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Temporary migration and wage inequality: The effects of skills, nationality and migration status in Aotearoa New Zealand

Ahmed Zohirul Islam[1,2] | Francis L. Collins[3] | Omoniyi B. Alimi[1,4]

[1]Te Ngira: Institute for Population Research, The University of Waikato, Hamilton, New Zealand

[2]Department of Population Science and Human Resource Development, University of Rajshahi, Rajshahi, Bangladesh

[3]Sociology, School of Social Sciences, University of Auckland, Auckland, New Zealand

[4]School of Accounting, Finance and Economics (SAFE), The University of Waikato, Hamilton, New Zealand

Correspondence
Ahmed Zohirul Islam, Te Ngira: Institute for Population Research, The University of Waikato, Hamilton, New Zealand.
Email: zohirul.18@gmail.com

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Abstract

This study focuses on the labour market dimensions of temporary migration by quantitatively exploring the relationship between temporary migration and wage inequality. Over recent decades, there has been a growing emphasis on migration management in shaping migration policies across the world, especially in the Anglophone settler societies. At the same time, temporary migration policies have been criticized for contributing to the creation of inequalities. This study investigates wage inequality among temporary migrants between 2010 and 2019 in Aotearoa New Zealand, a period when the number of people holding temporary visas more than doubled. Despite the increase in this population of temporary migrants, our analysis of administrative data has shown that the overall level of wage inequality of temporary migrants holding work visas declined between 2010 and 2019. The study uses the Shapley-value decomposition approach to quantify the contributions of skills, nationality and migration status on wage inequality, factors that are associated with the migration system and the composition of migrants. Results suggest that skills and nationality were the key factors that have led to decrease wage inequality over the period. In contrast, migration status has a small countervailing effect on the decreases in wage inequality. Our analysis concludes that wage inequality is shaped by two factors in the case of temporary migration. The first is the migration system itself which sets different conditions for migrants in terms of skills and migration status, and the second is the composition of the migrant population.

KEYWORDS

inequality, migration, regression-based decomposition, Shapley-value decomposition, temporary migration, wage inequality

1 | INTRODUCTION

Immigration is viewed as a means of nation-building in traditional settler countries such as Aotearoa New Zealand, Australia, and Canada. For much of the 19th and 20th centuries, immigration policy was oriented towards encouraging permanent settlement, initially of white immigrants only and latterly in more multicultural human capital focused policies (Spoonley & Bedford, 2012; Walia, 2013). Over recent decades, however, there has been shifts towards increased temporary migration alongside stagnating permanent settlement in these Anglophone settler countries (Vosko, 2022). Temporary migration, which refers to the movement of people across international borders within migration programmes that limit how long migrants can remain in a country, is a global phenomenon that has significant implications for both countries of origin and destination (Castles & Ozkul, 2014). Temporary migration programmes have become a common way to manage which migrants are permitted to enter, what conditions they live under and how long they can remain. While temporary migration is claimed to bring significant economic benefits to both migrants and migrant-receiving countries, it also raises important questions about the rights and inclusion of people who hold temporary status (Lenard & Straehle, 2012). This study focuses on the labour market dimensions of temporary migration by quantitatively exploring the relationship between temporary migration and wage inequality.

In the context of Aotearoa New Zealand, the policy shift towards temporary migration has been criticized for contributing to the heightening of inequalities (Collins, 2020). Accounts of migrant exploitation have become more common in media and research in recent years, indicative of the way that temporary migration programmes have created categories of people who are viewed as workers and not residents or citizens. Moreover, research has highlighted how the temporary nature of migrant status and limited access to social security and support has resulted in migrant workers being vulnerable to exploitation and inequality, including low wages, poor working conditions, and limited opportunities for upward social mobility (Stringer et al., 2022). This has led to concerns about the ethical implications of temporary migration programs and the need for stronger policies to protect the rights of migrants (Collins, 2020). Despite these concerns there remains limited quantitative evidence of the extent of inequality experienced by temporary migrants.

This paper aims to contribute to understanding the relationship between temporary migration and inequality through an analysis of linked administrative data on wage and migrant status in Aotearoa New Zealand. By employing linked administrative data, the study goes beyond merely addressing wage inequalities among temporary migrants; it contributes crucial insights to broader immigration dynamics. We focus our analysis between 2010 and 2019, a period when the number of migrants holding temporary work and study visas increased substantially from 157,761 to 304,836, approximately 6.1% of the population in Aotearoa New Zealand by early 2020 (Collins & Stringer, 2022). As a result, people on temporary visas also made up an increasing proportion of the overall overseas-born/migrant population, growing from 15.2% of the overseas-born population at the 2013 census to 20.8% at the time of the 2018 census.

The context of Aotearoa New Zealand offers a useful case to examine temporary migration and wage inequality for a number of reasons: the rapid shift from permanent settlement-oriented towards temporary migration programmes since the early 2000s; the similarities in regulatory settings to Australia, Canada and other countries; and the availability of linked administrative data for analysis of wage inequality. Our analysis highlights the impact of skills, nationality and visa status on wage inequality, factors that are associated with the migration system and the composition of migrants. The results advance understandings of the relationship between temporary migration and inequality and are of relevance to scholars, policymakers, and practitioners concerned with the impact of temporary migration on economic growth and social stability. The paper begins with a discussion of existing literature on the relationship between income inequality and migration generally and then specifically temporary migration. The subsequent sections discuss policy settings around temporary migration in Aotearoa New Zealand, describe the methodologies and data sources, and present results from the descriptive statistics and decomposition analyses followed by discussion.

2 | LITERATURE REVIEW

2.1 | International migration and income inequality

International migration can contribute to both increases and reductions in wage inequality. Some studies argue that international migration can increase wage inequality by creating a concentration of low-wage workers in certain regions or industries such as agriculture, hotel, transport and cleaning (Friberg, 2016; Longhi, 2020; Xu et al., 2018). These workers may be subjected to insecure temporary employment, lower wages, poorer working conditions, reduced social protections, limited opportunities for promotion and sometimes their own communities can even influence their economic performances and chance of success (Foley & Hoge, 2007; Friberg, 2016; Longhi, 2020). On the other hand, other studies suggest that migration can reduce wage inequality by creating a more flexible labour market, which can increase the supply of labour, reduce wage premiums for high-skilled workers, and provide low-skilled workers with better job opportunities (Baycan-Levent & Nijkamp, 2009; Xu et al., 2016). These insights suggest that to understand the inequality generating effects of migration, greater attention needs to be paid to the position of migrants in labour markets and the conditions under which they migrate.

Over recent decades, there has been a growing emphasis on migration management in shaping migration policies globally (Geiger & Pécoud, 2010; Lewis et al., 2015). In the Anglophone settler societies of Aotearoa New Zealand, Australia and Canada, the managerial turn in migration policies has entailed the creation of targeted programmes for selecting migrants, a focus on monitoring and outcomes and a growing variety of migration pathways (Collins, 2020; Lenard & Straehle, 2012). In particular, these countries have transitioned from policies focused on permanent settlement to implementing temporary migration programmes for work or study, with limited opportunities for long-term settlement (Collins, 2020; Robertson, 2015; Vosko, 2022). Temporary migration programmes amplify differences in the socio-legal inclusion and exclusion of migrants, and as a result have an important role in generating inequality amongst temporary migrants and between migrants and resident and citizen populations (Anderson, 2010; Lenard & Straehle, 2012; Lewis et al., 2015).

