Worker mobility across regions in New Zealand: the role of house prices and the impact on earnings

Guanyu Zheng

A thesis submitted to Auckland University of Technology in fulfilment of the requirements for the degree of Master of Philosophy

2026

School of Economics

Faculty of Business, Economics and Law

Abstract

This thesis investigates the complex relationship between house prices, geographic worker mobility, and earnings growth within New Zealand. Geographic worker mobility – defined as the movement of workers across regions within a country as they change jobs or seek better employment opportunities – plays a critical role in driving economic activity and social integration. However, the interplay between housing prices and worker mobility remains underexplored in the New Zealand context. This thesis specifically examines how regional house prices influence inter-regional worker mobility and how such mobility affects short-term individual earnings growth. By addressing this gap, the research aims to provide insights into three interconnected questions:

1. In any given year, how many workers move to a different region to take a new job, and how does this geographic mobility vary across different worker characteristics?
2. How do house prices affect inter-regional worker mobility?
3. How does geographic worker mobility influence individual earnings growth in the short run?

The empirical analysis leverages data from Statistics New Zealand's Integrated Data Infrastructure, which provides a large and de-identified dataset on employment, housing, and demographic trends across regions of New Zealand. The study employs advanced econometric techniques, including gravity models, to analyse worker mobility patterns and their determinants.

Between 2000 and 2020, the average geographic worker mobility rate was 4.5 per cent. Analyses of worker demographics reveal that younger workers and those of non-European ethnicity are more likely to relocate compared to other groups. In terms of destination preferences, workers predominantly move to large urbanised regions (e.g., Auckland, Wellington, and Canterbury) or neighbouring regions. These patterns highlight the importance of agglomeration and proximity in shaping inter-regional mobility decisions.

Findings reveal that house price fluctuations significantly impact worker mobility decisions. Higher house prices in the region of origin increase outflows, while higher

house prices in destination regions deter inflows. These effects, however, vary considerably across worker demographics. Notably, older workers are more responsive to rising house prices. One possible reason is that they have greater equity in their homes and are more likely to capitalise on higher property values to fund migration. Younger workers, who may have less equity or face higher barriers to relocation, are less affected by changes in house prices.

Worker mobility correlates positively with earnings growth, but outcomes vary. Migrating to large urban regions – particularly those aged 25-29 and 40-54, males, European and Asians – saw faster earnings growth, suggesting urban wage premiums. Conversely, workers leaving large regions experience slower growth, potentially trading earnings for housing affordability or limited high-paying jobs in smaller regions.

This research underscores the importance of integrating housing affordability into regional economic policies and migration strategies. By understanding how house prices influence worker mobility, policymakers can design targeted interventions to support workers affected by housing market challenges while fostering sustainable regional development.

Table of contents

List of Figures

List of Tables

Attestation of authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Student signature: Guanyu Zheng
Date: 29 March 2025
Student ID: 21132925

Acknowledgements

First and foremost, I extend my deepest gratitude to my supervisors, whose expertise, patience, and support made this research possible.

Professor Gail Pacheco has been an extraordinary role model, both as an academic economist and leader during the Productivity Commission. Your encouragement during moments of doubt – especially amid the challenges of government restructuring – kept me motivated and focused. Your belief in my potential gave me the courage to push forward, even when the path seemed unclear.

To Dr. Andrew Coleman, I am grateful for your intellectual partnership. Collaborating with you on regional labour market research in the past not only sharpened my analytical skills but also ignited my passion for this thesis. Your technical mastery and creative problem-solving guided me through technical hurdles and transforming obstacles into learning opportunities.

To Dr. Leon Iusitini, thank you for your meticulous attention to clarity and coherence. Your exceptional writing skills and ability to turn complex ideas into compelling narratives elevated the quality of this thesis. Your work taught me the art of academic writing, and I will carry those lessons forward as I continue to grow as a researcher.

I am deeply indebted to my former managers - Adam Richardson (Reserve Bank of New Zealand), Scott Usher, Dr Kirsten Lovelock (Ministry of Business, Innovation and Employment), and Tom O'Brien (Health New Zealand) - for their generosity and flexibility. Your financial support for my studies, coupled with the flexibility to balance work and academic commitments, provided the foundation for this achievement.

A special thanks to Professor Jacques Poot from the University of Waikato for sharing your unparalleled expertise on gravity models. Your guidance fortified my analytical confidence, and your invitation to present preliminary findings at the Australia New Zealand Regional Science Association in Canberra opened my eyes to new horizons. That experience reinforced my desire to continue contributing to this field.

To my dear friends - Marea Sing, Christopher Ball, Julie Lok, Meltem Chadwick, Penny Mok, and Alex Wang - you offered invaluable companionship and advice during challenging times. This journey would be far longer without your companionship.

Lastly, I am deeply grateful to my family: Becky Chen (wife), Kyle Zheng (son), and my parents for their unwavering love and understanding. Their constant encouragement provided emotional support during stressful periods, essential for sustaining my academic efforts.

Thank you all for your contributions; without your support, this thesis would not have been possible.

Disclaimers

Access to the data used in this study was provided by Stats NZ under conditions designed to give effect to the security and confidentiality provisions of the Statistics Act 1975. The results presented in this study are the work of the author, not Stats NZ or individual data suppliers.

The results are based in part on tax data supplied by Inland Revenue to Stats NZ under the Tax Administration Act 1994 for statistical purposes. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

Chapter 1: Introduction

1.1 Background

Worker mobility refers to the ability to find and take another job. It is measured when a worker changes jobs, which is known as a 'job-to-job transition'. Job-to-job transitions may also involve *geographical* mobility if the new job is located in a different local labour market or region or country and the worker relocates their place of residence to take the job. The study of worker mobility and its relationship with the housing market and wage dynamics is crucial for understanding the labour market and economic trends. Understanding the patterns, drivers, and implications of worker mobility is essential for policymakers, researchers, and businesses to make informed decisions and create effective labour market policies. This thesis analyses job-to-job transitions within regions and across regions of New Zealand. However, the focus is on job-to-job transitions *across* regions, referred to as 'inter-regional job-to-job transitions' or 'inter-regional worker mobility' or 'inter-regional worker flows' (these terms are used interchangeably throughout the thesis).

Worker mobility plays a significant role in facilitating economic adjustments, especially in response to economic shocks and changes in job opportunities across industries and regions. It enables workers to seek higher wages, better job matches, and career advancement. Research has shown that job changes are often associated with increased earnings. For instance, studies in the United States have indicated that job changes are linked to estimated earnings increases of 3.5% to 9%, and even higher for young workers under 30 years of age (Hyatt & McEntarfer, 2012). Similarly, in Denmark and New Zealand, job-to-job transitions have been found to contribute to aggregate wage growth (Ball et al., 2020; Zheng & Sing, 2023). It is evident that worker mobility is closely linked to wage dynamics and overall economic growth.

However, there have been concerning trends indicating a decline in worker mobility in various economies, including the United States, Australia, and New Zealand (Ball et al., 2020; Causa et al., 2021; Deutscher, 2019; Hyatt & Spletzer, 2013). The decline in job-to-job transition rates raises important questions about the implications for workers, businesses, and the overall economy. Slowing worker mobility can lead to challenges for workers in finding new job opportunities and advancing their careers.

The housing market plays a critical role in shaping worker mobility, as house prices directly influence individuals' decisions to move (Cavalleri et al., 2021; Greenwood, 1997; Sjaastad, 1962; Stillwell, 2009). High house prices in prosperous regions can discourage the inflow of workers from other areas, especially for those with limited financial resources. When housing becomes unaffordable, potential migrants may be deterred from relocating to regions with better job opportunities. Conversely, rising house prices can also push existing residents out of high-cost areas, as they will seek more affordable living conditions elsewhere.

In New Zealand, the housing market has experienced a significant upswing in property values over the past two decades, leading to decreased housing affordability (Housing Affordability Inquiry, 2012). By 2022, the average house price had risen to 8.7 times the average household income, up from 5 times in 2005. [1] This sharp increase in house prices has exacerbated affordability concerns, making it increasingly difficult for many New Zealanders to maintain their standard of living. As house prices continue to rise, many individuals and households may find it challenging to secure affordable alternatives, further limiting their mobility.

Understanding the intricate relationship between worker mobility, the housing market, and earnings dynamics is crucial for informing policy decisions and addressing economic challenges. By studying the impact of housing market dynamics on worker mobility and wage growth, researchers can provide valuable insights into potential interventions to support workers and address housing affordability issues. Furthermore, the implications of housing market trends on worker mobility are intertwined with broader economic and social considerations, making it a critical area of research and policy development.

1.2 Research questions

This thesis contributes to the literature on the relationship between house prices and labour market outcomes by answering the following research questions: (1) In any given year, how many workers move to a different region to take a new job, and how does this geographic mobility vary across different worker characteristics?

[1] The house-price-to-income ratio statistics are derived from Infometrics (https://rep.infometrics.co.nz/new-zealand/income-and-housing/housing-affordability).

(2) How do house prices affect inter-regional worker mobility? and (3) how does inter-regional worker mobility affect individual earnings growth in the short run? This thesis addresses these questions using employment data from Statistics New Zealand's Integrated Data Infrastructure, which is a large research database that holds de-identified administrative and survey microdata about people, households, and businesses linked across a range of life domains for the whole population of New Zealand.

The remainder of this thesis proceeds as follows: Chapter 2 discusses the literature on worker mobility and its link to housing markets and earnings dynamics; Chapter 3 describes the data source and the variables used in the analysis; Chapter 4 presents estimates of worker mobility (job-to-job transition rates) for the total New Zealand population and for demographic sub-groups; Chapter 5 describes the method for analysing the impact of house prices on inter-regional worker mobility and presents results from the modelling; Chapter 6 describes the method for estimating the effect of inter-regional worker mobility on individual earnings growth and presents results; and Chapter 7 concludes.

Chapter 2: Literature review

This chapter presents a selective review of the literature on internal migration and relevant evidence for the analyses presented in this thesis. Section 2.1 discusses the definition of geographic worker mobility, and section 2.2 discusses four broad data sources used to measure mobility. Section 2.3 discusses the micro-level and macro-level economic approaches for internal migration analysis, giving emphasis to the macro-level perspective, as it forms the primary analytical framework for this study. Section 2.4 outlines empirical evidence of internal migration both across countries and in New Zealand. Section 2.5 highlights the key contributions of this study to the literature.

2.1 Definition of worker mobility

Geographic worker mobility refers to the movement of workers from one location to another within a country as they change jobs or seek better employment opportunities. This form of mobility is distinct from international mobility or migration, focusing solely on internal movements or migrations within a national border.

Geographic mobility has been widely studied and defined in various ways. For instance, the United Nations (1970) defines mobility as "*a move from one migration-defining area to another (or a move of some specified minimum distance) that was made during a given migration interval*." Greenwood (1997) defines geographic mobility as "the relocation of individuals or groups for the purpose of improving their economic or social circumstances." Similarly, Champion (2001) emphasises that geographic mobility involves "the physical movement of people between different geographic areas, usually measured over a specific time period."

These definitions are largely similar. They qualify as a geographic movement if the individual must move between two locations within a specific time period. The spatial and temporal elements are essential to measuring geographic mobility.

The terms geographic worker mobility and internal migration are conceptually related, as both refer to the geographic movement of individuals from one location to another. However, it is important to note their distinct scopes. Internal migration describes the migration patterns of the entire population living in the country, including those under 15, employees, business owners, retirees and the unemployed. In contrast, geographic worker mobility is a subset of internal migration, focusing on individuals who are employed. Despite these differences, both terms share similar analytical frameworks and are often explained using common economic theories, such as human capital theory and the spatial equilibrium model.

2.2 Measurement of geographic mobility

The measurement of geographic mobility has been approached through various methods and data sources. Kirchberger (2021) highlighted five types of data sources used to study migration. They are Census and cross-sectional data, longitudinal data, Randomised Control Trials (RCTs), administrative data, and big data. Each data source offers unique strengths and limitations.

Census and cross-sectional data

Census data provide a comprehensive snapshot of population movement, often capturing information about residences. These data are typically self-reported, with respondents indicating both their current and former places of residence. Such data enable researchers to track migration patterns.

One of the key advantages of this method is simplicity (Hall, 2023). It only requires two questions in the Census questionnaire, such as "*Where do you currently live?*" and "*Where did you previously live?*". However, this approach has two notable limitations. First, it is susceptible to recall errors, where respondents may forget or misreport their previous locations. Smith and Thomas (2003) found that better-educated respondents tended to report more accurate answers to migration-related questions than those with lower educational attainment in the Malaysian Family Life Survey. Another limitation is the infrequency of censuses. For example, the New Zealand Census occurs every five years and only captures data on the current place of residence and the place of residence five years prior. This means migration movements within the five-year interval may be missed entirely. Consequently, if a person has moved multiple times during this period, the census data will fail to capture the complexity of their migration patterns accurately.

Longitudinal data

Longitudinal data collection tracks the same individuals over time and provides detailed insights into the timing and frequency of migration events, offering a more dynamic view of migration flows. Beegle et al. (2011) utilised the Kager Health and

Development Survey (KHDS) to study migration and economic mobility in Tanzania, tracking a sample of 915 households from the fall of 1991 to January 1994. Similarly, the Indonesian Family Life Survey (IFLS) began in 1993 with 7,200 households (approximately 33,000 individuals) randomly selected from 13 of Indonesia's 27 provinces. These households were followed up in 1997, 2000, and 2014 (Pardede et al., 2020).

Despite its advantages, longitudinal data collection faces significant challenges, particularly in terms of cost and sample attrition. First, designing and maintaining a longitudinal data system requires substantial time, as well as human and technological resources (Joshi, 2016; Osborne et al., 2023). Second, sample attrition—where participants drop out over time—poses a serious threat to data validity and is costly to address. Attrition reduces sample size and can introduce selection bias if dropouts are non-random. For instance, younger individuals, who are often more mobile, are more difficult to track compared to older participants, resulting in potentially skewed data. Addressing attrition often requires costly follow-up efforts, with diminishing returns on investment. Moreover, alternative techniques such as imputation and weighting are often insufficient in minimising attrition bias, especially when data are missing in complex or non-random patterns (Kristman et al., 2005).

Randomised control trials

RCTs have a similar set-up to panel data but are primarily employed in experimental studies. For example, Baseler (2023) investigated the effect of providing accurate urban earnings information on migration behaviours in 497 rural households in Keyna. The study divided the sample into two groups: 248 households in the treatment group received information about average individual earnings and business profits in neighbouring cities, while the remaining households formed the control group. Migration data were subsequently collected from most households at six months, one year, and two years after the initial interview.

Similarly, McKenzie et al. (2013) conducted a natural experiment using a ballot lottery to divide prospective Tongan migrants into various study groups. The study examined how misreporting employment and income in New Zealand (the migration destination) influenced migration decisions over the next two years.

RCTs are considered the gold standard for establishing causal relationships because randomisation ensures comparability between treatment and control groups, and high-quality and well-designed data enable evaluating outcomes accurately (Fernainy et al., 2024; Gale et al., 2023). Often, results from RCTs are straightforward to interpret since they only require average outcomes between randomised groups. In contrast, other data (e.g. panel data, administrative data) often need complex econometric adjustments and rely on stronger assumptions to draw statistical inferences (Imbens & Rubin, 2015).

Administrative data

Administrative data have gained significant traction across various research fields due to its breadth, timeliness and reliability. Sourced from government records such as tax filings, education enrolments, social benefits, immigration records and employment registries, it captures detailed individual information and behaviours across entire populations. In contrast, traditional survey data and longitudinal data can suffer from recall bias or larger variations in estimates from small sample sizes.

For instance, the National Change of Address registry from the United States Postal Service offers precise move dates and address changes, making it well-suited for studying internal migration patterns across counties and states (Foster et al., 2024). In New Zealand, McLeod (2018) utilised the Integrated Data Infrastructure (IDI) to compile address records from border movements, tax, school enrolment, health and social welfare systems, generating comprehensive annual international and internal migration statistics. In addition, Coleman and Zheng (2020) analysed data from the Linked Employer-Employee Database (LEED) to investigate patterns of industrial and regional job-to-job transitions across 31 major and secondary urban areas in New Zealand.

Despite its advantages, administrative data have some limitations. It often lacks qualitative details about individual motivations or barriers to migration. In this case, surveys such as the Survey of Dynamics of Motivation and Migration in New Zealand and the Household, Income and Labour Dynamics in Australia survey are better equipped to obtain this information. Additionally, population coverage, data quality and linking accuracy vary among administrative data sources, posing more complex data treatments.

