|   Percentage starting a new job | 0.090 | 0.145 | 0.088 |
| Percentage with a resident visa in |  |  |  |
|   1 year | 0.062 | 0.603 | 0.044 |
|   2 years | 0.128 | 0.794 | 0.107 |
|   3 years | 0.212 | 0.852 | 0.190 |
| Num. entries | 6123 | 189 | 5934 |
| Num. workers | 3465 | 186 | 3363 |
| Num. lotteries | 48 | 33 | 48 |

Table A3 describes our sample of workers who entered a lottery for either a Pacific Access Category visa or a Samoan Quota visa while already in New Zealand on an Essential Skills visa. Residents of Tuvalu and Kiribati entered separate lotteries; their proportions are combined in this table only to preserve anonymity. The average number of dependants is measured only among primary entrants. Age, number of dependants, months in New Zealand, gender, and location are all measured at the time of the lottery. Earnings are expressed in 2020 New Zealand dollars.

## Table A4: How winning a resident visa lottery affects other outcomes

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Employed in New Zealand | Located in New Zealand | Colleagues' log earnings |
| Second-stage slope coefficient | 0.027 | 0.066 | -0.011 |
| | [0.037] | [0.021] | [0.034] |
| First-stage slope coefficient | 0.676 | 0.676 | 0.714 |
| | [0.027] | [0.027] | [0.027] |
| First-stage F statistic | 635.464 | 635.464 | 692.279 |
| Control mean | 0.851 | 0.908 | 8.305 |
| Number of observations | 149439 | 149439 | 109746 |
| Number of workers | 3465 | 3465 | 3150 |

Table A4 reports two-stage least squares estimates of the linear IV system (5). Standard errors are clustered at the worker level. The system is estimated using months 12–36 following the lottery; columns (3)–(4) additionally restrict to observations with positive earnings and a unique firm, and exclude workers' first and last months at a firm. Standard errors are clustered at the worker level. See Section 3 for data sources and Subsection 5.2 for details on the analytic sample and estimator.

## Table A5: Sample of occupation-month observations for our analysis of Essential Skills in Demand lists

|  | Occupations never on an Essential Skills in Demand list | Occupations sometimes on an Essential Skills in Demand list | Occupations always on an Essential Skills in Demand list |
|---|---|---|---|
| Mean age | 40.8 | 40.7 | 39.9 |
| Proportion men | 0.598 | 0.665 | 0.734 |
| Mean real monthly earnings | 5218.4 | 7376.3 | 8520.1 |
| Proportion with an Essential Skills visa | 0.135 | 0.153 | 0.152 |
| Proportion with a non-resident and non-Essential Skills visa | 0.081 | 0.072 | 0.086 |
| Proportion with a resident visa or citizenship | 0.784 | 0.775 | 0.762 |
| Number of workers | 1690026 | 633693 | 372288 |
| Number of occupation-month observations | 107868 | 30054 | 12456 |
| Number of occupations | 750 | 198 | 81 |

Table A5 describes the occupation-by-month sample used in Section 6 to analyse the effect of including an occupation on an Essential Skills in Demand list. The table reports unweighted means of occupation-month observations, where the occupation-month observation is itself either a mean or a proportion. These means are estimated using only worker-month observations with nonmissing occupation and thus over-represent Essential Skills migrants, who are more likely to have their occupation listed in administrative data. See Section 3 for data sources and Section 6 for details on the analytic sample.

## Table A6: Worker characteristics, by the effect of expanding migrants' job options on their log wages

Panel A: Effects on Migrants

| Effect of expanding migrants' job options on log wages | Number of migrants | Mean baseline log wage | Mean prop. migrant among initial colleagues | Proportion who move firms | Proportion who benefit |
|---|---|---|---|---|---|
| < −0.1 | 2442 | 3.497 | 0.481 | 1.000 | 1.000 |
| −0.1 to −0.08 | 156 | 3.405 | 0.465 | 1.000 | 1.000 |
| −0.08 to −0.06 | 156 | 3.439 | 0.440 | 1.000 | 1.000 |
| −0.06 to −0.04 | 195 | 3.399 | 0.436 | 1.000 | 1.000 |
| −0.04 to −0.02 | 180 | 3.359 | 0.460 | 1.000 | 1.000 |
| −0.02 to 0 | 279 | 3.461 | 0.365 | 0.710 | 0.710 |
| 0 to 0.02 | 894 | 3.458 | 0.256 | 0.205 | 1.000 |
| 0.02 to 0.04 | 498 | 3.376 | 0.433 | 0.355 | 1.000 |
| 0.04 to 0.06 | 294 | 3.372 | 0.460 | 0.510 | 1.000 |
| 0.06 to 0.08 | 297 | 3.321 | 0.494 | 0.737 | 1.000 |
| 0.08 to 0.1 | 222 | 3.313 | 0.508 | 0.770 | 1.000 |
| > 0.1 | 3756 | 3.175 | 0.640 | 0.928 | 1.000 |
| All migrants | 9369 | 3.336 | 0.515 | 0.823 | 0.991 |