Research in Aotearoa New Zealand (Collins & Stringer, 2022) and other contexts (Lee, 2004) suggest that much of the income inequality amongst migrants is due to discrimination. For instance, migrants aligning with the dominant ethnic group tend to secure higher-paying professions in various industries and organizations in a country. Conversely, some organizations may intentionally allocate low-paying jobs to migrants from minority groups (Lee, 2004). This practice can contribute to disparities in wages and opportunities for progression among migrants of different nationalities in the labour market. Inequality and discrimination are inherent within the social environments where migrants arrive, work, and strive to establish their lives (Grosfoguel et al., 2015). Racialization profoundly influences the types of jobs considered suitable for migrants of specific ethnicities or nationalities (Collins & Bayliss, 2020), their prospects for promotion within those roles (Rafferty, 2020) and their exclusion from other opportunities (Stevens et al., 2012). Others argue that immigration policies establish hierarchies among migrants that align with the intersection of social identities such as nationality, race/ethnicity, religion, gender, and class (Ellermann, 2020).

Extant research also highlights how forms of exploitation emerge alongside the development of temporary migration programmes. For example, studies suggest that host countries provide avenues for employers to exploit workers by resorting to temporary migrant labour instead of raising wages and enhancing working conditions, which are necessary for employing local workers (Walzer, 2008). Temporary migrant workers frequently take on precarious, challenging, physically demanding, dirty, and occasionally demeaning jobs that native-born workers generally avoid (Anderson, 2010; Dauvergne & Marsden, 2014; Morris, 2002). Temporary migrants, especially low-skilled workers, often step in to fill positions where manual labour is particularly required and where workers of the host countries are reluctant to take jobs (Peri & Sparber, 2009).

It is evident in the extant literature that migration policies often make temporary migrants vulnerable to exploitation and inequality (Collins, 2020; Lenard & Straehle, 2012). While immigration policies are portrayed as mechanisms to safeguard the employment rights of immigrants, they can actually weaken labour protections by fostering uncertainty due to the reliance on employers. (Anderson, 2010). Smith (2019) claimed that restrictions on work rights imposed on temporary migrants compel them to pursue a limited range of employment options, often tying them to a single employer, thereby distorting market forces. Anderson (2010) argued that not only are essential protections lacking in law for temporary migrants who work in violation of immigration controls, but also some legally employed temporary migrants remain unprotected.

In the context of Aotearoa New Zealand, temporary migration programmes have created inequalities by limiting the access of migrant workers to workplace rights and social resources (Collins, 2020). This can lead to exploitation, poor working conditions, and a lack of access to basic services such as healthcare and education. It can also result in a two-tiered workforce, where temporary migrants are paid lower wages and have fewer rights and protections compared to their New Zealand-born or permanent resident counterparts. Employer-assisted visas and visa status are another key mechanism for the management and exploitation of temporary migrants. The dependency of temporary migrant workers on their employer for their visa status, employment and ability to remain in Aotearoa New Zealand can create a power imbalance that can lead to exploitation (Collins & Stringer, 2022). Employers may use this power to pay lower wages, provide poorer working conditions, and offer less job security to migrant workers, who may be less likely to speak out or seek assistance to the authorities due to fear of losing their visa or being deported (Stringer, 2016). This can contribute to the creation and perpetuation of inequalities in the labor market.

Building on these insights, we argue that wage disparities arise from the intersection of different factors, particularly nationality, skill level, and visa status. Migration status is determined by the visa an individual obtains, but it is also linked to the assessed skill level of the individual. This assessment, however, is not objective but rather shaped by a specific system of valuing different migrant characteristics (Anderson, 2010). Skills, in this context, serve as a mechanism for immigration regulation. However, the evaluation of skills varies significantly across nationalities, genders, and other factors. Certain skills are often perceived as being associated with particular nationalities, leading employers to express preferences for certain nationalities for specific types of work (Collins & Bayliss, 2020). Additionally, the nebulous nature of nationality compounds this complexity, as nationality can signify both formal status (i.e., citizenship) and membership of an ethnicity or a culture. These factors, though distinct, intersect to shape the employment situation and wage structures for migrants. Thus, an examination of wage inequality among temporary migrants necessitates a holistic consideration of each factor's impact, transcending a simplistic binary of migrant/nonmigrant categorization.

2.2 | Measuring wage inequality

Building on qualitative scholarship on temporary migration in Aotearoa New Zealand (Collins, 2020; Stringer et al., 2022), the present study attempts to provide quantitative evidence through the assessment of the contribution of different factors to wage inequality among temporary migrants using a regression-based decomposition technique.

There is a significant body of literature on inequality decomposition methods, including traditional methods such as decomposition by income sources (Shorrocks, 1982) and by population sub-groups (Mookherjee & Shorrocks, 1982; Shorrocks, 1984). The former method allows for the estimation of the contribution of individual income components to overall inequality, while the latter allows for the measurement of inequality within and between sub-groups of the population. The latter methods are typically descriptive and provide information on the sources of income or role of sub-groups that contribute to inequality and are typically unwieldy in examining the role of multiple factors. Consequently, the usefulness of this information for policymakers seeking to address income inequality may be limited.

In contrast to conventional techniques, the regression-based strategies employed in this study offer an advantage by not limiting the analysis of inequality to just income components or specific population sub-groups. Instead, they permit the incorporation of a wide range of factors, including demographic and socioeconomic variables, which can influence income inequality, regardless of whether they are categorical or continuous.

The regression-based decomposition methodology is a powerful tool for understanding the factors that contribute to income inequality. The approach was first proposed in the early 1970s by Blinder (1973) and Oaxaca (1973), but it gained more attention in the early 2000s when Morduch and Sicular (2002) and Fields (2003) extended the decomposition by income sources to develop a regression-based decomposition by income determinants. The method involves estimating an income-generating function, such as a linear regression model, which allows for the calculation of the inequality weight of every explanatory variable using the estimated coefficients.

Fields (2003) proposed regression-based decomposition method to identify the factors that contribute to the levels and changes of income inequality. One of the advantages of this approach is that it allows for the examination of multiple factors contributing to inequality simultaneously, which is not possible with the traditional population sub-groups decomposition approach. However, this method may not account for all portions of income inequality, especially when the R-squared value of the regression model is low. In such cases, this method is expected to leave a substantial portion of inequality unexplained. In contrast, the Shapley-value decomposition approach proposed by (Shorrocks, 2013) does not depend on the fit of the regression model, and its performance is evaluated based on the marginal impact of each factor. This impact can vary depending on the choice of the inequality index used to measure income inequality (Manna & Regoli, 2012). Moreover, Fields (2003) method does not account for the correlation among the regressors while the Shapley-value decomposition approach overcomes this caveat (Manna & Regoli, 2012). The Shapley-value approach allows for the simultaneous analysis of multiple factors that contribute to income inequality. It can also be used to compare the contributions of different factors to income inequality in different groups or over time.