Big data

More recently, big data containing individual locations from digital trace data have become a new source of data on internal migration. It comes in many forms, such as cellular calls, text, GPS information from smartphone applications, geotags from social media smartphone apps, and credit card uses. With the global adoption of communication technology, digital trace data has become increasingly available and created new opportunities for migration analysis. Digital trace data have some unique features, as outlined by Kirchberger (2021, p.8): *"(i) flexibility in defining a migration episode; (ii) observed (rather than self-reported) moves, and (iii) continuous coverage of a possibly large portion of the population at low cost with little delay".*

For instance, Chi et al. (2020) used geotags from Twitter to track internal migrations, and Rampazzo et al. (2024) monitor shifts in international immigration to the UK using Facebook's Advertising Platform. Results are optimistic - migration estimates from Twitter and Facebook are helpful in identifying geographic movements on a timely basis and show somewhat similar patterns to estimates from other data sources.

The development of big data for migration is at an early stage, and some studies have addressed some important limitations, such as improving statistical techniques to validate migration movements, data representativeness, and incomplete migration trajectories.

In New Zealand, migration research and analyses are primarily built from censuses (Cochrane & Poot, 2021; Coleman & Zheng, 2019; Grimes et al., 2018; Maré et al., 2007) and administrative data (Coleman & Zheng, 2020; Hyslop & Maré, 2009; McLeod, 2018). These studies have shown that both data sources are crucial to producing robust estimates across different demographic groups, from small areas (e.g., statistical area 2) to larger regions (e.g., local labour market catchments or regional councils).

2.3 Economic frameworks for understanding geographic mobility

People move for various reasons, with job or employment opportunities being the primary motivator. Individuals often choose new employers and job locations to enhance their well-being, such as higher wages, better work experiences, living in a more favourable climate, or proximity to home. The decision-making process involves evaluating the costs and benefits of leaving the current place and relocating to a new one. For example, prospective migrating workers residing in rural areas may choose to move if alternative job locations offer greater earnings and improved amenities that outweigh the costs of living in the new location.

These costs and benefits are influenced by both personal factors (e.g. characteristics and circumstances of individuals) and locational factors (e.g. characteristics of regions), which can lead to varying migration outcomes. The literature on internal migration primarily offers two distinct approaches to model their impacts on migration decisions. They are the micro-level and macro-level approaches (Greenwood, 1997, Cushing & Poot, 2004; Stillwell, 2009).

<u>Micro-level approach</u>

The micro-level approach centres on the behaviour of individuals or households, addressing questions such as why people migrate and how they choose between locations. In the pioneering work by Sjaastad (1962), the decision to move from one region to another is considered a human capital investment in which individuals aim to enhance their marketable value in the labour market. Individuals make migration decisions based on returns to and costs of migration. Returns include both monetary gains (e.g. income) and non-monetary benefits (e.g. locational preferences), while costs cover monetary expenses (e.g. moving costs) and costs from adapting to a new environment. Individuals will weigh returns against costs and work out net benefit to pick a new location.

In the mathematical terms, the net benefit is measured as the net present value (NPV) of migration. In its simplest form (Borjas, 2013, p. 324), it is calculated as in Equation 1:

Equation 1 Net Present Value equation for migration decisions

$$NPV = \sum_{t=0}^{T} \frac{Y_t}{(1+r)^t} - C$$

Where:

T is time horizon over which the individual expects to benefit from migration.

Y_t is expected returns at year *t* from changing location.

C is the expected costs of the move.

r is the discount rate.

The NPV is the summation of the yearly discounted returns from migration less moving costs. In the case of a positive NPV, the gross returns, $\sum_{t=0}^{T} \frac{Y_t}{(1+r)^t}$, from migration outweighs the costs C, indicating migration is a positive investment that improves human capital (e.g., better income and a better job match between employee and employer). NPV will decrease as the costs associated with the move increase, or it takes longer to move. Under Sjaastad's (1962) framework, individuals aim to maximise NPV.

With advancements in micro-data availability (e.g. longitudinal data and administrative data), researchers can now utilise spatially disaggregated, administratively linked data from individual records to follow inter-regional movements over time. This has been crucial to extend the micro-level model to cover many important dimensions, including individual/household characteristics (e.g. age, education, household structure, housing tenure) and locational attributes (e.g. wages, unemployment rates, and the housing market). For instance, Coulter and Van Ham (2013) used micro-level data from the British Household Panel Survey (BHPS) to examine how housing tenure and affordability influence residential mobility. They find that individuals in rental housing are more likely to move than homeowners and that housing affordability constraints often push households to relocate to less expensive areas. Similarly, Coulson and Grieco (2013) studied the relationship between mobility and mortgage debt using data from the Panel Survey of Income Dynamics (PSID) and found that homeowners in the US exhibited lower mobility rates than renters due to higher moving costs (realtor fees, transfer taxes, and fees required to take new mortgages).

These selected studies highlight the micro-level approach's capability to capture the nuanced ways in which housing market dynamics influence individual migration decisions. However, its focus on disaggregated data makes it less suitable for analysing large-scale migration trends, which are the focus of this study.

Macro-level approach

The macro-level approach examines *aggregated* migration, focusing on patterns and determinants of gross flows between regions. It addresses questions such as where migrants are coming from and where they are going to, emphasising the role of region-specific factors like regional economic conditions, population and amenities.

One of the most prominent frameworks in macro-level migration analysis is the gravity model. Rooted in Newton's law of gravity and the law of migration (Ravenstein,1885, 1889), the gravity model of gross migration flows between two regions is typically formulated as shown in Equation 2:

Equation 2 Simple gravity model

$$Y_{ij} = \frac{P_i^{\beta_1} \times P_j^{\beta_2}}{D_{ij}^{\beta_3}} G$$

Where:

Y_{ij} is the migration flow between region i (origin) and j (destination).

P_i and P_j are the population size in region i and j.

D_{ij} is the distance between two regions (e.g. physical distance or travel time)

G is a constant.

Coefficients β_1, β_2, β_3 are elasticities of population of region i and j and bilateral distance, respectively.

The gravity model reflects how economic opportunities and geographic proximity influence the intensity of migration flows. Inter-regional migration flows are modelled proportional to population sizes of origin and destination locations and inversely proportional to the distance between them. These relationships reveal the following:

- Larger populations generate and attract more migrants. From the destination perspective, urbanised regions with large populations offer greater employment opportunities, more competitive wages and salaries, and better infrastructure and consumption amenities (Glaeser, 1999; Krugman, 1991). These benefits make populated areas more attractive as destinations for migrating workers. Conversely, more populous origin locations have a bigger pool of potential migrating workers, contributing to higher outflows.

- Inter-regional migration decreases as the distance between the origin and destination regions increases. Distance serves as a proxy for monetary, social, and opportunity costs, acting as a deterrent to migrating individuals (Greenwood, 1997).

The gravity model is a powerful tool for analysing large-scale migration data, integrating multiple factors from origin and destination locations into a single equation (Poot et al., 2016, Ramos, 2016). Poot et al. (2016) pointed out three unique strengths of the gravity model compared with other macro-migration models: "*Firstly, its intuitive* *consistency with migration theories; secondly, ease of estimation in its simplest form; and, thirdly, goodness of fit in most applications*".

Recent applications of the gravity model have expanded it beyond its simplistic form, incorporating additional factors such as housing affordability, social networks, and environmental conditions to capture the evolving dynamics of migration flows better. For example, studies by Cavalleri et al. (2021), Liu (2018), Poghosyan (2018), and Stawarz et al. (2021) used gravity models and found highly heterogeneous impacts of house prices on internal migration in various countries. The gravity model provides a versatile framework for examining the key research question central to this thesis and serves as the foundation for the model specifications.

This section has briefly discussed differences between micro-level and macro-level approaches to internal migration and sets the stage for the following section, which will delve into recent applications and findings regarding inter-regional migration of residents or workers.

2.4 Empirical evidence across countries and in New Zealand

Internal migration and worker mobility have long been key drivers of labour market fluidity, enabling workers to move to regions or jobs where their skills are better matched and valued. However, recent decades have witnessed a global decline in internal migration rates in many advanced economies, including the US (Molloy et al., 2016), the UK (Champion & Shuttleworth, 2017), Canada (Coulombe, 2006) and Italy (Bonifazi et al., 2021). This trend carries both potential benefits and drawbacks, depending on its underlying causes. On the one hand, it may reflect positive labour market developments, such as efficient job matching between employees and employers, which reduces the need for workers to relocate. On the other hand, it could stem from unfavourable factors, such as barriers to mobility due to housing market constraints and labour market rigidities.

The decline in worker mobility has significant implications for workers' ability to climb the job ladder. The concept of the job ladder emphasises that workers advance their careers and incomes by leaving underpaid jobs and moving into better-paid ones (Causa et al., 2022; Cavalleri et al., 2021; Haltiwanger et al., 2018). Declining mobility could mean slower wage growth and exacerbated income inequality (Cavalleri et al., 2021). In the US, the decline in mobility reflects the fact that returns to internal migration have been diminishing as the anticipated incomes of relocating are outweighed by rising housing costs (Bayoumi & Barkema, 2019).

This implication could be alarming to many New Zealand workers. Meehan (2020) and Zheng et al. (2021) found relatively poor allocative efficiency of labour across the productivity distribution. Allocative efficiency is a measure of how labour is distributed in the economy. From international evidence (Melitz & Polanec, 2015; Petrin & Sivadasan, 2011), an optimal allocation of labour would ideally see a larger share of workers employed in high-productivity firms and a smaller share in low-productivity firms. This distribution ensures that resources are directed toward the most efficient and productive firms, maximising economic productivity potential and worker utilisation. The New Zealand situation falls short of this ideal. Meehan (2020) pointed out that low productivity firms are larger than the optimal level. Zheng et al. (2021) highlighted that over 40% of New Zealand's workforce is concentrated in average-productivity firms, whereas in other small advanced economies, a similar share is in higher-productivity firms. Poor allocative efficiency is not good news as it suggests many New Zealand workers are stuck in average-paid jobs and struggle to climb up the job ladder.

On top of poor allocative efficiency, New Zealand has one of the least affordable housing markets in the world as a result of persistent undersupply of houses, strong population growth, and higher building materials costs (New Zealand Productivity Commission, 2012). The house-price-to-income ratio in New Zealand was 8.2 in 2023, higher than Canada (5.6), the UK (5.0) and the US (4.9). Auckland was the least affordable city in the country, with a house price to income ratio of 8.6. The unaffordable housing situation may either disincentivise migration decisions or make migration more expensive.

Understanding the role played by house prices in worker mobility has received growing attention from academics and policymakers over the last couple of decades. Two main ways through which rising house prices within a region affect worker geographic mobility are identified. Increasing house prices are expected to reduce worker inflows to the region (negative effect) while simultaneously encouraging outflows from the region (positive effect). In other words, house prices can influence worker mobility through both 'push' and 'pull' effects.

To quantify these effects, recent research has expanded the simple gravity model (Equation 2) by adding house price variables from both the origin and destination areas. Often, they are transformed into the log-linear form,[2] as shown in Equation 3.

Equation 3 Log-transformed gravity model with house price variables

$$\ln Y_{ijt} = \beta_1 lnP_{it} + \beta_2 lnP_{jt} - \beta_2 lnD_{ijt} + \alpha_1 lnHP_{it} + \alpha_2 lnHP_{jt} + \mu_i + \mu_j + \ln G_{ijt} + \varepsilon_{ijt}$$

where μ_i and μ_j are region-specific fixed effects in origin i and destination j regions, respectively. The last term (ε_{ijt}) is the error term and is independently and identically distributed.

The additional variables, $lnHP_{it}$ and $lnHP_{jt}$, are log house prices at origin i and destination j at time t, respectively. The corresponding coefficients, α_1 and α_2, return marginal effects on house prices at the origin and destination regions on inter-regional flows. They can be interpreted as the magnitudes of push and pull housing factors.

The signs of these coefficients can provide insights into the role of the housing market in shaping region-to-region movements. A positive α_1 suggests a positive push effect as rising house prices encourage outflows of people from the origin region. On the other hand, a negative α_2 indicates a negative pull effect since higher house prices deter inflows.

Table 1 provides selected evidence from recent studies modelling house prices in gravity models, covering multiple advanced economies, such as Spain, Australia, the U.S., and the U.K. Most of these studies highlight the negative impact of high house prices on inflows. If a region experiences soaring house prices, it will expect to see a smaller inflow of people from other regions. However, evidence regarding the positive effect of high house prices on outflows is relatively scarce. For example, Australian results (Cavalleri et al., 2021, p. 22) show a negative effect (-0.35) on house prices at the destination region and a null effect (-0.0074) of house prices at origin region – indicating that a 10% increase in real house prices is associated with a 3.5% drop in the number of people moving to the region. As the negative impact on inflows outweighs the positive impact on outflows, total people flows between regions are expected to drop and, therefore, the rate of internal migration declines.

[2] It is possible to have different forms of the gravity model. The log-transformed equation is chosen due to its popularity and simplicity.

Evidence for the New Zealand context is limited. Based on a thorough review of the literature, the most relevant economic research is summarised in the last two papers listed in Table 1. Both studies examine geographic mobility between urban areas in New Zealand.

Coleman and Zheng (2020) examined whether worker mobility is driven by relative house prices between destination and origin areas. Their analysis of the overall working-age population did not yield convincing evidence of a significant relationship between house prices and mobility. However, when applying gravity models to different industries, they found that geographic mobility for workers in the agriculture, health, manufacturing, and construction industries was negatively affected by house prices. This highlights how housing affordability may act as a barrier to mobility for certain workers.

Grimes et al. (2019) investigated the determinants of migration for residents aged between 30 and 59, with a particular focus on the role of consumption (e.g. climate) and productivity (e.g. income levels, business communities) amenities as attractions for different types of migrants. While the study did not directly examine house prices, local amenities are generally positively associated with house prices. For instance, Fleming et al. (2018) found that homebuyers paid more for properties if they were exposed to decent sunlight. Grimes et al. (2019) demonstrated both types of amenities are important, but that they attracted different demographic groups. International migrants were more likely to move to areas with productivity amenities, whereas domestic migrants favoured places with consumption amenities. These findings might suggest house prices were not a barrier for migration, as the pull factors of amenities appeared to outweigh housing costs.

Table 1 Selected studies of worker geographic mobility using gravity-type models

Title & Authors	Data used for migration	Geographic units	Estimation method	Results on house prices/costs on migration
Inter-regional migration: The UK experience (Biswas et al., 2009)	National Health Service Central Register data, annual from1975 to 2006	Four broad regions: England, Northern Ireland, Scotland and Wales	OLS and fixed-effects panel regressions	Negative effects of house price at destination on migration inflows
Intermetropolitan migration and housing prices: simultaneously determined? (Potepan, 1994)	Annual housing survey between 1976 and 1979	52 metropolitan areas in the US	Two-stage least squares	Higher house prices discourage net migration
Regional labor mobility in Spain (Liu, 2018)	Various publicly available mobility flow data sources in Spain from 1998 to 2016. Only covers the working-age population between 16-64 years old	17 NUTS level 2 regions (Nomenclature of Territorial Units for Statistics).	Fixed-effects panel regressions	High house prices in destination regions discouraged migration inflows, while the effect of house prices as a push factor from origin regions is less significant.
Regional labor mobility in Finland (Poghosyan, 2018)	Migration flows data from Statistics Finland for the years 2000-2016. Only the working-age population was selected (15-64).	19 NUTS level 2 regions	Fixed-effects panel regressions	Higher house prices in destination regions tended to push people to move out, while lower house prices in destinations attract in-migrants.
Internal migration and housing costs – a panel analysis for Germany	Annual intercounty migration flows from the Federal Statistical Office	The municipalities (Gemeinden) are nested	Fixed-effects Poisson regressions	Asking rents per m^2 was used instead of house prices. Higher rents at the

(Stawarz et al., 2021)	Germany and the Statistical Office of the Länder for the years 1997-2017 were used.	within 401 counties (Landkreise and kreisfreie Städte) and 16 states (Länder)		destination act as a barrier to inflow migrations. Rents also pushed residents to somewhere else.
Migration, housing and regional disparities: a gravity model of inter-regional migration with an application to selected OECD countries (Cavalleri et al., 2021)	Annual bilateral migration estimates are derived from population statistics in official statistics agencies and are mostly available from the early 2000s to 2017/2018.	Either smaller local units or larger regions (TL2 or TL3 regions defined by OECD) in Australia, Canada, Denmark, Finland, Italy, Japan, Korea, Netherlands, Poland, Spain, Sweden, Switzerland, the UK and the US	OLS and fixed-effects panel regressions	House prices (at destination) are an important barrier to migration in many countries. The 'barrier' effects are particularly strong in Australia, Sweden, Italy, Spain and Canada. House prices have no significant impact on migration within Finland, the Netherlands, and Poland.
The contrasting importance of quality of life and quality of business for domestic and international migrants (Grimes et al., 2019)	Censuses from 1986 to 2013, Statistics New Zealand	31 urban areas	Fixed-effects linear panel regressions	Locations with good business amenity values attracted international migrants. Domestic residents tended to move to locations with abundant consumption amenities (e.g. warmer, longer sun hours)
Job-to-job transition and the regional job ladder (Coleman & Zheng, 2020)	Linked Employer-Employee Database, 2000-2018	31 urban areas and one for allocative businesses.	Fixed-effects linear panel regressions with auto-	Results did not support the statistical significance

			regressive serial correlation	on the relationship between house prices and mobility in the 15-64 working-age population. However, results vary depending on the industries in which workers were employed.