Panel B: Effects on Residents

| Effect of expanding migrants' job options on log wages | Number of residents | Mean baseline log wage | Mean prop. migrant among initial colleagues | Proportion who move firms | Proportion who benefit |
|---|---|---|---|---|---|
| < −0.1 | 1842 | 3.684 | 0.004 | 0.961 | 0.679 |
| −0.1 to −0.08 | 150 | 3.303 | 0.005 | 0.620 | 0.440 |
| −0.08 to −0.06 | 246 | 3.378 | 0.001 | 0.524 | 0.402 |
| −0.06 to −0.04 | 423 | 3.226 | 0.001 | 0.305 | 0.227 |
| −0.04 to −0.02 | 2538 | 3.184 | 0.000 | 0.044 | 0.031 |
| −0.02 to 0 | 595965 | 3.574 | 0.000 | 0.000 | 0.000 |
| 0 to 0.02 | 124923 | 3.563 | 0.014 | 0.001 | 1.000 |
| 0.02 to 0.04 | 6666 | 3.409 | 0.135 | 0.017 | 0.995 |
| 0.04 to 0.06 | 2655 | 3.385 | 0.234 | 0.047 | 0.984 |
| 0.06 to 0.08 | 1590 | 3.299 | 0.291 | 0.079 | 0.983 |
| 0.08 to 0.1 | 732 | 3.360 | 0.325 | 0.180 | 0.955 |
| > 0.1 | 3588 | 3.236 | 0.218 | 0.625 | 0.786 |
| All residents | 741318 | 3.566 | 0.007 | 0.007 | 0.190 |

Table A6 depicts the heterogeneous effects of allowing migrants to work at any firm, using the equilibrium simulations discussed in Section 8. Each row describes a different set of workers, with sets defined by the worker's visa status and by the effect that allowing migrants to work at any firm would have on the worker's log wage. 'Mean baseline log wage' measures the mean log hourly wage in the initial equilibrium. To calculate 'mean prop. migrant among initial colleagues' we first calculate, for each firm-occupation cell, the migrant proportion of labor mass in the initial equilibrium (treating labor as continuous). We then assign this proportion to each worker on the basis of their initial firm, and take the mean across workers. 'Proportion who move firms' measures the proportion of workers whose firm in the initial equilibrium differs from their firm in the counterfactual equilibrium. 'Proportion who benefit' measures the proportion of workers with higher utility in the counterfactual equilibrium than in the initial equilibrium.

## Table A7: Firm characteristics, by the effect of expanding migrants' job options on their log profits

| Effect of expanding migrants' job options on log profits | Number of firms | Mean employees | Mean productivity | Mean prop. migrant among employees | Prop. which employ any migrants | Mean effect on log mean wages | Mean effect on log employees |
|---|---|---|---|---|---|---|---|
| < −0.1 | 1161 | 2.929 | 4.131 | 0.629 | 1.000 | 0.238 | -0.413 |
| −0.1 to −0.08 | 180 | 5.778 | 4.239 | 0.339 | 1.000 | 0.077 | -0.135 |
| −0.08 to −0.06 | 210 | 9.429 | 4.282 | 0.287 | 1.000 | 0.062 | -0.107 |
| −0.06 to −0.04 | 366 | 10.656 | 4.300 | 0.207 | 0.984 | 0.047 | -0.078 |
| −0.04 to −0.02 | 765 | 19.085 | 4.327 | 0.144 | 0.976 | 0.028 | -0.046 |
| −0.02 to 0 | 19824 | 8.313 | 4.233 | 0.031 | 0.591 | 0.002 | -0.003 |
| 0 to 0.02 | 109851 | 6.500 | 4.292 | 0.004 | 0.289 | -0.002 | 0.004 |
| 0.02 to 0.04 | 2268 | 1.940 | 3.998 | 0.003 | 0.122 | -0.022 | 0.050 |
| 0.04 to 0.06 | 480 | 1.438 | 3.992 | 0.001 | 0.069 | -0.038 | 0.086 |
| 0.06 to 0.08 | 117 | 1.667 | 4.051 | 0.004 | 0.128 | -0.050 | 0.116 |
| 0.08 to 0.1 | 81 | 1.605 | 4.266 | 0.001 | 0.000 | -0.070 | 0.161 |
| > 0.1 | 129 | 1.318 | 4.089 | 0.001 | 0.070 | -0.112 | 0.259 |
| All firms | 135432 | 6.714 | 4.276 | 0.016 | 0.343 | 0.001 | 0.000 |

Table A7 depicts the heterogeneous effects of allowing migrants to work at any firm, using the equilibrium simulations discussed in Section 8. Each row describes a different set of firms, with sets defined by the effect that allowing migrants to work at any firm would have on the firm's log profits. 'Mean employees' measures the mean number of employees in the initial equilibrium. To calculate 'mean productivity' we first measure firm-level productivity by taking the firm-level mean of the firm-occupation productivity terms $\phi_{o,f}$, weighting by the number of employees in each occupation. We then average these firm-level productivity terms across the relevant set of firms. 'Mean prop. migrant among employees' measures the mean proportion of firms' employees who are migrants in the initial equilibrium. 'Prop. which employ any migrants' measures the proportion of firms which employ any migrants in the initial equilibrium. 'Mean effect on log mean wages' measures the mean firm-specific effect of expanding migrants' job options on log mean wages. 'Mean effect on log employees' measures the mean firm-specific effect of expanding migrants' job options on log employee count.