2.3 | Temporary migration in Aotearoa New Zealand

Over the last two decades, successive New Zealand governments have shifted their approach to migration policy, away from prioritizing permanent settlement to the regulation of large numbers of temporary migrants (Collins, 2020). These changes build on an earlier reconfiguration of migration policy established in the late 1980s and early 1990s (similar to earlier shifts in Australia and Canada) that moved migrant selection from a previous preference for 'traditional source' countries, namely Britain and Ireland, towards a focus on human capital prioritizing skills and financial resources (Ongley & Pearson, 1995). Subsequently, in 2003, a Skilled Migrant Category was introduced that incorporated a more targeted focus on job offers, qualifications, and work experience (Bedford, 2004). These and subsequent policy changes led to the growth of people on temporary migrant visas because people seeking long-term residence rights often needed to spend time on a work or study visa before applying for residence (Collins, 2020).

In 2017, another crucial policy change occurred that reinforced distinctions between temporary migrants in terms of the type of work they undertook and the wages they earned. Before that point, work visa length and conditions were determined by skill level assessed in the Australian and New Zealand Standard Classification of Occupations (ANZSCO[1]). Changes to the Essential Skill Work (ESW) visa in 2017 meant that applicants were assessed based on whether they were earning below, at or above the median wage. Visa holders earning at least the median wage were approved for a maximum of 3 years visa, could support work or visitor visas for their partner and visitor or student visas for dependent children. On the other hand, migrants earning below the median wage were approved for a visa duration of 12 months initially, with a maximum limit of two renewals. These temporary migrants could only support a visitor visa for their partner and dependent children without any work or study rights. These changes sharpened the distinctions between people on work visas and the rights that they are accorded. More recently and beyond the scope of this study, work visa policy underwent further revisions in 2022, leading to the introduction of the Accredited Employer Work Visa, which also uses the median-wage threshold as a skill indicator.

As a consequence of these policy shifts, many industries such as farming, healthcare, hospitality, tourism, transport and logistics, construction, retail, and others have become increasingly reliant on temporary migrants to fill labour shortages (Stringer et al., 2022). Collectively, the shifts in migration policy and the increasing dependence of vital industries on temporary migration have significantly impacted the overall number of temporary migrants as well as their composition. In the fiscal year ending on 30 June 2010, Immigration New Zealand granted approval for a total of 81,378 temporary work visas. However, by 30 June 2019, the number of approved temporary work visas had significantly increased, reaching its peak at 190,209 (Figure 1). These figures indicate a substantial growth in the employment of temporary migrant workers in between 2010 and 2019. This is also a period that has been associated with increasing reports of exploitation and growing attention on the outcomes of immigration (New Zealand Productivity Commission, 2022). Our focus is on this period and the evidence and explanation of wage inequality amongst temporary migrants.

The present study focuses on temporary migrants who hold employer-linked work visas who require working full-time to keep their visa valid (primarily the ESW visa and the Work-to-residence visa). The essential skills policy is designed to facilitate the entry of temporary migrant workers who can fill labour market shortages. Applicants must demonstrate their suitability for the position based on their qualifications and experience. They must also have a job offer for a position listed on the essential skills in demand lists; have a job offer from an employer who has obtained approval for recruiting the migrant; and employer must convince Immigration New Zealand that no suitable New Zealand residents are available or can be readily trained to fill the position. Between 2010 and 2019, the number of ESW visa holders rose significantly from 21,432 to 52,752. Similarly, the number of Work-to-residence visa holders increased from 2748 in 2010 to 14,640 in 2019 (Figure 2). Though temporary migrants have legal rights to reside and work in Aotearoa New Zealand for limited periods of time, they do not have same access to social, economic, political and legal rights as citizens (Collins, 2020). For example, only some ESW visa holders have the right to access health care, education for their children or indeed be accompanied by their children and/or partners. Both ESW and Work-to-residence visa holders can only change employers if they gain approval first from Immigration New Zealand.

3 | METHODS

This study used the Shapley-value regression-based decomposition approach developed by (Shorrocks, 2013) to answer two questions. First, what factors influence the level of wage inequality among temporary migrants in Aotearoa New Zealand (*levels question*)? Second, what determines the change in wage inequality over time (*differences question*)?

The Shapley-value decomposition approach taken here uses a regression framework to calculate the average marginal effects of each explanatory variable on any measures of inequality such as the Mean Log Deviation (MLD) index, Theil index and Gini index. This is done by introducing each variable into a regression model and measuring its contribution to the measures of inequality. The marginal effect of a variable is not unique and depends on the order in which the factors are included in the regression. Therefore, the average of all marginal effects of each variable in all possible orderings is considered as the contribution of that explanatory variable to inequality in the dependent variable.

To perform the Shapley value decomposition, we can begin with the estimation of an income generating function:

$$y_i = \alpha_i + \sum_{k=1}^{m} \beta_k X_{ik} + \varepsilon_i \tag{1}$$

where y_i measures the average monthly income of individual *i*. The variables X_{ik} represent the *k*-th income determining characteristics of individual *i*. The term $\beta_k X_{ik}$ refers to the share of income that flows from the factor X_k of individual *i*. The term ε represents a random error.

Once the income generating function is estimated, the Shapley value decomposition is used to calculate the contribution of each explanatory variable to income inequality as follows:

$$I(\hat{y}|X_1, \quad X_2, \quad \ldots, X_m) = C(X_1, I) + C(X_2, I) + \ldots + C(X_m, I) \tag{2}$$

where $I(\hat{y}|X_1, X_2, \ldots, X_m)$ represents any measures of income inequality calculated on predicted income. The term $C(X_1, I)$ is the contribution of X_1factor to income inequality.

The Shapley-value component of each estimated income sources to measured income inequality is the weighted mean of the marginal contributions of the income sources in all configurations. In other words, we calculate the average marginal effects of each explanatory variable to income inequality from all possible orderings of these variables. Thus, the contribution of X_k factor to income inequality is defined as

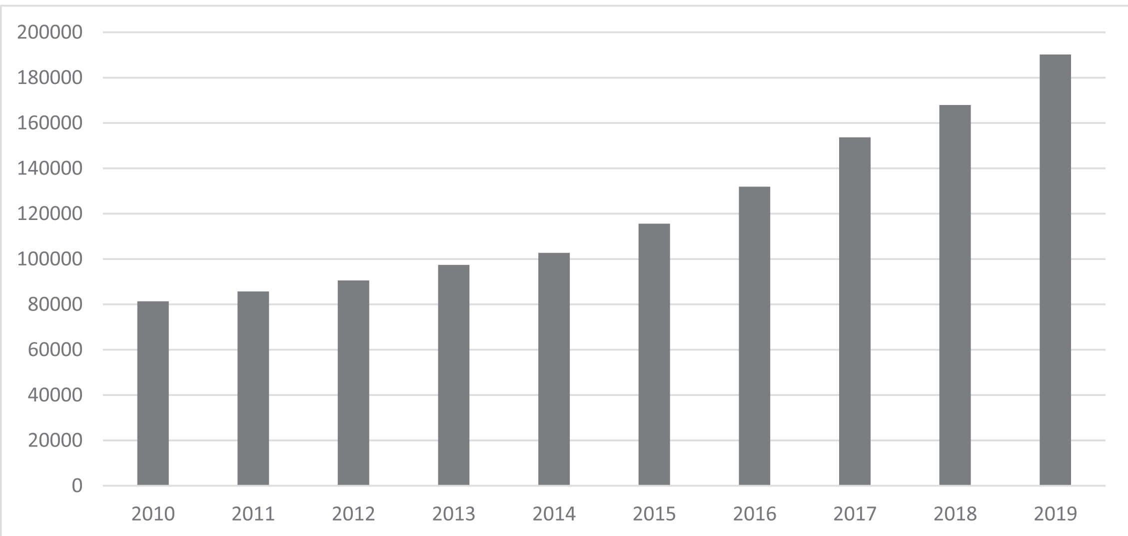

FIGURE 1 Population of temporary migrants holding work visa on 30th June each year. Data *Source*: Ministry of Business, Innovation and Employment (MBIE) Migration Data Explorer. Chart prepared by the authors.