Applications of gravity models presented in Table 1 are predominantly estimated by either the fixed-effects linear models or, if the dependent variable is not normally distributed, a fixed-effects non-linear model. Popular non-linear models assume either a Poisson or Negative-Binomial assumption. Most of these models allow region-specific fixed effects and use lagged predictor variables (on the right-hand side of Equation 3) to mitigate potential endogeneity bias. Endogeneity bias arises when predictor variables are correlated with the error term. It can significantly impact on the validity and robustness of empirical findings, particularly in predicting inter-regional worker flows based on house prices. Endogeneity comes in two main forms: omitted variable bias and reverse causality.

Omitted variable bias occurs when some relevant variables that influence the predictor variables and dependent variable are left out of the regression model, leading to wrong predictions and statistical inferences. Omitted variables, such as the quality of local amenities and life satisfaction, are generally unobserved and may influence the levels of inter-regional worker flows and house prices simultaneously. For example, a region with a warmer climate and better healthcare services may attract more workers from other regions and overseas, heighten housing demand, and, in turn, increase house prices. One solution is to include fixed effects, μ_i and μ_j, in regression models. These fixed effects control for time-invariant factors in each region. Inclusion of these fixed effects in panel regression models are often considered to eliminate potential estimation bias from omitted variables.

Reverse causality refers to the simultaneous relationship between the dependent variable and predictor variables. These variables influence each other and create a feedback loop, leading to biased regression estimates. For example, house prices can change the level of workers leaving or coming into a region, while at the same time movements of workers into and out of a region could also determine current and potentially future house prices.

To partial out potential reverse causality, one popular method in applied economic research is to replace the endogenous predictor variables with their lagged values. For example, log house prices in the current period, $lnHP_{it}$ and $lnHP_{jt}$, are replaced with values from the previous period, $lnHP_{it-1}$ and $lnHP_{jt-1}$. The logic of using lagged values is to assume that the level of worker flows in one period had no influence on the level of house prices in the previous period. Generally, this practice has been widely accepted across a wide variety of disciplines in economics and finance (Aschhoff &

Schmidt, 2008; Bansak et al., 2007; Poot et al., 2016b). However, it does not guarantee exogeneity if the imposed structure between the dependent variable and lagged predictor variables is wrong. Reed (2015) studied the practice of using lagged variables in linear models and pointed out that this practice does not guarantee avoiding simultaneous bias, stating, "*it is straightforward to generate examples where the researcher is likely to conclude that the effect of X on Y is opposite in sign to its true value, and to find that the associated, wrong-signed coefficient is statistically significant a majority of the time*". On the face of this evidence, using lagged variables can be problematic.

Alternatively, the Generalised Method of Moments (GMM) provides a more robust framework by leveraging instrumental variables (IVs) that act as exogenous "proxies" for house prices. These IVs isolate variations in house prices that are *unrelated* to worker mobility, thereby breaking the circular relationship between the two.

To be specific, IVs are additional variables Z in the regression system that satisfy two conditions. The first condition is exogeneity which mean they are uncorrelated with the error term. In mathematics expression, $E(Z'\varepsilon) = 0$, where Z is the IVs and ε is the error term in Equation 3. Secondly, the IVs are well correlated with the endogenous variables, $E(Z' lnHP_{it}) \neq 0$ and $E\left(Z' lnHP_{jt}\right) \neq 0$. The GMM method uses the orthogonality condition, $E(Z'\varepsilon) = 0$, and minmises the weighted sum of squared sample moment condition, $Q(\beta) = \left[\frac{1}{N} Z'(Y - X\beta)\right]' W \left[\frac{1}{N} Z'(Y - X\beta)\right]$, where N is the number of observations, $(Y - X\beta)$ is the residual term ε in the gravity model and W is the weight matrix. The choice of the weight matrix can be based on certain assumptions about the distribution of the error term, such as serial and cross-sectional correlations.

GMM estimators can employ external or internal instruments. External instruments, such as supply-side constraints that predict house prices but are exogeneous to worker flows, are commonly employed. One popular instrumental variable is local housing supply elasticities (Gyourko et al., 2008). It rests on the assumption that housing supply elasticities are not associated with unobserved local factors and have good predictive power on house prices. Graham and Makridis (2023) recently addressed the endogeneity problem using Bartik-style instruments. These authors combined the composition of local housing characteristics (such as age and number of bedrooms) with time-series variation in house prices associated with housing characteristics. Local housing characteristics are primarily predetermined and not affected by changes in house prices. On the other hand, internal instruments derived from past values of endogenous variables (such as $lnHP_{jt-1}$, $lnHP_{jt-2}$) can be used in dynamic panel models (Bang & MacDermott, 2019; Mayda, 2005), assuming that past house prices affect current migration patterns but are not influenced by contemporaneous migration shocks.

2.5 Worker mobility and earnings growth

Worker mobility plays a significant role in shaping labour market dynamics, influencing individual career paths and wage trajectories. One of the crucial dimensions of worker mobility is the relationship between job changes and wages. This relationship has been the subject of substantial research in the literature with scholars exploring how job transitions affect wage dynamics.

Empirical studies have shown that job-to-job transitions positively impact wages in New Zealand and other advanced economies. For example, Hyatt and Spletzer (2013) used linked employer-employee data from the US and found that job-to-job transitions were associated with an estimated 3.5% to 9% increase in earnings for most American workers. Similarly, Deutscher (2019) found that a one percentage point increase in the job-to-job transition rate, on average, led to a half percentage point increase in wages in Australia. In New Zealand, Ball et al. (2020), Karagedikli (2018), and Zheng and Sing (2023) found that higher job-to-job transitions at the national, regional, and industry levels simultaneously drive up wage growth.

Moreover, the impact of inter-regional job-to-job transitions on wages varies depending on where workers come from and where they move to. Urbanised areas usually offer higher wages and salaries compared to non-urbanised regions. Research suggests that this wage premium is a result of higher worker ability (e.g., highly educated and well-trained staff) and greater productivity of firms (e.g., more innovative and competitive). Workers who move to urbanised areas can expect to gain higher wages in the short and long term. Conversely, workers who leave urbanised areas and relocate to non-urbanised regions may experience immediate wage losses. Glaeser and Maré (2001) found that migrants in the US who moved from rural to urban areas experienced significant wage gains, but workers relocating from urban to rural regions experienced small wage losses. Lehmer and Ludsteck (201) found that younger workers and workers moving from rural to urban areas received the highest wage growths in Germany. German workers relocating from urban to rural areas encountered wage declines.

2.6 Contributions of this study

This thesis makes three key contributions to the literature on house prices and worker mobility in New Zealand.

1. Comprehensive geographic coverage

While prior studies have predominantly focused on urban areas, this thesis extends the analysis to all regions of New Zealand. By incorporating both urban and rural areas, the research provides a more holistic understanding of how housing prices influence migration patterns across diverse geographic contexts. The inclusion of smaller areas allows for a more nuanced examination of migration flows, shedding light on whether housing prices act as a barrier to mobility in less densely populated regions.

2. Richer demographic insights through gravity models

This study employs gravity models to analyse migration patterns, offering richer insights into how house prices affect different demographic groups. This approach allows for the disaggregation of migration flows by age, gender, and ethnicity. By identifying which demographic groups are most sensitive to housing price changes, the study provides policymakers with targeted evidence to address the specific needs of vulnerable populations.

3. Short-term labour market outcomes

A third contribution of this thesis is its investigation of the short-term impact of migration on workers' earnings. While existing studies have primarily focused on the determinants of migration, there is limited evidence on how migration influences labour market outcomes in the immediate aftermath of relocation. This study fills this gap by examining whether migrants experience changes in earnings shortly after moving, and whether these changes vary by region or demographic group. This analysis provides valuable insights into the economic consequences of migration, helping to inform policies aimed at enhancing labour market efficiency and reducing regional inequalities.

Chapter 3: Data

3.1 Data source

This thesis makes use of data on changes in workers' jobs held in Statistics New Zealand's Integrated Data Infrastructure (IDI). The IDI is a comprehensive research database containing de-identified administrative and survey microdata about people, households, and businesses linked across a range of life domains for the whole population of New Zealand. The IDI links together data at the person level drawn from multiple sources including government agencies, Statistics New Zealand's surveys, and non-governmental organisations.

Each person in the IDI has a unique anonymised identifier which is used to link the person's data across different data sources, spanning health, education, income, social welfare and other areas. Statistics New Zealand receives new data regularly and updates the IDI quarterly. When integrating new data into the IDI, Statistics New Zealand links each person's records across multiple datasets before removing all identifiable features such as names and identification numbers (such as National Health Index numbers). Thus, people can be tracked longitudinally through time, including changes in their jobs and the locations of their jobs.

The IDI includes a dataset from Inland Revenue called the Employer Monthly Schedule (EMS). Each month, all employers must file an EMS return with Inland Revenue showing the employees working at the firm that month, the wages paid to them, and the income tax deducted from them. EMS is a mandatory reporting requirement for all employing firms in New Zealand. Statistics New Zealand maps the filers of EMS returns to individual business enterprises and maps the taxpayers on EMS returns to individual employees. Thus, the EMS dataset identifies the jobs of individual workers. The IDI contains EMS data for all paid jobs back to April 1999.

EMS returns do not collect the job locations of individual workers, so Statistics New Zealand allocates workers to the physical location of the business. For businesses that have more than one plant/office location, Statistics New Zealand uses an algorithm that uses the shortest commuting distance between workers' residential addresses and the locations of plants/offices (see Statistics New Zealand (2009) and Fabling and Maré (2015)). Some plants/offices change their economic activities and locations over time. For example, if a plant changes its industry code from "cake and pastry manufacturing” to “biscuit manufacturing”, a standard algorithm will indicate that the employees of the plant had changed jobs to another plant in a different industry with the same location (Coleman & Zheng, 2020). However, in the current analysis, such a change would not constitute a job-to-job transition. To deal with such issues, in the current analysis each business and its associated plants/offices is assigned to a predominant industry code and location based on the industry and location in which the plant/office employed the largest share of employees over its life span. [3]

In New Zealand, geographic areas are broadly categorised into three classes: administrative areas, statistical areas, and functional labour market areas. Administrative areas, including regional councils and territorial local authorities, set boundaries for regional and local governments that are responsible for managing natural resources, and planning and delivering local services across many communities. Statistical areas, including statistical areas 1 and 2, are maintained and updated by Statistics New Zealand. They cover all of New Zealand (including rural areas and inlets) and are mainly used for reporting Census data. Functional labour market areas are constructed by analysing commuting patterns between residential and employment locations. Often these geographic units are considered as self-contained areas where local residents live, work and commute. Unlike the other two types of geographic areas, these areas are determined by economic activities. Davies and Maré (2020) revealed 29 functional market areas based on 2013 Census commuting data.

In this thesis, workers’ job locations are mapped to regional council areas (based on 2018 geographical boundaries). There are 16 regional council areas (11 regional councils and 5 unitary authorities, excluding Chatham Islands Council) in New Zealand: Northland, Auckland, Waikato, Bay of Plenty, Gisborne, Hawke’s Bay, Manawatu-Whanganui, Taranaki, Wellington, Nelson, Tasman, Marlborough, West Coast, Canterbury, Otago and Southland.

The adoption of regional councils is due to two primary reasons. First, regional statistics, such as GDP, unemployment rates, and population, are regularly published at the regional council level. Second, their scale mitigates confidentiality risks associated with microdata. The 5th Microdata Output Guide from Statistics New

[3] From our observations, around 5% and 3% of plants/offices changes their locations and industry codes over the period of 1999-2021.

Zealand requires random rounding and the suppression of data derived from very small populations. Regional councils have sufficiently large populations, ranging from approximately 33,000 usual residents in West Coast to 1.66 million in Auckland. Consequently, the use of regional councils minimises the risk of data suppression, ensuring that statistical outputs and regression estimates remain robust and usable. Employing smaller geographic units (e.g., territorial local authorities) could lead to excessive suppression, rendering much of the data unusable.

Jobs are coded to industries based on level 1 (division) of the Australian and New Zealand Standard Industrial Classification (ANZSIC) 2006.

It is important to note that some errors in workers' job locations occur in the data, due to inaccurate residential address information in the IDI or misallocation of workers to job locations by Statistics New Zealand's algorithm. These errors may result in spurious job changes, where a worker appears to have changed job location when in fact they have not, thus overstating the number of job-to-job transitions in the economy.

3.2 Sample selection

The sample selection process follows a similar approach to Coleman and Zheng (2020). To begin with, worker mobility is analysed by comparing job information between two annual snapshots. A snapshot is taken of workers' jobs during March months (with positive earnings of at least $1) from 1999 to 2021 in the EMS and the resulting job information is compared between two consecutive years. The earliest comparison is between March 1999 and March 2000 and the latest comparison is between March 2020 and March 2021. Thus, the thesis analyses worker mobility over a 21-year period. March years are chosen because most New Zealand businesses use 31st March as the end of the accounting year. Note that not all job changes that occur within each 12-month period are captured in the analysis (only the March-to-March comparison is analysed). Workers with more than one job appear more than once in the data. Hence, the unit of analysis is 'person-jobs' (i.e., combinations of workers and their job or jobs). This process results in a population of 43,739,300 unique person-job records.

Three exclusion criteria are then applied to this population. First, working proprietors (self-employed workers, business owners, or partners) are excluded from the sample. Working proprietors are identified if (1) the Inland Revenue number for payee and payer are the same on the EMS, or; (2) positive incomes are observed in at least one of an individual tax return (IR3), partnership income/loss distribution (IR7p), or company shareholders' details (IR4). Working proprietors often have different motivations compared to employees. According to Benz and Frey (2008), self-employed individuals tend to prioritise autonomy and the rewards of being their own boss, while employees may prioritise job stability, career progression, and income progression. This divergence in goals can impact decision-making regarding job changes. Working proprietors are therefore dropped from the target population, which reduces the population of interest to 42,772,900.

Next, the population is restricted to workers aged between 15 and 64 years with non-missing gender and ethnicity information, as retiring workers have different work patterns than workers aged under 65 years and demographic information is needed for later analyses. This reduces the population to 40,614,800.

Finally, workers are restricted to having a maximum of two jobs. Thus, workers with two jobs are counted twice in the analysis. For workers with three or more jobs, only the two highest-paid jobs are retained in the analysis. This leaves a final sample of 40,299,500 unique person-job records over the 21-year period. However, for ease of exposition, this thesis refers to the sample as being comprised of 'workers' rather than 'person-jobs'.

3.3 Measuring worker mobility

This thesis adopts the methodology pioneered by Davis and Haltiwanger (1998) and Burgess et al. (2000) who developed the idea of tracking workers' job information in order to quantify the magnitude of job-to-job transitions. The EMS data described above is used to classify worker mobility into five categories:

1. Stays: the worker had the same job in the two years being compared (current year t and future year t+1, both measured in the month of March).
2. Entries: the worker had a particular job at year t+1 but did not have any job at year t.
3. Exits: the worker had a particular job at year t but no longer had any job at year t+1.
4. Intra-regional job-to-job transitions: the worker changed jobs between year t and year t+1 and the new job was located in the same region.
5. Inter-regional job-to-job transitions: the worker changed jobs between year t and year t +1 and the new job was located in a different region.