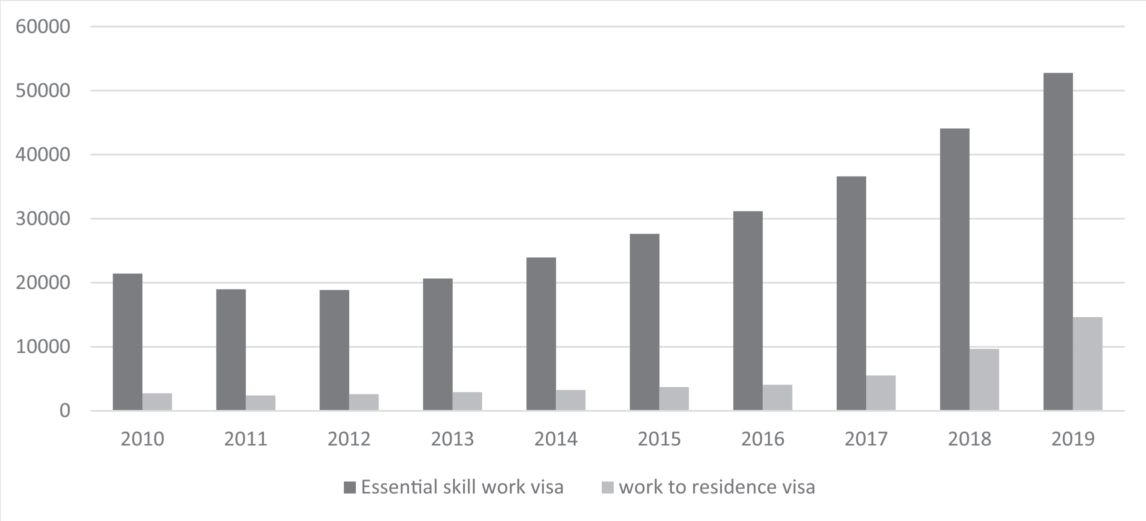

FIGURE 2 Population of temporary migrants holding essential skills work visa and work-to-residence visa on 30th June each year. Data *Source*: MBIE Migration Data Explorer. Chart prepared by the authors. MBIE, Ministry of Business, Innovation and Employment.

$$C(X_k, I) = \frac{1}{m!} \sum_{\pi \in \prod_m} [I(\hat{y}) \quad B(\pi, X_k) \cup \quad \{X_k\}) - I(\hat{y}) \quad B(\pi, X_k))] \tag{3}$$

where $\prod_m$ is the set of all possible orderings (i.e. permutations) of the explanatory variables. $B(\pi, X_k)$ is set of variables that precedes X_k in the ordering π.

The calculation of the contribution of each factor requires the estimation of 2^{m-1} number of income generating models and also the derivation of the measures of income inequality $I(\hat{y})$ for every model. This means that the number of calculations required increases exponentially with the number of variables included in the model. Therefore, including a large number of variables in the model can be computationally intensive in terms of data processing, computation time and storage capacity.

Then the relative contribution of each factor to income inequality can be calculated as follows:

$$S_k = \frac{C(X_k, I)}{I(y)} \tag{4}$$

The contribution of each factor to the change in income inequality between 2 years, A and B, can be calculated as follows:

$$\Delta_k = \frac{S_{kB} I_B(y) - S_{kA} I_A(y)}{I_B(y) - I_A(y)} \tag{5}$$

where S_{kA} and S_{kB} are relative factor inequality weight for the year A and B respectively. The term $I_A(y)$ and $I_B(y)$ represent the measures of inequality for the year A and B respectively. For a more detail mathematical description of the approach, please refer to Shorrocks (2013), Kolenikov and Shorrocks (2005), Manna and Regoli (2012), Gunatilaka and Chotikapanich (2006) and Sastre and Trannoy (2002). We used the Distributive Analysis Stata Package version 3.03 software package developed by Araar and Duclos (2022) to perform the decomposition analyses.

4 | DATA AND VARIABLES

4.1 | Data

This study uses linked administrative data on individuals—immigration data, international travel and migration data, Inland Revenue's (IR) tax data and business register data—available in the Statistics New Zealand's Integrated Data Infrastructure (IDI). The ability to access and link administrative data through the IDI provides scope for a particularly detailed account of the relationship between temporary migration and wage inequality because we are able to analyze individual data on wages and immigration status for the entire population of interest. This type of analysis is particularly significant because it is unlikely to be viable in a number of other countries, such as for example the United States of America where data on parallel temporary migration programmes is simply not available or accessible. We used the immigration data to identify our population of interest. The target population of this study are those who have been granted skilled work visas (i.e., ESW visa and other employer-linked work visa) or Work-to-residence visas (see Supporting Information S1: Appendix A for details) to stay in Aotearoa New Zealand and are required to work full-time to keep their visa valid. We excluded individuals holding student visas, marriage/partnership visas, and section 61[2] visas due to their potential flexibility in work hours or employers, which could affect wage data. We used IR tax data which records monthly income from all sources (wages and salaries, government transfer and payment, remuneration of shareholders or directors, etc.) received by the individual.

4.2 | Dependent variable

Our focus in this paper is the monthly wages of temporary migrants who are required to work full-time to keep their visa valid. We considered the monthly income of individuals earned from wages and salaries. The exclusion of income starts from when the visa status of these temporary migrants changed from temporary work visa to residence visas or student visas or marriage or partnership visas or section 61 visas because their visa type is changed from temporary to either permanent status or they are no longer required to work full-time to keep their visa valid. When someone's visa type changes from temporary to permanent they have been granted the right to stay in the country for an indefinite period of time. This can lead to changes in their employment status, such as being able to work for any employer without restrictions or not being required to work full-time. Similarly, if someone is no longer required to work full-time to keep their visa this may provide them with more flexibility in terms of their employment options and potentially lead to changes in their income and overall financial situation. Therefore, our analysis includes their wage while they were on the temporary work visas but not once they were approved for other types of visas. We then excluded wage of the first month of individuals who joined a new job because they might join in any week of a month and therefore earn a fraction of real wage of that month. We also excluded wage of the last month of individuals who resigned from a job because they might earn higher than their usual wage in that month by adding annual leave payments or other payments with real wage of the last month. Finally, we calculate the average monthly wages of individuals who had at least 3 months of income. We calculate total wage of an individual by adding his/her wage of each month and dividing it by the number of months he/she had income to calculate monthly wages (hereinafter wage).

4.3 | Explanatory variables

In this study, the explanatory variables are age, sex, region, ANZSCO skill levels (hereinafter skills/skill level), occupations, nationality, and visa status. The core theoretical questions of the study are driven by skills, nationality, and visa status, while age, sex, region, and occupation serve as control variables. For the Shapley value decomposition approach, as the number of explanatory variables increases in the model, the number of possible orderings also increases rapidly leading to an exponential increase in the number of calculations required to estimate the Shapley values. Including many variables in the model can be computationally intensive and may require high data processing time and storage capacity. Therefore, we categorized the explanatory variables to a limited number to balance the number of variables included in the model with the computational resources available in the IDI data laboratory, as well as the theoretical and practical relevance of the factors being examined.

5 | RESULTS

5.1 | Descriptive analyses

Descriptive statistics were employed to provide an overview of the characteristics of the study populations. Continuous variables were presented as mean and standard deviation to summarize the central tendency and variability of the data while categorical variables were presented as percentages. Descriptive statistics are presented in Table 1.

It is observed from Table 1 that the percentage of temporary migrants from UK, Ireland, North America and South Africa decreased from 30% to 21% between 2010 and 2019 while it increased for migrants form other nationalities. In 2010, Work-to-residence visa holders constituted 6% of migrants, whereas this percentage increased to 22% in 2019. On the contrary, the percentage of skilled work visa holders dropped from 94% to 78% between 2010 and 2019. The relative share of migrants in different skill level categories also shifted. In 2010, 34% of migrants were categorized as skill level 1 (highest-skilled) but this declined to 20% by 2019. Migrants categorized as skill level 2–3 (mid-skilled) increased only slightly from 40% to 43% in 2010 and 2019 respectively, while those categorized as skill level 4–5 (lowest-skilled) increased from 26% to 37%.[3]

5.2 | Level of wage inequality

Figure 3 displays the three most commonly-used measures of inequality such as MLD index, Theil index and Gini index. These measures quantify the levels of income inequality. This study demonstrates that all these measures show a similar pattern of wage inequality of temporary migrants. However, we report the MLD index because it is less sensitive to uncertainty about incomes in the upper end of the income distribution while the Theil index is affected by changes in both the upper and lower tails of the income distribution (Cowell & Flachaire, 2007). The MLD index is less sensitive to extreme values, such as extremely high or low incomes, while the Gini index and Theil index can be influenced by extreme values which can make them difficult to interpret (Cowell & Flachaire, 2007).

We observed from Figure 3 that wage inequality remained relatively stable between 2010 and 2013. However, a significant decrease in wage inequality (0.1021) was observed in 2014, followed by a continued decline, reaching 0.063 in 2019. By considering 2010 as the base year, two noticeable shifts in wage inequality were identified: in 2014 and 2019. So, we examined what proportion of total wage inequality, and its changes can be accounted for by different observable factors in these 3 years in the following sections.

5.3 | Decomposition of wage inequality

5.3.1 | Regression analyses

In the first step of the decomposition analysis, we ran the earnings functions (see Equation 1). We used the semi-log model specification that means the dependent variable of this study is wage, measured in logs. Taking the logarithm of wage facilitates the interpretation of the parameter estimates so that they represent percentage changes in

TABLE 1 Descriptive statistics: Aotearoa New Zealand, 2010–2019.

Variables	2010 (%)	2011 (%)	2012 (%)	2013 (%)	2014 (%)	2015 (%)	2016 (%)	2017 (%)	2018 (%)	2019 (%)
Sex										
Female	36.2	34.98	32.54	30.29	28.79	28.76	29.48	28.37	28.18	26.66
Male	63.8	65.02	67.46	69.71	71.21	71.24	70.52	71.63	71.82	73.34
ANZSCO *Skill levels*										
Level 1	33.92	35.64	35.88	33.59	29.16	27.43	26.47	24.13	22.67	19.68
Level 2–3	39.82	38.22	38.29	41.29	42.97	43.75	43.7	42.58	41.75	43.35
Level 4–5	26.25	26.14	25.83	25.12	27.88	28.82	29.83	33.29	35.58	36.96
Region										
Auckland	39.34	41.37	38.01	34.93	34.86	36.22	37.67	39.93	39.82	41.52
Wai, Wel, Can, Otag[a]	40.97	39.68	44.08	47.09	48.34	47.19	46.45	43.95	43.91	41.14
Other	19.71	18.95	17.9	17.97	16.79	16.58	15.88	16.14	16.26	17.35
Nationality										
UK, Ire, NA, SA[b]	29.61	30.97	31.89	31.61	27.95	25.16	25.87	23.86	22.17	20.76
Other	70.39	69.02	68.14	68.39	72.05	74.84	74.12	76.14	77.83	79.23
Occupations										
Managers/professionals	39.37	41.8	42.11	41.19	37.11	35.87	34.09	30.86	28.93	24.72
Technicians/trade workers	25.89	24.95	24.93	27.3	28.34	29	29.65	30.22	29.8	31.48
Other	34.73	33.25	32.95	31.53	34.55	35.13	36.25	38.9	41.28	43.81
Visa status										
Work to residence	6.18	7.64	8.27	8.51	8.36	8.2	8.96	15.17	17.16	22.09
Skilled work	93.82	92.37	91.72	91.49	91.65	91.8	91.04	84.83	82.85	77.9
Age (average)	33.91 (8.62)	33.71 (8.59)	33.51 (8.59)	33.25 (8.49)	32.98 (8.39)	32.89 (8.19)	32.95 (8.09)	33.22 (7.99)	33.34 (7.75)	33.75 (7.85)
Wage (average)	4048 (2685)	4210 (2832)	4384 (3007)	4440 (3019)	4343 (2602)	4317 (2535)	4436 (2464)	4635 (2500)	4899 (2473)	5021 (2269)
Number	20,913	20,397	20,802	22,893	26,556	29,934	32,283	37,506	43,506	55,740

Note: All frequency counts have been rounded using Random Rounding-base three (RR3). Percentages and averages are based on RR3 rounded counts. [a]Waikato, Wellington, Canterbury, and Otago. [b]United Kingdom, Ireland, North America, and South Africa. Standard deviations are presented in parentheses.

Abbreviation: ANZSCO, Australian and New Zealand Standard Classification of Occupations.

Source: calculated by the authors using Stata 16.

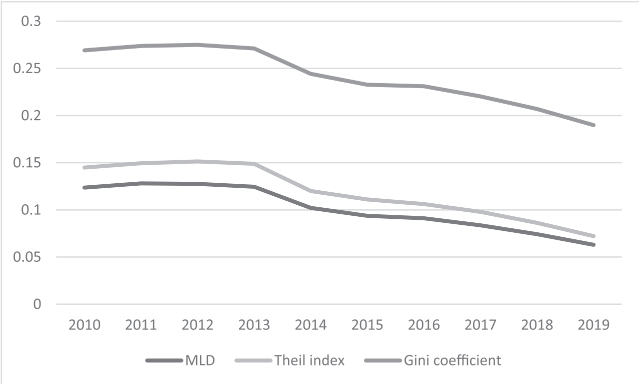

FIGURE 3 Level of income inequality, 2010–2019, Chart prepared by the authors.

wage corresponding to 1% or one unit change in the observable factors. The empirical results are presented in Table 2.

We observed from Table 2 that migrants with skill level 2–3 and 4–5 earned lower wages than those with skill level 1. However, the earning gap between skill level 2–3 and level 1 decreased between 2010 and 2019, while this gap remained relatively stable between migrants with skill level 4–5 and level 1.

Visa status matters in the earnings of temporary migrants in New Zealand. Skilled work visa holders earned lower wages than migrants who had Work-to-residence visa. The former group earned 27% lower wage than the latter group in 2010 but this gap narrowed over time and became 19% in 2019.