Entries occur when EMS job information is observed in year t+1 but not observed in year t due to being unemployed or not in the labour force (e.g., a student) or not in New Zealand in year t (but had immigrated into New Zealand by year t+1). Exits occur when EMS job information is observed in year t but not in year t+1 due to becoming unemployed, leaving the labour force, emigrating out of New Zealand, or being deceased in year t+1. IDI data on deaths, immigration, education, and social welfare benefit receipt are used to help determine when entries and exits have occurred.

Workers in each of the five mobility categories are presented as either headcounts or rates. The headcounts indicate the absolute volume of workers in each category. The rates are expressed as percentages, calculated by dividing the number of workers in a given category by the average number of workers at time t and t+1. For example, if a region had a workforce of 40,000 in 2003 and 42,000 in 2004, and there were 1,000 workers in the inter-regional job-to-job transition category, the rate in 2003 would be calculated as $\frac{1000}{(40000+42000)/2} \times 100\% \approx 2.43\%$.

The fifth category, inter-regional job-to-job transition, is the primary focus in this study. This category specifically captures workers who change employers and relocate to a different region from one year to the next. The next chapter, chapter 4, provides descriptive analysis of inter-regional job-to-job transitions over time, across regions, and by various demographics.

With 16 regional council areas, there are 240 distinct region-to-region movements that a worker could make (16 regions of origin multiplied by 16 regions of destination, minus within-region (e.g., Auckland-to-Auckland) permutations). In chapter 5, inter-regional job-to-job transitions made by individual workers are aggregated to these 240 distinct region-to-region movements (which become the unit of analysis in chapter 5) and analysed in relation to relative house prices (region-to-region differences in house prices).

3.4 Measuring house prices

Chapter 5 analyses the effect of house prices on worker mobility in New Zealand. House price data come from the Real Estate Institute of New Zealand (REINZ). REINZ has published monthly data on median house prices by region since 1992. These data are used to compute the average median house price over the period 2000 to 2021 for each region.

3.5 Measuring earnings growth

Chapter 6 analyses the effect of job-to-job transitions on workers' earnings. Workers' earnings are derived from EMS data on wages and salaries in each of the two years being compared. However, simply using each workers' earnings for the calendar month of March is problematic, because 1) calendar months have uneven numbers of days and pay periods (often weekly or fortnightly), 2) hours of work may change due to changes in job situations (e.g. leaving the current job or moving from part-time to full-time employment) and 3) some workers may present short breaks in payment, possibly a short period holiday on leave without pay. In short, earnings levels are affected by the timing of pay, the number of pay periods, changes in actual hours of work and short breaks in payments in a month.

To address these measurement issues, earnings per person-job in March are calculated as the average earnings in March and adjacent months, from January to May. The rationale for using average earnings, rather than the actual earnings in March, draws on the methodology of Fabling and Maré (2015).

Table 2 provides examples of March earnings for seven cases. In case A, the March earnings are the average earnings between January and May, where a worker stays with the same employer throughout the period.

However, some workers may start or end their jobs within this five-month window. In such cases, average earnings are calculated using earnings information from previous or future months where possible. Fabling and Maré (2015) observed that earnings in the first month (starting a job) and the last month (leaving a job) were typically lower than in other months, likely because workers worked partial months (e.g. starting or leaving mid-month). To adjust for this, these authors proposed using earnings from up to two adjacent months in the same job to adjust start- and end-month earnings, under the assumption that wage rates remain stable over a short period of time.

For example:

- In case B, where a worker starts in February, March earnings are calculated as the average of earnings from March, April, and May.

- In case C, where a worker starts in March, March earnings are the average of April and May earnings.

Conversely, for workers ending their employment:

- In case D, where a worker ends in April, March earnings are the average of earnings from January, February, and March.
- In case E, where a worker ends in March, March earnings are the average of earnings from January and February.

In case F, the situation is similar to case A, except there is a break in employment payment in March. The earnings are calculated as the average of earnings from January, February, April and May. In the last case (case G), where a worker is only employed for the single month of March, their earnings would simply be the actual earnings from March.

Section 6.2 describes in more detail how earnings are averaged over the five-month period, adjusted for full-time equivalent workload, adjusted for inflation, and then compared across two consecutive years.

Table 2 Calculation of March earnings for some case studies

Case	January	February	March	April	May	Comments	Calculations of the average March earnings
A						A worker stays in the same job and works through the five-month period.	Average monthly earnings from January to May, where earnings are available
B						A worker starts a new job in February.	Average monthly earnings from March to May, where earnings are available
C						A worker starts a new job in March.	Average monthly earnings from April and May, where earnings are available
D						A worker leaves the current job in April	Average monthly earnings from January to March, where earnings are available
E						A worker leaves the current job in March	Average monthly earnings from January and February, where earnings are available
F			Break			Similar to case A, but there is a payment break in March.	Average monthly earnings from January, February, April and May, where earnings are available
G						A worker spends only a month in a job	Only the March earnings are used.

Note: Grey-shaded cells indicate active employment. Blank cells are the opposite case, where workers are not employed in specific time periods.

Chapter 4: Estimates of worker mobility in New Zealand

In this chapter, the employment data described in Chapter 3 is used to estimate worker mobility in New Zealand from 2000 to 2020, with a focus on job-to-job transitions and in particular inter-regional transitions. Rates of job-to-job transitions are estimated at the national and regional levels and inter-regional job-to-job transition rates are estimated separately for different groups of workers.

4.1 Job-to-job transition rate at the national level

Table 3 presents a time series of data on worker mobility in New Zealand from 2000 to 2020. It reports the share of all person-jobs falling into the five categories of worker mobility defined in Chapter 3 (section 3.1.3). On average over the 21-year analysis period, 51.9% of workers in employment remained in the same job over a year, 20.9% entered employment, 13.6% of workers exited employment, and the remaining 14.6% changed jobs (9.1% within regions and 4.5% across regions). Compared to US evidence (Golan et al., 2007), New Zealand appears to have a comparable degree of worker mobility with a slightly higher rate of entries and a lower rate of job-to-job transitions.

Over the past few years, there have been notable changes in worker mobility. One of the significant changes was that the percentage of workers who stayed in the same job has increased from 47.0% in 2000 to 56.5% in 2020. Fewer people are entering or leaving or changing jobs. It is interesting to note that this trend is not only limited to New Zealand but has been observed in many other advanced economies (Causa et al., 2021; Deutscher, 2019; Hyatt & McEntarfer, 2012).

Another important feature of the worker mobility patterns is persistently higher entry rates than exit rates, reflecting that more "new" workers joined the labour market than left. On average, the entry rate was 20.9%, while the exit rate remained at a moderate rate, 13.6%. Throughout the study period, employment growth kept pace with a strong inflow of immigrants as the New Zealand government promoted and implemented active, skill-based migration policies, such as the accredited employer scheme and the essential skilled work visa. Consequently, the number of temporary work visa holders and permanent residents in New Zealand has more than doubled between 2009 and

2020, rising from 83,000 to 198,000 for temporary work visas and from just under 500,000 to over one million for permanent residents (New Zealand Productivity Commission, 2022). According to the Productivity Commission (2022), migrants were disproportionately represented in specific regions (e.g., Auckland) and industries (e.g., Agriculture and Hospitality).

Immigrants to New Zealand are captured in all categories of worker mobility defined above: very recent arrivals (either new migrants or returning long-term migrants) will be recorded as Entries, while migrants who worked in New Zealand but decided to leave are classified as Exits, Stays if they obtained a job in New Zealand and remained in it between year t and year t+1, or as a job-to-job transition (if they changed job between year t and year t+1). While it is beyond the scope of this study to analyse how international immigrants affect patterns of worker mobility, it is important to note that the size and composition of international migration into and out of New Zealand (and the geographic distribution of migrant settlement and departure) is likely to affect the flows and rates of worker mobility estimated in this thesis.

It can be observed from Table 3 that job changes within the same region are more common than changes between different regions. On average over the period, only about one-third of job-to-job movements involved a change of region. Over time, the rate of job-to-job transitions within the same region has decreased, while the rate across regions has increased (although not by as much as the within-region decrease). This has led to an overall decrease in job-to-job transitions.

Moreover, the rate of job-to-job transitions in the same region has decreased from an average of 10.2% in the 2000-2007 period to 8.3% in the 2008-2020 period, as shown in Figure 1. On the other hand, the job-to-job transition rate across regions has shown a steady increase, peaking at 5.3% in 2018.

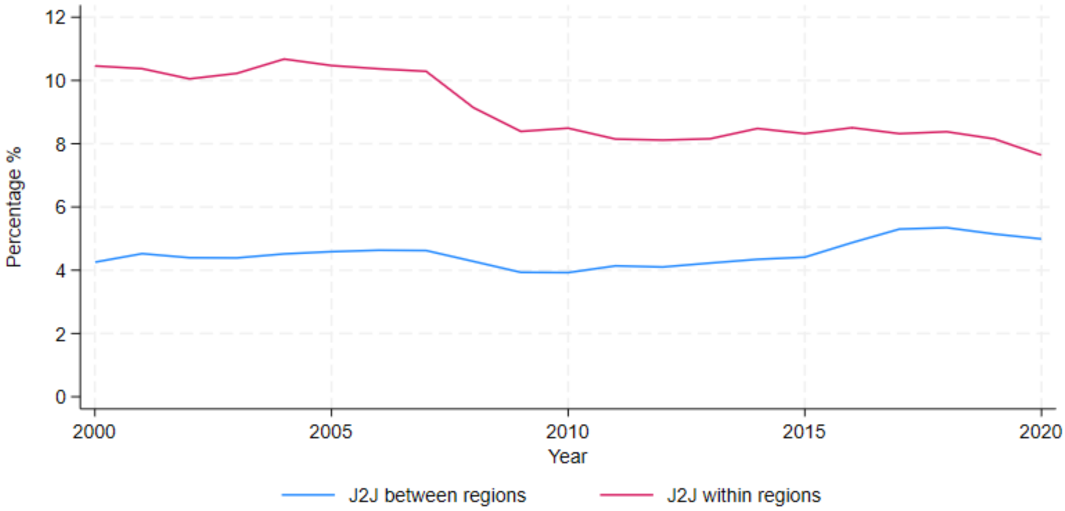
Table 3 Categories of worker mobility in New Zealand by year, 2000-2020

Year	*Stays*	*Entries*	*Exits*	*Job-to-job transitions*		
				TOTAL	WITHIN REGIONS	ACROSS REGIONS
2000	47.0%	23.7%	14.6%	14.7%	10.5%	4.3%
2001	47.8%	23.0%	14.3%	14.9%	10.4%	4.5%
2002	49.0%	22.6%	13.9%	14.4%	10.1%	4.4%
2003	48.9%	22.9%	13.5%	14.6%	10.2%	4.4%
2004	48.4%	22.8%	13.7%	15.2%	10.7%	4.5%
2005	48.5%	22.2%	14.3%	15.1%	10.5%	4.6%
2006	48.6%	21.8%	14.6%	15.0%	10.4%	4.6%
2007	48.8%	21.9%	14.4%	14.9%	10.3%	4.6%
2008	51.7%	19.5%	15.4%	13.4%	9.1%	4.3%
2009	54.8%	18.8%	14.1%	12.3%	8.4%	3.9%
2010	54.3%	19.6%	13.7%	12.4%	8.5%	3.9%
2011	54.2%	19.1%	14.4%	12.3%	8.1%	4.1%
2012	54.5%	20.1%	13.2%	12.2%	8.1%	4.1%
2013	54.5%	20.0%	13.1%	12.4%	8.2%	4.2%
2014	54.2%	20.5%	12.5%	12.8%	8.5%	4.3%
2015	54.3%	20.4%	12.6%	12.7%	8.3%	4.4%
2016	53.2%	20.8%	12.6%	13.4%	8.5%	4.9%
2017	52.8%	20.8%	12.8%	13.6%	8.3%	5.3%
2018	52.8%	20.2%	13.2%	13.7%	8.4%	5.3%
2019	54.0%	20.1%	12.6%	13.3%	8.2%	5.1%
2020	56.5%	18.6%	12.3%	12.6%	7.6%	5.0%
Average	51.9%	20.9%	13.6%	13.6%	9.1%	4.5%

Source: Author's calculations using IDI data.

New Zealand's inter-regional job-to-job transition pattern is somewhat different from other advanced economies. In contrast to New Zealand, the rate of interstate worker mobility has declined in the US (Molloy et al., 2016; Azzopardi et al., 2020). Similarly, declining inter-regional labour mobility rates have also been observed in a number of European countries (Liu, 2018).

Figure 1 Job-to-job transition rates within and across regions of New Zealand over 2000-2020



Source: Author's calculations using IDI data.

4.2 Job-to-job transition rates at the regional level

Table 4 displays the average job-to-job transition rates for New Zealand's 16 regional councils over the 21-year period. The regions are ranked from the one with the largest working-age population (Auckland) to the one with the smallest (West Coast). The rates of job-to-job transitions (in total, both within and across regions) are evenly distributed across all regions, which indicates that the transition rates are not affected by the population size of the regions. Based on these findings, it can be concluded that all regions experience similar rates of worker turnover between jobs.

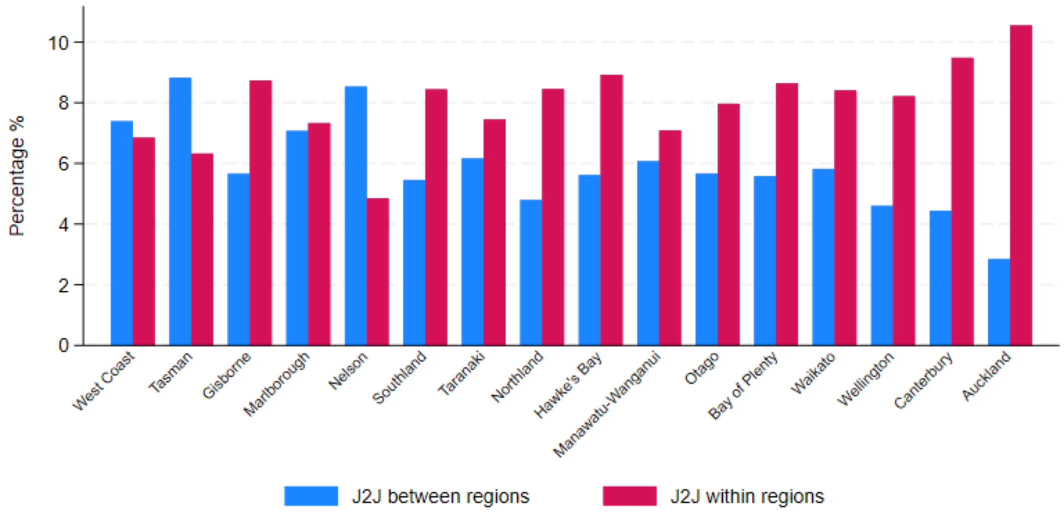
Table 4 Job-to-job transition rates by region of New Zealand, average 2000-2020

	Job-to-job transitions across regions	*Job-to-job transitions within regions*	*Job-to-job transitions*	*Population*
Auckland	2.9%	10.5%	13.4%	781,185
Canterbury	4.4%	9.5%	13.9%	305,676
Wellington	4.6%	8.2%	12.8%	277,095
Waikato	5.8%	8.4%	14.2%	196,228
Bay of Plenty	5.6%	8.6%	14.2%	133,666
Otago	5.7%	8.0%	13.6%	114,942
Manawatu-Wanganui	6.1%	7.1%	13.2%	112,881
Hawke’s Bay	5.6%	8.9%	14.5%	86,152
Northland	4.8%	8.4%	13.2%	63,227
Taranaki	6.2%	7.4%	13.6%	54,838
Southland	5.5%	8.4%	13.9%	52,292
Nelson	8.5%	4.9%	13.4%	28,571
Marlborough	7.1%	7.3%	14.4%	24,547
Gisborne	5.7%	8.7%	14.4%	23,566
Tasman	8.8%	6.3%	15.1%	23,450
West Coast	7.4%	6.8%	14.2%	16,338

Source: Author’s calculations using IDI data.

When regions are compared, there are clear differences between across-region and within-region transition rates. In this case, the assumption of independence between the population size and job transitions is no longer valid. Figure 2 illustrates two opposing correlations. Firstly, inter-regional job-to-job transition rates have a negative correlation with population size. Secondly, intra-regional job-to-job transition rates have a positive correlation with population size.

Figure 2 Relationship between population size and job-to-job transition rates (within and across regions of New Zealand over 2000-2020)



Source: Author's calculations using IDI data.
Note: Regions on the horizontal axis are ordered from the smallest population count (left) to the largest population count (right).