Nationality and sex also play important roles in determining wage among temporary migrants. Migrants from UK, Ireland, North America and South Africa, white-majority countries or where the majority of immigrants are assumed to be white, earned higher wage than migrants from other nationalities who are likely to be perceived as ethnic minority as they are distinct from the white majority population of New Zealand. Migrants with other nationalities earned 15% lower wage than migrants from UK, Ireland, North America and South Africa in 2019 while it was 26% in 2010. Male migrants earned 12% higher wage than female migrants in 2010. The male-female earnings gap was widened by 2% between 2010 and 2019. The effects of occupations and regions are also statistically significant in determining income in New Zealand. We then analysed how much wage inequality of temporary migrants is accounted for by each of these explanatory factors in the following section.

5.3.2 | Decomposition of the level of wage inequality

This study attempts to answer the *levels question*: what the contributions of the factors in accounting for the levels of wage inequality are. We applied the Shapley value regression-based decomposition method to answer the question. The results from the decomposition analysis for each year of our study period are presented in Table 3. The contributions of each factor to the levels of wage inequality in absolute terms ($C(X_k, I)$) are presented in the first column, the factor inequality weights (S_k) are presented in the second column and the percentage of the explained inequality (P_k) are shown in the third column.

Given that the results from the Shapley value decomposition may be influenced by which inequality measures are chosen, this study presents estimates for three measures of inequality: the MLD index, Theil index and Gini index. Results from these three inequality indices showed similar patterns of contribution of the factors to wage inequality of temporary migrants. In what follows we describe the results from MLD estimates in the rest of this paper.

In 2019, the most important factor in determining the explained wage inequality was skills, with the relative shares in wage inequality of 40%. The next important factors with sizeable relative shares in determining the explained wage inequality were visa status (21%), age (15%) and nationality (14%). Smaller weights were observed for sex (6%), occupations (3%) and regions (1%) in 2019.

This study reveals that the contribution of skills in accounting for the level of wage inequality remained the highest throughout the study period; however, it decreased from 50% in 2010 to 40% in 2019. Nationality and visa status are the other two most influential factors in accounting for wage inequality. The relative share of visa status in accounting for the level of wage inequality increased from 9% in 2010 to 21% in 2019. So, its relative share in explaining wage inequality increased by more than twofold over the 10 years. On the other hand, the contribution of nationality in explaining wage inequality slightly dropped from 25% to 14% over the last decade; however, its relative share in explaining wage inequality remained high in 2019. Overall, the relative contributions of visa status and nationality sum up to 35% of the explained wage inequality in 2019 compared to 34% in 2010.

This study also demonstrates that the relative share of age to account for the level of wage inequality increased from 4% in 2010 to 15% in 2019. Similarly, though sex accounted for a small share of income inequality, the percentage of its contribution increased a little over the last decade. On the contrary, the contribution of occupations in accounting for income inequality fell from 8% to around 3% between 2010 and 2019, respectively. Region accounted for barely 1% of wage inequality in 2010 and its contribution remained the same throughout the period between 2010 and 2019.

We also decomposed another measure of inequality- the variance of logarithms of wage-considering broad categorizations of the explanatory variables. We applied both the Shapley value and Fields (2003) regression-based decomposition approaches and found qualitatively similar results (see Supporting Information S1: Appendix B and Appendix C) with our reported findings. These indicate that the broad conclusions of our study are neither method-dependent nor inequality index-dependent.

5.3.3 | Decomposition of change in wage inequality

We turn our attention now to the *differences question* of how much of the change in wage inequality was due to each of these observable factors. The answer to this question is presented in Table 4. A positive sign indicates that the factor contributes to the change in wage inequality in

TABLE 2 Regression results in Aotearoa New Zealand, 2010–2019.

Variables	2010	2014	2019
Sex			
Male	0.119*** (0.006)	0.152*** (0.005)	0.135*** (0.003)
Region			
Waikato, Wellington, Canterbury, and Otago	−0.058*** (0.007)	−0.009 (0.005)	−0.026*** (0.003)
Other	−0.013 (0.008)	−0.010 (0.007)	0.003 (0.004)
ANZSCO skill levels			
Level 2–3	−0.378*** (0.012)	−0.330*** (0.009)	−0.288*** (0.006)
Level 4–5	−0.296*** (0.018)	−0.263*** (0.013)	−0.283*** (0.008)
Occupations			
Technicians/trade workers	−0.006 (0.012)	0.001 (0.009)	0.010 (0.005)
Other	−0.097*** (0.016)	−0.088*** (0.012)	−0.024*** (0.007)
Nationality			
Other	−0.258*** (0.007)	−0.248*** (0.005)	−0.148*** (0.003)
Visa status			
Skilled work visa	−0.266*** (0.013)	−0.232*** (0.009)	−0.193*** (0.003)
Age	0.005*** (0.000)	0.010*** (0.000)	0.009*** (0.000)
Constant	8.670*** (0.019)	8.485*** (0.013)	8.582*** (0.007)
Number of observations	17,325	23,358	49,245

Note: Standard errors in parentheses; All frequency counts have been rounded using Random Rounding-base three (RR3).

***Refers to the 1% significant level.

Source: Computed by Authors using Stata 16.

the direction in which the change occurred. In our analysis, wage inequality of temporary migrants declined over time. So, a positive sign of a factor represents that it contributes to the decrease in wage inequality while a negative sign indicates that the factor is driving to increase wage inequality.

The decomposition results show that the main drivers that contribute to decrease wage inequality over the period were skills and nationality. The contribution of skills to decrease wage inequality between 2010 and 2014 was 27%, while it became 16% between 2014 and 2019. On the other hand, the contribution of nationality increased from 9% between 2010 and 2014 to 15% between 2014 and 2019. Though the contribution of occupations was small, it increased from 4% between 2010 and 2014 to 5% between 2014 and 2019. Age and sex also had a small contribution 5% and 2% respectively to decrease wage inequality between 2014 and 2019. In contrast to these factors, visa status had a small countervailing effect on the change in wage inequality, −2% between both 2010-2014 and 2014-2019.

6 | DISCUSSION AND CONCLUSION

The shift towards temporary migration in Aotearoa New Zealand (Collins, 2020), and in similar countries such as Australia (Robertson, 2015) and Canada (Vosko, 2022), has been associated with inequality and exploitation associated with the stratification of temporary migrants' work rights. This study has focused on a period (2010–2019) when the number of people holding temporary visas more than doubled in Aotearoa New Zealand. Despite the increase in this population of temporary migrants, our analysis of administrative income data has shown that the overall level of wage inequality of temporary migrants holding work visas declined between 2010 and 2019 and especially between 2014 and 2019. We also observe three notable trends in descriptive analysis that are significant for our more detailed analysis of levels and changes in wage inequality over time. First, there is a shift in the nationality makeup of temporary migrants such that the proportion of people from UK, Ireland, North America and South Africa (white majority countries) declined from 30% to 21% over this period and other nationalities increased accordingly; this shift occurred between 2014 and 2019. Second, the proportion of people holding the Work-to-residence visa, which accords more rights to migrants, increased from 6% to 22% over the period, with most growth occurring between 2016 (9%) and 2019 (22%). Finally, the proportion of highest-skilled (level 1) migrants dropped from 34% to 20% over the last decade while it increased accordingly for mid-skilled (level 2–3) and lowest-skilled (level 4–5) migrants; these changes occurred especially between 2014 and 2019. As outlined earlier, the transitions in migration policies, moving from nationality-based criteria to human capital considerations, and subsequent

TABLE 3 Factor contribution to wage inequality levels in Aotearoa New Zealand, 2010–2019.

	2010			2014			2019		
Variables	$C(X_k, I)$	$100 * S_k$	P_k	$C(X_k, I)$	$100 * S_k$	P_k	$C(X_k, I)$	$100 * S_k$	P_k
	MLD index								
Sex									
Male	0.0016	1.26	3.56	0.0022	2.13	5.47	0.0016	2.48	6.49
Region									
Wai, Wel, Can, Otag[a]	0.0005	0.40	1.13	0.0000	0.04	0.11	0.0002	0.38	1.00
Other	−0.0001	−0.08	−0.23	0.0000	−0.03	−0.09	0.0000	0.01	0.01
ANZSCO Skill levels									
Level 2–3	0.0128	10.33	29.25	0.0092	8.98	23.03	0.0027	4.32	11.29
Level 4–5	0.0089	7.22	20.44	0.0067	6.57	16.86	0.0068	10.83	28.32
Occupations									
Technicians/trade workers	0.0001	0.11	0.31	0.0000	−0.01	−0.02	0.0000	−0.03	−0.07
Other	0.0034	2.76	7.82	0.0027	2.63	6.76	0.0007	1.03	2.71
Nationality									
Other	0.0110	8.89	25.17	0.0091	8.90	22.83	0.0033	5.17	13.53
Visa status									
Skilled work visa	0.0039	3.13	8.87	0.0044	4.32	11.08	0.0052	8.18	21.39
Age	0.0016	1.31	3.70	0.0056	5.45	13.97	0.0037	5.87	15.34
Total explained inequality	0.0437	-	100	0.0398	-	100	0.0241	-	100
Unexplained inequality	0.0800	64.67	-	0.0623	61.01	-	0.0389	61.76	-
Observed inequality	0.1237	100	-	0.1021	100	-	0.0630	100	-
	Theil index								
Sex									
Male	0.0018	1.23	3.34	0.0021	1.73	4.25	0.0014	1.95	4.92
Region									
Wai, Wel, Can, Otag[a]	0.0005	0.37	1.01	0.0001	0.06	0.15	0.0003	0.37	0.94
Other	−0.0002	−0.11	−0.31	−0.0001	−0.05	−0.12	0.0000	0.01	0.02
ANZSCO skill levels									
Level 2–3	0.0163	11.25	30.50	0.0119	9.94	24.39	0.0043	5.94	14.98
Level 4–5	0.0109	7.49	20.32	0.0082	6.80	16.69	0.0079	11.00	27.75
Occupations									
Technicians/trade workers	0.0002	0.12	0.33	0.0000	−0.01	−0.02	−0.0001	−0.08	−0.21
Other	0.0040	2.77	7.52	0.0031	2.61	6.41	0.0007	1.03	2.60
Nationality									
Other	0.0130	8.98	24.36	0.0110	9.18	22.53	0.0041	5.64	14.22
Visa status									
Skilled work visa	0.0043	2.98	8.07	0.0050	4.13	10.13	0.0055	7.59	19.14
Age	0.0026	1.79	4.86	0.0076	6.35	15.59	0.0045	6.21	15.66
Total explained inequality	0.0535	-	100	0.0489	-	100	0.0286	-	100
Unexplained inequality	0.0915	63.13	-	0.0711	59.24	-	0.0436	60.35	-
Observed inequality	0.1450	100	-	0.1200	100	-	0.0722	100	-

(Continues)

TABLE 3 (Continued)

Variables	2010 $C(X_k, I)$	2010 $100 * S_k$	2010 P_k	2014 $C(X_k, I)$	2014 $100 * S_k$	2014 P_k	2019 $C(X_k, I)$	2019 $100 * S_k$	2019 P_k
	Gini index								
Sex									
Male	0.0080	2.96	6.36	0.0099	4.06	8.17	0.0085	4.46	8.85
Region									
Wai, Wel, Can, Otag[a]	0.0037	1.38	2.95	0.0005	0.19	0.37	0.0018	0.93	1.85
Other	0.0002	0.07	0.16	0.0002	0.07	0.15	0.0001	0.05	0.09
ANZSCO Skill levels									
Level 2–3	0.0353	13.10	28.12	0.0281	11.52	23.19	0.0150	7.87	15.63
Level 4–5	0.0234	8.71	18.69	0.0195	8.00	16.10	0.0233	12.26	24.33
Occupations									
Technicians/trade workers	0.0004	0.14	0.31	0.0000	0.00	0.01	0.0004	0.22	0.43
Other	0.0092	3.42	7.34	0.0081	3.33	6.71	0.0024	1.27	2.53
Nationality									
Other	0.0289	10.75	23.07	0.0253	10.35	20.84	0.0110	5.81	11.53
Visa status									
Skilled work visa	0.0094	3.49	7.48	0.0115	4.69	9.45	0.0178	9.39	18.63
Age	0.0069	2.57	5.51	0.0182	7.45	15.00	0.0154	8.13	16.13
Total explained inequality	0.1254	-	100	0.1213	-	100	0.0957	-	100
Unexplained inequality	0.1438	53.41	-	0.1230	50.34	-	0.0942	49.62	-
Observed inequality	0.2692	100	-	0.2443	100	-	0.1899	100	-

Abbreviation: DASP, Distributive Analysis Stata Package.

Note: $C(X_k, I)$ is the absolute contribution of each factor to inequality, S_k is factor inequality weights (percentage of observed inequality), P_k is the relative share (%) of each factor to the total explained inequality (percentage of explained inequality). [a] Waikato, Wellington, Canterbury, and Otago regions.

Source: Computed by Authors using Stata 16 and the DASP 3.03 software developed by Araar and Duclos (2022).

adjustments—particularly the policy changes in 2017, incorporating skills and remuneration bands—could influence the composition of migrants in terms of nationality, skills, and migration status. These trends intersect in important ways with our more detailed analysis of the level of wage inequality and its change over time that highlight the significance of three factors: skills, nationality and visa status.

The results of our analysis clearly indicate that the dominant factor in explaining the level of wage inequality of temporary migrants was skills, maintaining its prominence throughout the study period, although its significance diminished from 50% in 2010 to 40% in 2019. The two other leading factors contributing to wage inequality were nationality and visa status. The relative importance of visa status in accounting for wage inequality increased from 9% in 2010 to 21% in 2019, more than a twofold increase in its explanatory role. In contrast, the role of nationality in explaining wage inequality declined from 25% to 14%.

This study also reveals that the principal factors that have led to decrease wage inequality over the period were skills and nationality. Between 2010 and 2014, skills accounted for a 27% reduction in wage inequality, which then decreased to 16% between 2014 and 2019. In contrast, the contribution of nationality increased from 9% between 2010 and 2014 to 15% between 2014 and 2019. Occupations, age and sex had small contributions to decrease wage inequality among temporary migrants between 2014 and 2019.

Skill level is both a compositional factor and a migration system-related factor because different measures of skills are created by classifications within the migration system (Raghuram, 2012), which have implications for the visas allocated to and thus rights accorded to migrants. The skill composition of migrants is likely to play a significant role in affecting wage inequality because migrants with the highest skills tend to earn higher wages compared to those with mid-level and lowest skills. Shifts in the composition of skills can potentially lead to changes in wage inequality. We have found that the proportion of highest-skilled migrants dramatically dropped between 2010 and 2019 while the proportion of lowest-skilled migrants increased. Because of the association between skill level

TABLE 4 Factor contribution to the change in wage inequality in Aotearoa New Zealand, 2010–2019.