Regions such as Tasman and the West Coast have smaller local labour markets that offer fewer job opportunities and less competitive wages and salaries than larger regions like Auckland and Wellington. Local workers in these small regions may opt to change regions when they find new job opportunities due to limited options in their local area. On the other hand, workers in larger regions like Auckland and Wellington face an abundance of job opportunities. They are less likely to consider taking a job in another region as an attractive option.

4.3 Job-to-job transition rates across regions by worker characteristics

This section delves deeper into the job-to-job transition rates across regions by examining variations by age, gender, and ethnicity. The aim is to provide a more comprehensive understanding of the different factors that influence workers' geographic mobility and how these vary across different groups.

4.3.1 Age

Table 5 presents inter-regional job-to-job transition rates by age group over the period 2000 to 2020. This shows that inter-regional job-to-job transition rates are negatively related to age. On average over the period, the highest job-to-job transition rate is observed in the youngest age group (15-24 years) at 6.1%, followed by the 25-39 and 40-54 groups. The transition rate was the lowest for the oldest age group (55-64 years).

Over time, workers of all age groups have become more active in changing jobs to different locations. Surprisingly, the two older age groups (40-54 and 55-64) showed a relatively faster rate of change. In the second half of the period (2010-2020), the average rate of inter-regional job-to-job transitions for the 40-54 and 55-64 age groups were 7% and 11% higher than in the 2000s. In contrast, the younger age groups (15-24 and 25-39) experienced only moderate changes, with a 7% increase for the 15-24 group and a 5% increase for the 25-39 group.

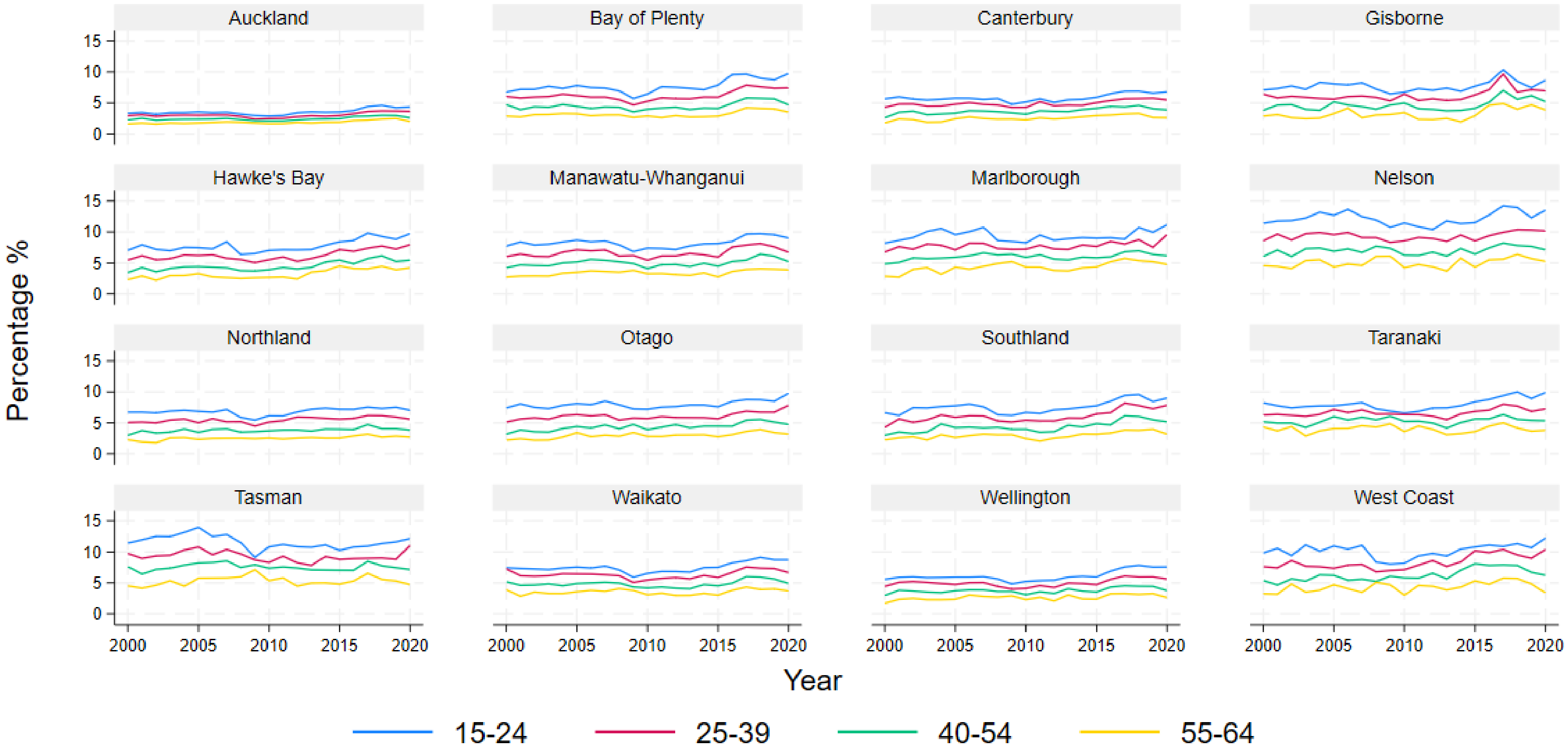
Figure 3 plots the age-specific inter-regional transition rates by region. The negative relation between inter-regional job-to-job transitions and age remains broadly true for all regions, although the age differences are notably smaller in Auckland. Similar to Figure 3, workers in larger regions are less likely to move to other regions.

Table 5 Inter-regional job-to-job transition rates by age groups

Year	*15-24*	*25-39*	*40-54*	*55-64*	*Total*
2000	5.7%	4.6%	3.3%	2.3%	4.3%
2001	6.0%	4.8%	3.7%	2.4%	4.5%
2002	5.8%	4.7%	3.5%	2.4%	4.4%
2003	5.9%	4.7%	3.5%	2.4%	4.4%
2004	6.0%	4.9%	3.7%	2.5%	4.5%
2005	6.1%	4.9%	3.8%	2.7%	4.6%
2006	6.0%	4.9%	3.8%	2.8%	4.6%
2007	6.1%	4.9%	3.9%	2.8%	4.6%
2008	5.6%	4.5%	3.7%	2.8%	4.3%
2009	5.0%	4.1%	3.5%	2.8%	3.9%
2010	5.3%	4.2%	3.3%	2.5%	3.9%
2011	5.5%	4.5%	3.5%	2.6%	4.1%
2012	5.5%	4.4%	3.5%	2.5%	4.1%
2013	5.8%	4.6%	3.6%	2.6%	4.2%
2014	5.8%	4.6%	3.8%	2.7%	4.4%
2015	5.9%	4.7%	3.8%	2.7%	4.4%
2016	6.5%	5.2%	4.1%	3.1%	4.9%
2017	7.0%	5.7%	4.5%	3.4%	5.3%
2018	7.2%	5.6%	4.6%	3.4%	5.3%
2019	6.8%	5.5%	4.3%	3.3%	5.1%
2020	7.1%	5.5%	3.9%	2.9%	5.0%
Average	6.1%	4.9%	3.8%	2.8%	4.5%

Source: Author's calculations using IDI data.

Figure 3 Inter-regional job-to-job transition rates by age group and region



Source: Author's calculations using IDI data.

4.3.2 Gender

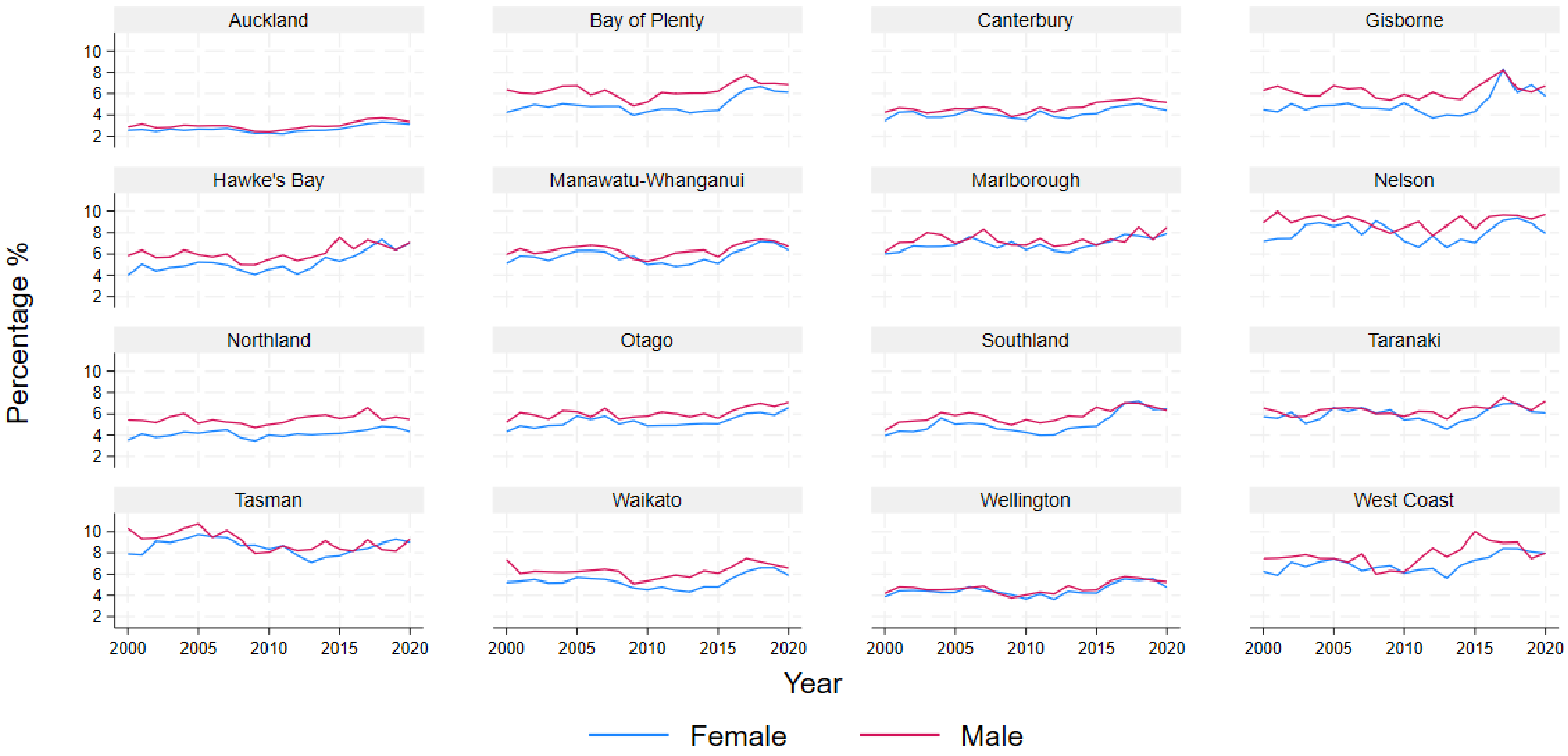
Table 6 shows inter-regional job-to-job transition rates for males and females over time. Rates are slightly higher for males than females in all years, indicating that males have a higher tendency to change jobs compared to females. Figure 4 plots the gender-specific inter-regional job-to-job transition rates by region. This shows that higher inter-regional transitions among males remains the case in most regions in most years, but the gender gap is markedly smaller in the larger regions of Auckland, Wellington, and Canterbury.

Table 6 Inter-regional job-to-job transition rates by gender

Year	*Female*	*Male*	*Total*
2000	3.8%	4.7%	4.2%
2001	4.2%	4.9%	4.5%
2002	4.2%	4.7%	4.4%
2003	4.1%	4.7%	4.4%
2004	4.1%	4.9%	4.5%
2005	4.3%	4.9%	4.6%
2006	4.4%	4.8%	4.6%
2007	4.3%	4.9%	4.6%
2008	4.1%	4.5%	4.3%
2009	3.8%	4.0%	3.9%
2010	3.7%	4.2%	3.9%
2011	3.9%	4.5%	4.2%
2012	3.7%	4.5%	4.1%
2013	3.8%	4.7%	4.2%
2014	4.0%	4.7%	4.4%
2015	4.0%	4.8%	4.4%
2016	4.6%	5.2%	4.9%
2017	5.0%	5.6%	5.3%
2018	5.2%	5.5%	5.3%
2019	5.0%	5.3%	5.2%
2020	4.8%	5.2%	5.0%
Average	4.2%	4.8%	4.5%

Source: Author's calculations using IDI data.

Figure 3 Inter-regional job-to-job transition rates by gender and region



Source: Author's calculations using IDI data.

In terms of the trend over time, the data show that the job-to-job transition rates for both males and females have been increasing over time. For instance, in 2000, the job-to-job transition rate for males was 4.6%, while that of females was 3.6%. In 2018, the job-to-job transition rate for males had increased to 6.0%, while that of females had increased to 4.5%. This upward trend suggests that workers, irrespective of their gender, are becoming more active in changing jobs to different locations. Similar results are seen in all 16 regional councils. Overall, the data show that while gender differences exist in job-to-job transition rates, both males and females are becoming more geographically mobile in their careers over time. However, the gender gap in inter-regional job-to-job transition rates has remained relatively constant over the years.

4.3.3 Ethnicity

Table 7 shows inter-regional job-to-job transition rates by ethnic group in New Zealand. The data highlight significant ethnic differences in job-to-job transition rates. On average over the period, the inter-regional job-to-job transition rate was the highest for Māori at 5.6%, followed by European at 4.7%, Asian and others at 3.9%, and Pacific at 3.7%.

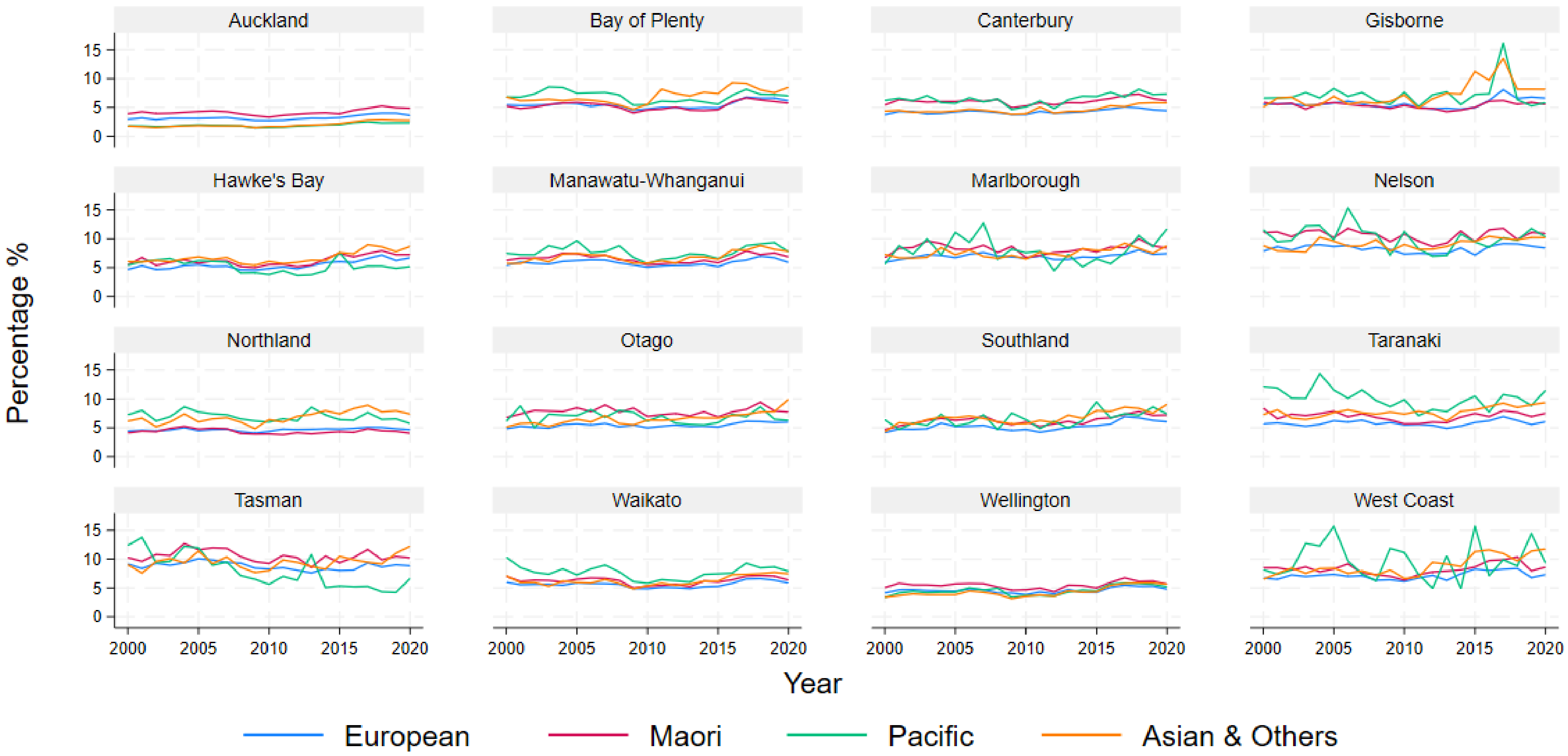
Over the last two decades, inter-regional job-to-job transition rates for all ethnic groups have increased. For instance, the job-to-job transition rate for Māori was 5.3% in 2000 and peaked at 6.5% in 2018. The same upward trend is observed across the other ethnic groups, indicating that workers from all ethnic backgrounds are becoming more active in changing jobs to different locations.

Figure 5 plots the ethnic-specific inter-regional job-to-job transition rates by region. The Auckland and Wellington regions had smaller ethnic differences than other regions. In Gisborne, Northland, Taranaki, West Coast and Bay of Plenty regions, Pacific and Asian and other workers tended to have higher rates of inter-regional job-to-job transitions than other ethnic groups, signaling that unusually higher fractions of workers left these regions.

Table 7 Inter-regional job-to-job transition rates by ethnicity

Year	*European*	*Māori*	*Pacific*	*Asian & Others*	*Total*
2000	4.3%	5.3%	3.3%	3.5%	4.3%
2001	4.6%	5.6%	3.4%	3.4%	4.6%
2002	4.5%	5.5%	3.3%	3.3%	4.4%
2003	4.5%	5.6%	3.5%	3.3%	4.5%
2004	4.7%	5.8%	3.6%	3.5%	4.6%
2005	4.7%	5.8%	3.6%	3.5%	4.7%
2006	4.8%	5.9%	3.8%	3.6%	4.7%
2007	4.8%	5.8%	3.7%	3.6%	4.7%
2008	4.4%	5.3%	3.6%	3.4%	4.4%
2009	4.2%	4.8%	2.9%	3.0%	4.0%
2010	4.1%	4.8%	3.0%	3.3%	4.0%
2011	4.3%	5.0%	3.2%	3.5%	4.2%
2012	4.3%	5.0%	3.1%	3.4%	4.2%
2013	4.4%	5.1%	3.5%	3.6%	4.3%
2014	4.5%	5.4%	3.7%	3.7%	4.4%
2015	4.5%	5.3%	3.8%	3.9%	4.5%
2016	5.0%	5.9%	4.1%	4.5%	5.0%
2017	5.5%	6.5%	4.6%	4.7%	5.4%
2018	5.5%	6.5%	4.5%	4.8%	5.4%
2019	5.3%	6.2%	4.3%	4.8%	5.2%
2020	5.0%	5.9%	4.3%	4.9%	5.1%
Average	4.7%	5.6%	3.7%	3.9%	4.6%

Figure 4 Inter-regional job-to-job transition rates by ethnic group and region



Source: Author's calculations using IDI data.

4.3.4 Geographic mobility patterns

Inter-regional job-to-job transitions provide crucial insights about differences in worker mobility patterns, but they do not provide information about specific movements from one region to another. This section takes a brief look into patterns of region-to-region movements.

Figure 6 presents a heatmap-style chart that shows the fraction of inter-regional job-to-job transitions from the origin location (vertical axis) to the destination location (horizontal axis) averaged over 2000 to 2020.[4] All fractions are classified into five mutually exclusive categories: 0-9%, 10-19%, 20-29%, 30-39% and 40% and higher. The chart is colour-coded: the darker the shade, the higher the fraction of inter-regional movement.

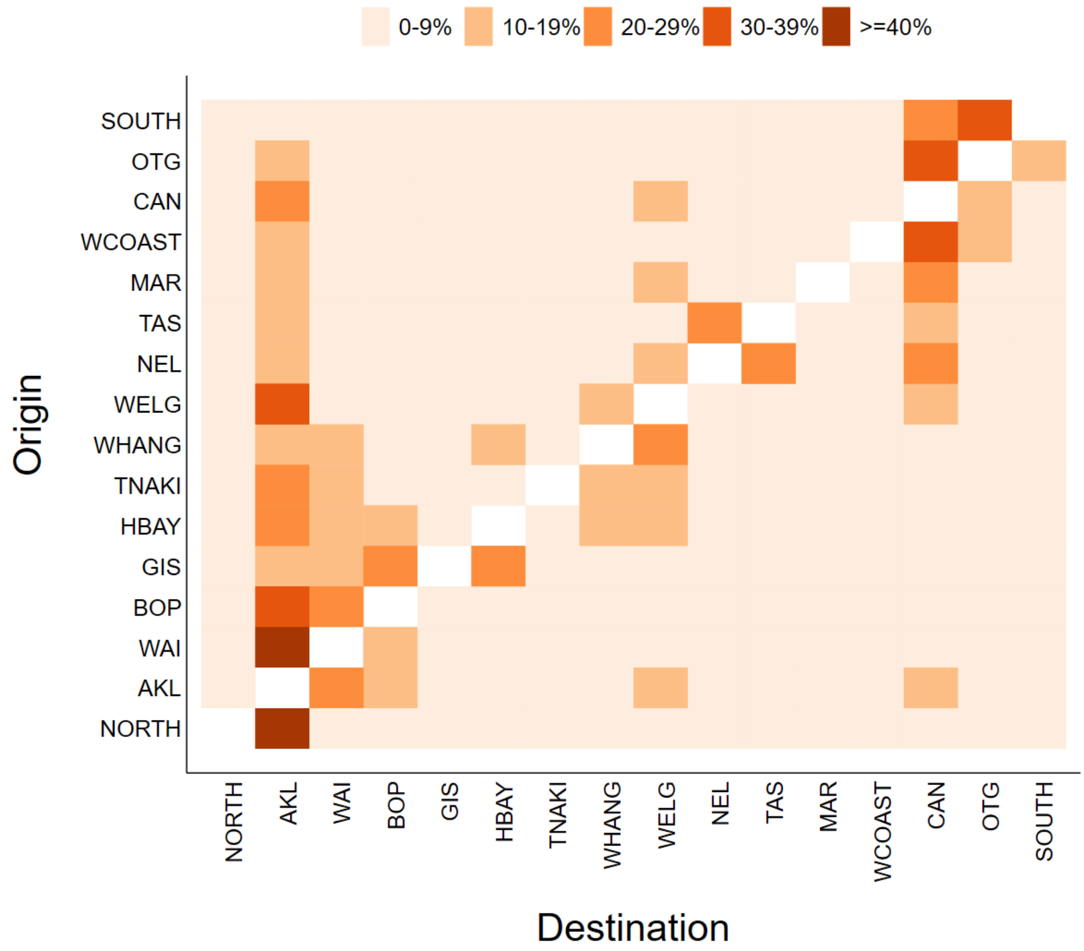
The figure illustrates two interesting patterns. Firstly, more than 50% of workers who changed job locations moved to highly populated regions such as Auckland, Wellington and Canterbury. These three regions accounted for over 50% of the total number of jobs and had higher productivity compared to other regions. This suggests that workers prefer areas with abundant job opportunities and higher-paying jobs.

Secondly, many workers relocated to neighbouring regions. For instance, the largest share of inter-regional transitions out of Waikato and Northland migrated to Auckland, while Southland attracted the largest share of its geographically mobile workers from the Otago region. This short-distance movement could be attributed to the high costs associated with longer-distance migration. Additionally, moving to a new place could be socially and culturally challenging, especially if it is far away from one's family and community.

These patterns are generally observed in different demographic groups. See Appendix 1 for equivalent charts specifically by age, gender, and ethnic groups.

[4] Movements within the same regions (the leading diagonal) are excluded.

Figure 5 Region-to-region movements arising from inter-regional job-to-job transitions, average 2000-2020



Note: NORTH=Northland, AKL=Auckland, WAI=Waikato, BOP=Bay of Plenty, GIS=Gisborne, HBAY=Hawke's Bay, TNAKI=Taranaki, WHANG=Manawatu-Whanganui, WELG=Wellington, NEL=Nelson, TAS=Tasman, MAR=Marlborough, WCOAST=West Coast, CAN=Canterbury, OTG=Otago and SOUTH=Southland.

Chapter 5: Estimating the impact of house prices on inter-regional worker mobility

This chapter analyses the relationship between inter-regional job-to-job transitions and house prices in New Zealand, for the entire working-age population as well as sub-populations. While chapter 4 analysed the *rate* of job-to-job transitions, chapter 5 analyses the number or volume of inter-regional job-to-job transitions, sometimes called 'inter-regional worker flows'. [5]

5.1 Exploratory analysis

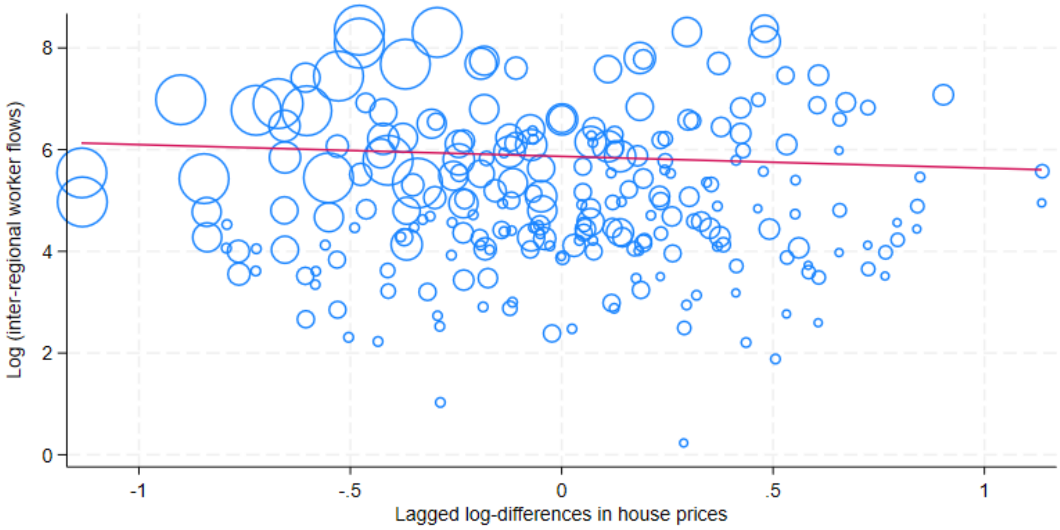
To explore the relationship between inter-regional job-to-job transitions and relative house prices, the volume of inter-regional job-to-job transitions are first aggregated up to the 240 distinct region-to-region movements that workers can make (averaged over the period 2000-2021). Note that these movements are permutations, which means that, for example, a Taranaki-to-Auckland movement is distinct from an Auckland-to-Taranaki movement. Figure 7 displays a scatter plot that demonstrates the relationship between the number (in natural logarithms) of inter-regional job-to-job transitions and relative house prices averaged over the period 2000-2020. Relative house prices refer to the difference in house prices between two regions. These are calculated as follows. First, median house prices in each region are averaged over the 21-year period. Second, the average median house price in the destination region is divided by the average median house price in the origin region. Third, the natural logarithm of this ratio is taken. A positive relative house price (right side of the graph) indicates that house prices in the destination region are more expensive than those in the origin region. A negative relative house price (left side of the graph) indicates that house prices in the destination region are cheaper than those in the origin region. All observations (depicted as circles) in the scatterplot are weighted by the local population at the origin region to control for the size of the region. The larger the circle, the larger the population in the region of origin.

The chart illustrates a slight negative correlation between the number of inter-regional job-to-job transitions and relative house prices. When house prices in the destination region are higher than those in the origin region (indicated by positive log relative house prices), the volume of job movements between regions tends to be lower.

[5] Inter-regional job-to-job transitions and inter-regional worker flows are used interchangeably, both referring to workers moving regions for employment opportunities.

Conversely, when a region has relatively lower house prices compared to others (indicated by negative log relative house prices), inter-regional job transitions are generally higher. This suggests that house prices may act as a deterrent or facilitator for inter-regional worker mobility, influencing the flow of workers between regions.

Figure 6 Scatterplot of inter-regional job-to-job transitions versus relative house prices, average 2000-2020

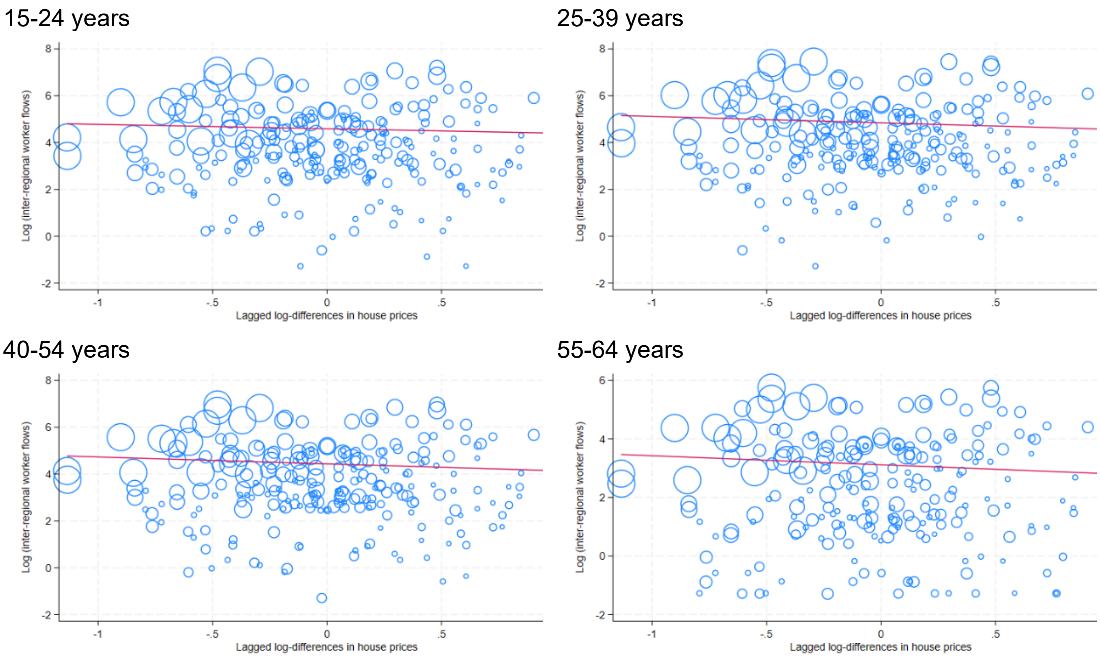


Source: Author's calculations using IDI data.
Notes:
1. Each circle represents a distinct region-to-region movement. The larger the circle, the larger the population of the region of origin. For presentational purposes, the natural logarithm of the number of region-to-region movements is used on the y-axis with movements of zero imputed as 1.
2. Red solid line is a best-fit line from a weighted regression.

When examining the data by different worker characteristics - namely age in Figure 8, gender in Figure 9, and ethnicity in Figure 10.

Figure 10 Scatterplots of inter-regional job-to-job transitions versus relative house prices, by ethnicity - the negative relationship between inter-regional job-to-job transitions and relative house prices generally persists, though with some moderate variations. The relationship is weaker among the youngest cohort (15 to 24 years of age) compared to older cohorts. This may be because many young workers are either still in formal education (high school or tertiary) and often work part-time jobs or are more sensitive to other costs, such as rent or travel costs to their families, making them less sensitive to house price differences. In contrast, older age groups, who are more likely to hold full-time or permanent positions or live with family members, tend to be more responsive to variations in house prices. Interestingly, the relationship does not show significant differences between male and female workers, suggesting that gender does not play a substantial role in moderating this dynamic.