Variables	2010–2014	2014–2019	2010–2019
Sex			
Male	−2.88	1.57	−0.01
Region			
Waikato, Wellington, Canterbury, and Otago	2.07	−0.50	0.42
Other	−0.31	−0.10	−0.17
ANZSCO Skill levels			
Level 2–3	16.70	16.50	16.57
Level 4–5	10.28	−0.29	3.48
Occupations			
Technicians/trade workers	0.66	0.02	0.25
Other	3.36	5.22	4.55
Nationality			
Other	8.85	14.91	12.75
Visa status			
Skilled work visa	−2.46	−1.91	−2.10
Age	−18.20	4.76	−3.43

Abbreviation: DASP, Distributive Analysis Stata Package.

Source: Computed by Authors using Stata 16, the DASP 3.03 software developed by Araar and Duclos (2022) and MS Excel.

and wages earned, this shift in the composition of temporary migrants is likely to be associated with a reduction in the proportion of temporary migrants earning higher wages, and a growth in those earning lower wages. Thus, a decrease in wage inequality is associated with changes in skill composition that does not necessarily mean that the earnings of temporary migrants have improved.

The nationality composition of migrants is likely to be associated with wage inequality because of the effects of labour market discrimination on migrants. Ethnic pay gaps are a significant issue in Aotearoa New Zealand (Maré, 2022) and as a white majority, Anglophone settler society, temporary migrants from Great Britain and Ireland are likely to earn higher wages than migrants from other nationalities (Collins & Pawar, 2021). As a result, changes in the nationality composition may alter wage inequality. In this case, we have observed that the percentage of temporary migrants from UK, Ireland, North America, and South Africa experienced a minor decrease from 2010 to 2014 and a noticeable decline between 2014 and 2019. This changing trend occurred alongside a pronounced decrease in wage inequality between 2014 and 2019. Like the reduction in the proportion of temporary migrants classified as higher skilled, these nationality composition changes are likely to contribute to reductions in wage inequality because of declines in the proportion of people earning higher wages.

Our analysis suggests that visa status has a different kind of impact on the levels of wage inequality. The contribution of visa status to wage inequality in 2019 was twice that in 2014, and unlike skills and nationality, visa status had a small countervailing effect on the decline in wage inequality between 2014 and 2019. The increase in the proportion of migrants holding Work-to-residence visas is likely to explain these effects given their ability to earn higher wages than skilled work visa holders. Work-to-residence visas are usually issued to people in higher-skilled occupations, where higher wages are earned. Work-to-residence visa holders also have more labour market rights and the ability to support family visas and have a secure pathway to residence rights. While overall wage inequality has declined because of the effects of skill and nationality, then, this analysis maintains that visa status contributes to increases in wage inequality because of its association with the labour market rights of temporary migrants (Anderson, 2010; Collins, 2020).

Temporary migration and its relationship to wage inequality is complex, shaped by the shifting rules and regulations of migration systems and their articulation with the characteristics of temporary migrants. Our analysis suggests that wage inequality is shaped by two factors in the case of temporary migration. The first one is the migration system itself which sets different conditions for migrants in terms of skill levels and visa status, including restrictions on the freedom to switch employers, the types of employment migrants can take up, the duration of their visa, the right to have family members accompany them, and access to essential social resources like education and healthcare. The second one is the composition of migrants. In particular, changes in the proportion of people from different nationalities entering a country can alter levels of wage inequality because of the racialised discrimination that migrants face in work. These insights are important because they reveal that rather than being a neutral filtering mechanism for managing labour market gaps, the rules and regulations of temporary migration systems and the composition of migrants generate different levels of inequality.

There are some limitations of this study. First, since we used the administrative data which were originally collected for a different purpose, we had limited control over the available variables and we considered only a limited number of variables available in the data laboratory for analysis. However, it is important to note that further analyses incorporating additional variables could provide valuable insights and enhance the understanding of the topic. Second, only the most recent temporary work visa held by migrants was considered, and the transition between different visa categories was excluded to maintain the focus of the study. This approach may have overlooked potential dynamics and changes in the migrants' visa statuses over time. It is important to consider these limitations when interpreting the findings and to acknowledge the potential for further research to explore additional variables and visa transition patterns for a more comprehensive analysis. Despite these limitations, the study still provided valuable insights into the specific research questions, analyzing unique and innovative administrative data outlined earlier. Finally, while this study explored the impact of various factors on wage inequality among temporary migrants, it did not specifically investigate variations in inequality across different segments of the wage distribution. As a result, this study highlights the need for further research examining whether inequality among migrants varies at different levels of the wage distribution.

This paper highlights the significance of investigating wage inequality and its connection to temporary migration, which holds relevance for several reasons. First, there is ongoing international and domestic debate regarding whether governments should be restructuring or abolishing temporary migration programmes (Dauvergne & Marsden, 2014; New Zealand Productivity Commission, 2022). Second, as mentioned earlier, there is discourse surrounding the ways in which migration schemes contribute to concurrent trends of labour market flexibility and diminishing worker rights (Collins, 2020). Finally, there is a debate concerning the politics of skill and the rationale behind the persistent focus on skill-based categorizations that are shown to be anything but objective measures (Osterman et al., 2022). This study highlights the importance of continued research in these areas and especially the significance of evidence that can measure the extent of inequality quantitatively and its links to migration policy. As we have shown, wage inequality is not simply a result of a migrant/nonmigrant binary but rather is influenced by the status that migrants hold and the skills they are assessed has having, and to nationality in relation to the likely effects of employment discrimination.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data utilized in this research are sourced from Statistics New Zealand; however, there are limitations on the availability of this data, as it was accessed under a license specifically for this study through a secure data laboratory and is not publicly accessible. Nevertheless, interested individuals can request access to this data directly from Statistics New Zealand.

ORCID

Ahmed Zohirul Islam http://orcid.org/0000-0002-7057-016X
Francis L. Collins http://orcid.org/0000-0001-9453-4465
Omoniyi B. Alimi http://orcid.org/0000-0002-7828-167X

ENDNOTES

[1] ANZSCO is a standardized classification system used to categorize and define occupations in Australia and New Zealand.

[2] Under Section 61 of the Immigration Act 2009, individuals who are unlawfully present in New Zealand may be able to make a request to Immigration New Zealand for a new visa. Decisions are made at the discretion of the Minister of Immigration (delegated to the Associate Minister of Immigration and to senior immigration officers), do not need to be justified and are not subject to appeal. See https://www.immigration.govt.nz/about-us/media-centre/common-topics/section-61.

[3] ANZSCO categorizes jobs into five skill levels, with Skill Level 1 being the highest, requiring a bachelor's degree or higher, such as for doctors and engineers, and Skill Level 5 being the lowest, requiring basic skills and minimal formal education, such as for cleaners and labourers. Intermediate levels include Skill Level 2 for technicians with diplomas, Skill Level 3 for trades requiring apprenticeships, and Skill Level 4 for roles like sales assistants needing certificates and on-the-job training.

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Additional supporting information can be found online in the Supporting Information section at the end of this article.

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