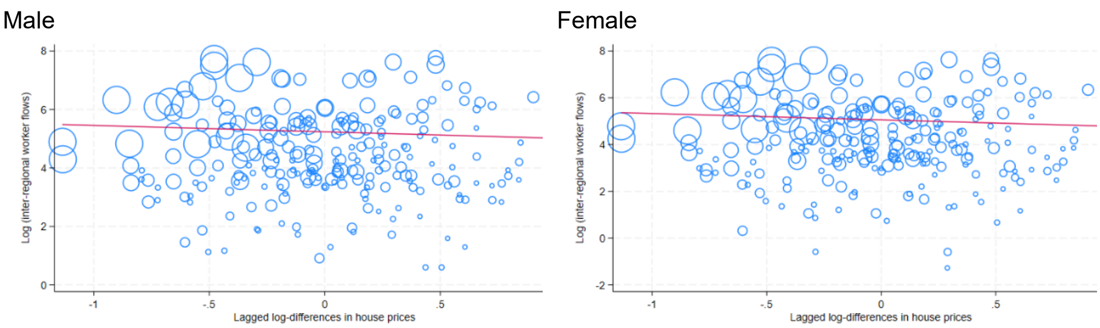
Figure 7 Scatterplots of inter-regional job-to-job transitions versus relative house prices, by age groups



Source: Author's calculations using IDI data.
Notes:

1. Each circle represents a distinct region-to-region movement. The larger the circle, the larger the population of the region of origin. For presentational purposes, the natural logarithm of the number of region-to-region movements is used on the y-axis with movements of zero imputed as 1.
2. Red solid lines are best-fit lines from weighted regressions.

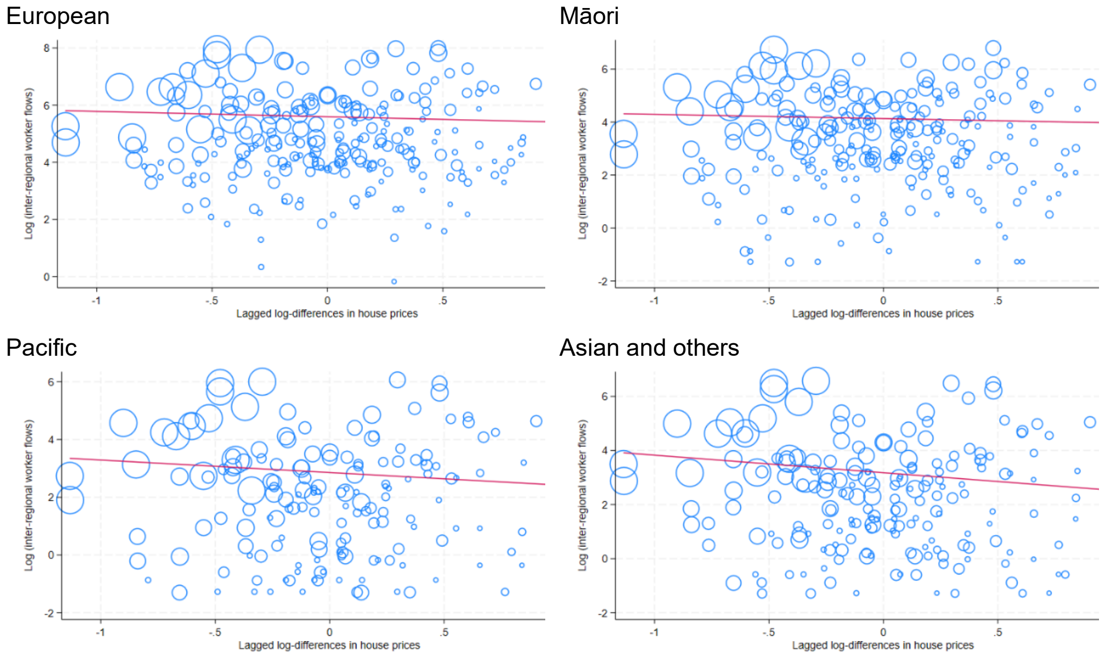
Figure 8 Scatterplots of inter-regional job-to-job transitions versus relative house prices, by gender



Source: Author's calculations using IDI data.
Notes:

1. Each circle represents a distinct region-to-region movement. The larger the circle, the larger the population of the region of origin. For presentational purposes, the natural logarithm of the number of region-to-region movements is used on the y-axis with movements of zero imputed as 1.
2. Red solid lines are best-fit lines from weighted regressions.

Figure 9 Scatterplots of inter-regional job-to-job transitions versus relative house prices, by ethnicity



Source: Author’s calculations using IDI data.
Notes:
1. Each circle represents a distinct region-to-region movement. The larger the circle, the larger the population of the region of origin. For presentational purposes, the natural logarithm of the number of region-to-region movements is used on the y-axis with movements of zero imputed as 1.
2. Red solid lines are best-fit lines from weighted regressions.

The negative relationship also persists across ethnic groups. But there is one notable difference between European and Māori workers compared to Pacific, Asian and other ethnic groups- there is a significantly higher proportion of zero regional movements among Pacific, Asian, and other ethnic groups. This can be partially attributed to the smaller size of their populations in certain regions. For instance, Pacific workers constitute only 2% of the working population in the West Coast region, making it highly likely that regional movements out of this area are minimal or zero. In addition, Pacific workers exhibit a stronger preference for working in large urbanised regions, such as Auckland, Canterbury, and Wellington. Such regional clustering further limits their regional mobility.

The exploratory analysis reveals consistent negative correlations between inter-regional job-to-job transitions and relative house price differences, as evident in most of the figures presented above. To rigorously assess the robustness of this relationship, the following sections outline the methodology and specifications of the econometric models employed, along with statistical tests to confirm the significance of the observed correlations.

5.2 Method

5.2.1 Baseline gravity model

To model the impact of house prices on inter-regional worker movements, the baseline gravity model applies a similar specification proposed by Cavalleri et al. (2021), Liu (2018) and Poghosyan (2018). The model specification includes a few macroeconomic variables and labour market conditions, shown below in *Equation 4*:

Equation 4 Baseline gravity model equation

$$Y_{ijt} = \beta_1 lnP_{it-1} + \beta_2 lnP_{jt-1} + \beta_3 SI_{i,j} + \beta_4 lnDist_{ij} + \alpha_1 lnHP_{it-1} + \alpha_2 lnHP_{jt-1} + \sum_{s=1}^{n} \left(\gamma_s Z_{ist-1} + \delta_s Z_{jst-1}\right) + \theta_{ij} + \rho_1 GDP_t + \varepsilon_{ijt}$$

where subscript i, j and t are origin region, destination region, and year, respectively.

The dependent variable, Y_{ijt}, is the number of worker flows from origin region i to destination region j in year t. Thus, unlike in the exploratory analysis above, in the gravity model each of the 240 region-to-region movements is analysed separately for each of the 21 years of the study period (rather than averaged over 2000-2020), giving a total of 5,040 observations. P_{it-1} and P_{jt-1} are the total populations in regions i and j in year t-1 (the log of these population sizes is used in the model). These population numbers are the estimated resident population figures from Statistics New Zealand.

$SI_{i,j}$ is a dummy variable for whether regions i and j are located on the same island. When the two regions are on the same island, it returns a value of 1 (otherwise, 0). $lnDist_{ij}$ is the log amount of travel time in minutes from the city centre of region i to the city centre of region j. This variable was created by Poot et al. (2016) who estimated travel time from Google Maps in 2013.[6] Travel time is held fixed at these 2013 values over the entire study period. While this assumption is unlikely to hold in reality - new roads, better transportation technology, and government legislation have gradually altered travel time between regions - no alternative public data on travel times was available at the time of writing.

HP_{it-1}, HP_{jt-1}, Z_{it-1} and Z_{jt-1} refer to a range of macroeconomic factors and labour market conditions in regions i and j at year t-1. They are often characterised as push

[6] In this thesis, three different variants of travel time variables were created and tested. Distance measured in minutes provided the best fit in the selected gravity model specification.

and pull factors. For example, favourable economic conditions (e.g., higher wages and better job opportunities) in a destination region is a positive pull factor that attracts greater numbers of workers to migrate from other regions. On the other hand, an origin region may push workers to leave if it struggles to recover quickly after negative economic shocks.

HP_{it-1} and HP_{jt-1} are the key variables of interest in this study. They are median house price in region i and region j at year t-1 (the log of these values is used in the model). Their corresponding coefficients, α_1 and α_2, quantify the impact of house prices on worker migration between regions. The signs of these coefficients are expected to be positive for HP_{it-1} and negative for HP_{jt-1}. A positive estimated coefficient for the region of origin (α_1) indicates an accelerated number of worker outflows to other destinations if the local house price increases. More expensive house prices add extra pressure to living costs for some workers who may struggle to stay and seek better opportunities elsewhere. If the estimated coefficient at the destination (α_2) is negative, higher house prices may lower economic benefits associated with migration and slow down worker inflows from other regions.

Z_{it-1} and Z_{jt-1} are region-level macroeconomic indicators covering log real GDP per capita, the unemployment rate, and shares of the workforce between ages 40 and 64 years, at both the origin i and destination j, respectively:

- Log real GDP per capita
  This variable measures the overall income and prosperity level of a region. Log real regional GDP per capita is calculated by dividing the nominal GDP per capita by the GDP deflator (a measure of general inflation) and then taking the natural logarithm. Nominal GDP per capita statistics are extracted from Statistics New Zealand's estimates of regional Gross Domestic Product for the years 2000 to 2021. [7] The Tasman and Nelson regions are combined in Statistics New Zealand's data. The GDP deflator is the output producer price index at the national level. Due to the unavailability of regional price indices, the derived real GDP per capita may contain measurement errors as the impact of price changes in the local economy is not taken into account. Maré (2016) estimated heterogeneous regional prices using market powers and found very

[7] The raw data are available in Table 4 of the downloadable excel file available at https://www.stats.govt.nz/information-releases/regional-gross-domestic-product-year-ended-march-2021/.

mild regional differences. Thus, the use of a national rather than regional price deflator is likely to have minimal impacts on regression estimates.

- Unemployment rate
  The unemployment rate is an important economic indicator that reflects the health of an economy. A high (low) unemployment rate in a local labour market can be a sign of an economic downturn (upturn), which affects individual choices regarding internal migration decisions. The variable is extracted from Statistics NZ's Household Labour Force Survey (HLFS) for the period 2000 to 2021.[8] However, regional unemployment rates are limited to 12 broad regional councils – Gisborne and Hawke's Bay regions are combined, and Tasman, Nelson, Marlborough and West Coast regions are merged into one broad region. Regional councils within the broad region are assumed to have the same unemployment rate as the broad region.

- Share of the labour force between 40 and 64 years of age
  This variable is derived from EMS and measures the size of the older workforce as a share of the total local labour force (15-64 years). There is some evidence showing that younger people represent a substantive share of regional migrations, while older people are less likely to move (Coleman & Zheng, 2020; Liu, 2018; OECD, 2020).

θ_{ij} are regional fixed effects that capture unobservable and time-invariant factors. Fixed effects are designed to mitigate omitted variable bias caused by correlations between unobservable factors and the independent variables. For example, regions with better job opportunities or education institutes tend to attract more workers from other areas. Previous New Zealand studies, including Poot et al. (2016) and Grimes et al. (2019), recommend a fixed-effects model that mitigates omitted variable bias.

GDP_{t-1} is economy-wide annual GDP growth in March quarters taken from National Accounts, and GDP_{t-1}^{e} is the expected annual GDP growth rate over the next 12 months from a survey of expectations by the Reserve Bank of New Zealand (RBNZ). It is expected that worker mobility could be influenced by both the current and future state of the economy. Lastly, ε_{ijt} is the residual term.

[8] Regional unemployment rate can be found at Statistics New Zealand's Infoshare website: https://infoshare.stats.govt.nz/.

All explanatory variables, except $SI_{i,j}$ and $lnDist_{ij}$, in the base model are lagged, t-1. Poot et al. (2016) recommends using lagged variables to avoid endogenous bias. A description of the variables and summary statistics are shown in Table 8.

Table 8 Summary statistics for variables used in gravity models

Variables	Number of observations	Mean	Standard deviation	Minimum	Maximum
The number of worker flows from the origin region to the destination region, 15-64	4,800	434.335	805.291	0	7300
The number of workers flows from the origin region to the destination region, 15-29	4,800	128.900	237.414	0	1990
The number of workers flows from the origin region to the destination region, 30-44	4,800	161.365	318.285	0	2900
The number of workers flows from the origin region to the destination region, 45-54	4,800	108.868	199.912	0	1710
The number of workers flows from the origin region to the destination region, 55-64	4,800	30.715	60.305	0	630
The number of workers flows from the origin region to the destination region, all male workers	4,800	229.262	423.493	0	3800
The number of workers flows from the origin region to the destination region, all female workers	4,800	204.726	387.912	0	3500
The number of workers flows from the origin region to the destination region, all European workers	4,800	329.861	579.018	0	4200
The number of workers flows from the origin region to the destination region, all Māori workers	4,800	81.664	144.201	0	1380
The number of workers flows from the origin region to the destination region, all Pacific workers	4,800	24.270	69.883	0	771

The number of workers flows from the origin region to the destination region, all Asian and other workers	4,800	41.707	138.932	0	1880
Log population	320	11.941	1.064	10.345	14.356
Log travel time	240	10.250	0.658	8.239	11.417
Log real median house price	320	12.640	0.409	11.409	13.703
Log real GDP per capita	320	10.839	0.209	10.406	11.520
Unemployment rate	320	5.003	1.567	2.025	10.700
Share of the labour force between 40 and 64 years of age	320	48.407	3.504	38.324	56.180
Annual GDP growth	20	2.639	1.634	-1.370	4.670
Expected GDP growth in the next 12 months	20	2.375	0.731	-0.240	3.230

Source: Author's calculations using IDI data.
Notes:
1. Averages, standard deviations, minima and maxima were calculated from randomly rounded worker flow counts.

5.2.2 Extended gravity model

In the baseline gravity model, the relationship between log median house price (origin and destination) and log inter-regional worker flows are linear. Under this assumption, the model predicts that all regions will experience the same change in inter-regional worker movements for a given percentage change in median house prices. While this linear assumption may hold true under certain conditions, it may not universally apply due to significant variations in house prices across regions.

For instance, the Auckland region stand out as the most expensive housing market, with an average nominal median house price of $864,166 in 2020. It was four times more expensive than the least expensive region, West Coast. However, median earnings in Auckland were only marginally higher (15%) compared to the West Coast. Consequently, living costs are notably higher in Auckland than in other regions. When house prices increase, workers may find it more challenging to live and work in the region and feel the push to find jobs elsewhere, possibly somewhere with more affordable houses. In contrast, workers in more affordable regions like the West Coast region may not feel the same push effect.

These observations suggest that the relationship between median house prices and worker movements could potentially be non-linear, with varying degrees of responsiveness depending on the specific region's housing affordability.

The extended gravity model introduces four interaction terms and estimates the region-specific impact of house prices on worker migrations between regions. The extended gravity model is shown in Equation 5:

Equation 5 Extended gravity model equation

$$\begin{aligned} Y_{ijt} = \; & \beta_1 lnP_{it-1} + \beta_2 lnP_{jt-1} + \beta_3 SI_{i,j} + \beta_4 lnDist_{ij} + \pi_1 I_{i\in large} \times HP_{it-1} \\ & + \pi_2 I_{i\in small} \times HP_{it-1} + \pi_3 I_{j\in large} \times HP_{jt-1} + \pi_4 I_{j\in small} \times HP_{jt-1} \\ & + \sum_{s=1}^{n} \left(\gamma_s Z_{ist-1} + \delta_s Z_{jst-1} \right) + \theta_{ij} + \rho_1 GDP_t + \varepsilon_{ijt} \end{aligned}$$

$I_{i\in large}$ and $I_{j\in large}$ are binary indicators for large urbanised regions at origin and destination locations, respectively. Large urbanised regions cover Auckland, Wellington, and Canterbury. They are the three largest regions (in terms of population) and capture over 50% of the country's jobs and households. Changes in house prices in these regions may be expected to have some impact on the overall inter-regional flows. The remaining 13 regions are classified as small regions, $I_{i\in small}$ and $I_{j\in small}$.

In Equation 5, $I_{i\in large} \times HP_{it-1}$ and $I_{i\in small} \times HP_{it-1}$ are interaction terms between house prices and large and small origin regions, respectively. Their corresponding coefficients (π_1 and π_2) provide estimates of the push effects of house prices in large and small regions. Additionally, the coefficients π_3 and π_4 provide estimates of the pull effects on house prices in large ($I_{j\in large} \times HP_{jt-1}$) and small ($I_{j\in small} \times HP_{jt-1}$) destination regions.

These additional interaction terms test whether the impact of housing costs on inter-regional worker flows varies between large and small regions. For instance, if $\pi_1 > \pi_2 > 0$, it means that house prices in larger regions have a stronger effect on pushing out local workers than those in smaller regions. In this case, an increase in house prices across all regions in New Zealand will result in a greater number of workers leaving large urban areas. On the other hand, if $\pi_3 < \pi_4 < 0$, it suggests that housing costs act as a significant barrier to worker migration, especially in large regions. Given that housing costs are generally higher in larger regions, an increase in the housing market will likely slow down worker migration to the region.

5.2.3 Estimation method

The most common practice in empirical applications of the gravity model is to transform variables by taking natural logarithms and to obtain regression coefficients using Ordinary Least Squares (OLS). This approach has two advantages: it requires less computation power and allows users to transform a complex nonlinear relationship into a simpler log-linear model (Linnemann, 1966). Nowadays, computer power is no longer a limiting factor. The recent literature on the gravity model has realised the weaknesses of the logarithm transformation and developed more reliable estimation methods.

Silva and Tenreyro (2006, 2022) extensively reviewed the application of OLS in log-linear gravity models and discussed two significant challenges. First, the logarithm transformation did not deal with flows of zero. Zero trade or migration between countries is not unusual. Ramos and Suriñach (2017) found 53% of international migrations between the European Union (EU) and its neighbouring countries were zero over the 1960-2010 period. Taking logarithms of such observations effectively drops zeros and truncates the sample to only those countries with positive trade/migration flows, as log(0) is undefined. In this case, the OLS estimator is built on relationships among pairs of countries or regions with positive flows of trade and migration. If these truncations are random, OLS is an unbiased estimator. However, zero observations may be systematically different from positive observations, and reflect such factors as strict trade regulation and political barriers. Thus, the OLS estimator crucially depends on a rather restrictive and unrealistic assumption and may lead to selection bias (Burger et al., 2009).

The second challenge concerns the violation of the homoscedasticity assumption. Under the homoscedasticity condition, the variance of ε_{ijt} is constant and independent of the regressors. This assumption is too restrictive as overwhelming evidence has found strong heteroscedasticity in the error term , suggesting the estimation method leads to inconsistent estimates of the elasticities of interest.

Two nonlinear estimation methods are commonly used to tackle these issues. The first nonlinear model is the Poisson estimation method. Given explanatory variables X, the dependent variable of interest Y follows a Poisson distribution in this model. The Poisson model has a probability density function $\Pr(Y = k|X) = \frac{\exp(-\lambda)\lambda^k}{k!}$, where $k!$ is k factorial. Subscripts i, j, and t are removed to help simplify notational expression. It has a single parameter λ which is equal to the conditional mean of the dependent variable, $\lambda = E(Y|X)$. In this study, λ is the expected number of workers who move from one region to another in a given year, conditional on economic factors in both regions. λ can be modelled with a parametric method, such as $\lambda = \exp(X\beta)$, so the coefficient β and its standard errors can be estimated for gravity model Equation 4 and Equation 5.

The Poisson method imposes a condition of variance-mean equality, $E(Y|X) = Var(Y|X)$. Under this condition, the conditional mean is equal to its conditional variance. Many studies (e.g., Bosquet & Boulhol, 2010; Burger et al., 2009) have found that the variance-mean equality condition is often violated, leading to overdispersion (where the conditional variance exceeds the conditional mean), commonly due to omission of relevant explanatory variables. [9]

The Negative Binomial (NegBin) estimator introduced by Cameron and Trivedi (1986) is another alternative nonlinear method. NegBin aims to capture the presence of overdispersion that is not considered by the Poisson model and provides flexibility to deal with more complex relationships between conditional mean and variance (Greene, 1994). Under NegBin, a new random variable v is introduced to the Poisson distribution and has a gamma distribution with unit mean (mean equal to 1) and $Var(v) = \eta$. The NegBin has a probability density function $\Pr(Y = k|X) = \frac{\exp(-v\lambda)(v\lambda)^k}{k!} = \frac{\Gamma(\eta^{-1}+k)}{\Gamma(\eta^{-1})\Gamma(k+1)}\left(\frac{\eta^{-1}}{\eta^{-1}+\lambda}\right)^{\eta^{-1}}\left(\frac{\lambda}{\lambda+\eta^{-1}}\right)^k$, where $\lambda = \exp(X\beta)$, $\Gamma(.)$ is the gamma integral, and η is the overdispersion parameter. Its conditional mean is identical to the Poisson model, $E(Y|X) = \lambda$. However, the conditional variance is different and follows a quadratic function, $Var(Y|X) = \lambda(1 + \lambda\eta) = \lambda + \lambda^2\eta$. The Poisson distribution is a special case of the negative binomial distribution when $\eta = 0$. When $\eta > 0$, it is a sign

[9] Under-dispersion - where the conditional variance is lower than the conditional mean - is less common.

of overdispersion as the conditional variance will exceed the conditional mean, $Var(Y|X) > E(Y|X)$. Overdispersion is common in many datasets (Burger et al., 2009; Yang et al., 2009). Due to its flexible specification, the NegBin model can capture dispersion features in variables.

Blackburn (2015) and Silva and Tenreyro (2011, 2022) counted extensive studies comparing the performance of Poisson and NegBin estimators using both simulated and real data. Their findings revealed no significance differences in the performance of these models under many conditions. A key conclusion from both papers is that Poisson models produce stable estimates even when applied to non-Poisson distributed data, including datasets with excess zeros. This is because both Poisson and NegBin estimators share the same conditional mean function, making the Poisson model well-suited for predicting averages.

However, the Poisson estimator could fall short when the goal is to predict probability distributions beyond the mean/average (Cameron & Trivedi, 2010). For instance, it may struggle to accurately estimate the likelihood of specific events, such as the probability of more than 200 workers moving from Wellington to Waikato. Additionally, Poisson models tend to underestimate the standard errors of regressors when the assumption of equal conditional mean and variance is violated (Cameron & Trivedi, 1986; Kennedy, 2008). This can lead to inflated Type 1 errors, where researchers may incorrectly identify significant relationships and draw incorrect conclusions.

Given these limitations, the NegBin method is generally preferred. It performs well on both Poisson and non-Poisson distributed data and returns more accurate standard errors, reducing the risk of false-positive findings. This thesis employs both Poisson and NegBin methods to ensure a comprehensive analysis. Specifically, Poisson-based gravity models are estimated using the PPML (Pseudo Maximum Likelihood) function, and NegBin-based gravity models are estimated using the nbreg function in Stata 18.

Furthermore, these functions do not produce conventional R-squared values to assess goodness of fit. Following the recommendation of Cameron and Trivedi (2010), this study applies the squared correlation between the model's fitted values and the actual counts of worker flows. This metric ranges from 0 to 1, with higher values indicating greater predictive accuracy. This metric is suitable for comparing both different model classes (Poisson vs NegBin) and alternative model specifications. This metric is named as ‘squared correlation’ in all regression tables in this chapter and in Appendix 2.

5.3 Regression results

This section presents the results from both the baseline and extended gravity models of inter-regional worker flows, first among all workers and then by age (section 5.3.2), gender (section 5.3.3), and ethnicity (section 5.3.4).

5.3.1 All workers

Table 9 shows three sets of coefficient estimates from baseline gravity models. Columns (1) and (2) in the Table 9 are estimates from Poisson models. The only difference between them is the number of regional fixed effects. The first Poisson regression (Poisson 1) uses 240 origin-destination fixed effects, while the second regression (Poisson 2) includes 32 regional fixed effects (corresponding to 16 origin and 16 destination regions). The third column presents regression estimates from negative binomial regression. For brevity, results for fixed effects are not shown.

Regression coefficients can be interpreted as the expected percentage change in inter-regional worker flows in response to a change in the explanatory variable, holding other variables unchanged. For instance, the coefficient of 0.979 for log population at destination in the negative binomial model indicates a 0.98% increase in the inter-regional flow count if the population at the destination region increases by 1%.

All models show sound goodness-of-fit, with R-squared values exceeding 0.9. Among them, the Poisson 2 model shows the lowest R-square (0.908), due to poor predictions for large regions, such as Auckland and Wellington. Figure 11 shows scatterplots of actual (vertical axis) versus predicted (horizontal axis) inter-regional job-to-job transitions from the baseline gravity models. Panel A displays this actual vs. predicted comparison for Poisson models 1 and 2, Panel B displays Poisson model 1 and the Negative Binomial model. Poisson model 2 shows fairly reliable predictions up to approximately 2,000. However, beyond this threshold, its predictions become either excessively high or low, indicating difficulties in accurately predicting inter-regional job-to-job flows for larger regions (i.e., job-to-job transitions into and out of Auckland, Wellington, and Canterbury). In contrast, Poisson 1 and Negative Binomial models do not exhibit this issue. This suggests that incorporating a set of origin-destination fixed effects not only enhances the predictive accuracy of the gravity models but also capture complex region-to-region migration patterns.

Poisson and NegBin methods differ considerably. The Poisson method (Poisson 1 in Table 9) identifies a positive and statistically significant coefficient for house prices in the origin region, suggesting that higher house prices act as a ‘push’ factor, encouraging workers to relocate their jobs. Specifically, a 1% increase in house prices in the origin region is associated with a 0.16% increase in the number of local workers moving to other regions.

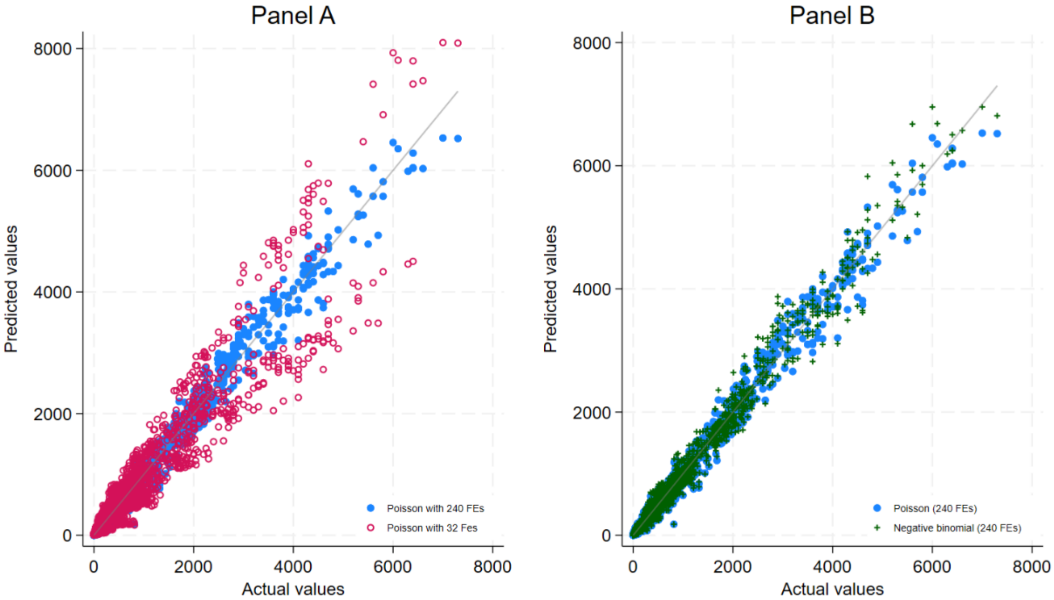
In contrast, the NegBin method (Negative binomial in Table 9) reveals statistically significant coefficients for house prices in both origin and destination regions. [10] For the origin region, the coefficient (0.180) is slightly larger than in the Poisson method. Additionally, the NegBin method identifies a ‘pull’ effect in the destination, with a negative coefficient of -0.133.

To visualise these findings, Figure 12 shows predicted values of inter-regional worker flows across the full range of house prices at both origin and destination It is clear that there is an upward trend between inter-regional worker flows and house prices at the origin, indicating that more workers tend to leave when local house prices rise or more workers tend to stay if local house prices come down. A downward trend is observed for house prices at the destination, suggesting that higher (lower) house prices at the destination slow down (speed up) worker flows into the region.

For the other variables in the gravity models, the Poisson method generally produces smaller coefficients compared to the NegBin method. For instance, variables such as population size in the origin and destination regions exhibit smaller magnitudes under the Poisson approach. Additionally, the Poisson model identifies fewer statistically significant variables (11 significant variables) compared to the NegBin model (15 significant variables). These discrepancies likely stem from the violation of the equidispersion assumption inherent in the Poisson method.

[10] House prices in the destination region is weakly significant, between the 5% and 10% statistical significance levels.

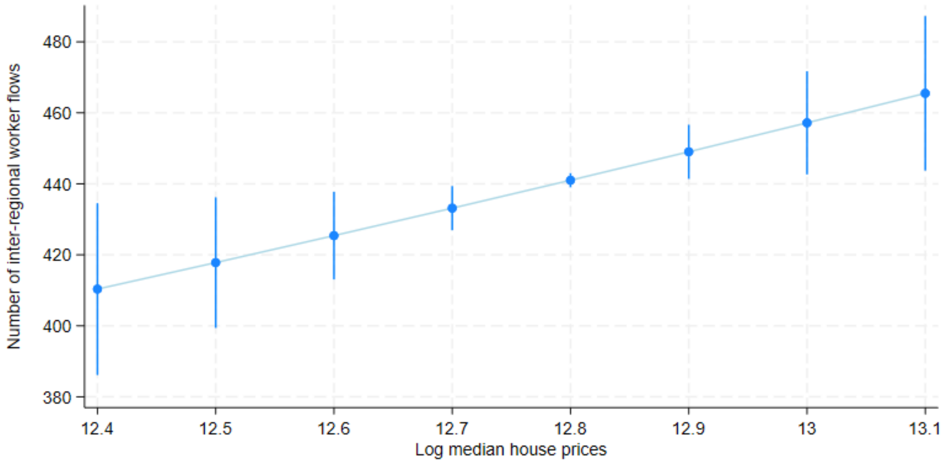
Figure 10 Scatterplots of actual vs predicted numbers of inter-regional worker flows from baseline gravity models



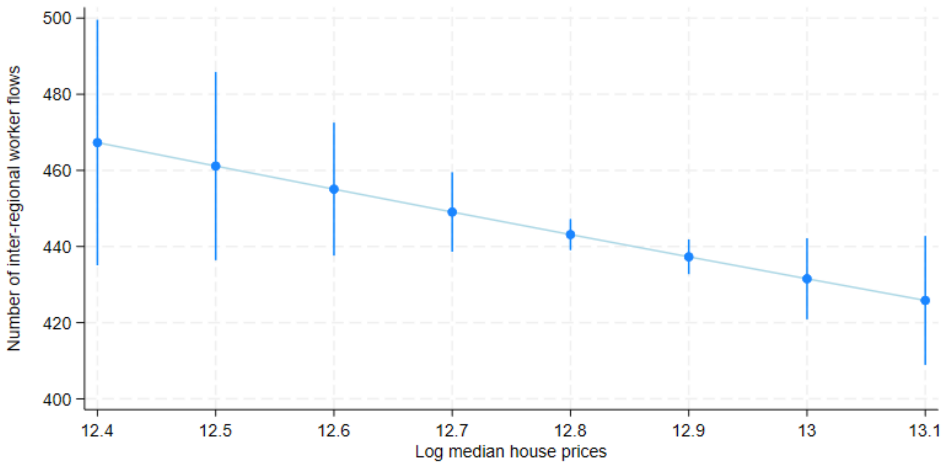
Source: Author's calculations using IDI data.

Figure 11 Predictions of inter-regional worker flows from the Negative Binomial model (baseline)

House prices at origin



House price at destination



Source: Author's calculations using IDI data.
Notes:
2. Predictions are derived from corresponding house price variables in the negative binomial model by holding other variables constant.
3. Vertical lines represent 95% confidence intervals of regression predictions.

When this assumption is violated (often due to overdispersion), the excess variance can distort the coefficients, leading to biased parameter estimates. The Negative Binomial model addresses this issue by explicitly accounting for overdispersion through an additional parameter, resulting in more robust and reliable estimates. In this analysis, the overdispersion parameter in the NegBin model is statistically significant, confirming the presence of overdispersion and reinforcing the preference for the NegBin method.

Table 9 Regression results from baseline gravity models of inter-regional worker flows in New Zealand

Variables	(1) Poisson 1	(2) Poisson 2	(3) Negative Binomial
Log population at destination	0.738***	0.728***	0.979***
	(0.186)	(0.189)	(0.314)
Log population at origin	1.175***	1.176***	1.310***
	(0.169)	(0.170)	(0.319)
Log travel time	-0.409***	-0.683***	-0.293***
	(0.0644)	(0.0678)	(0.0950)
Dummy for same island	1.659***	0.365***	2.340***
	(0.444)	(0.0841)	(0.769)
Log median house prices at destination	-0.0164	-0.0150	-0.133*
	(0.0497)	(0.0488)	(0.0787)
Log median house prices at origin	0.163***	0.162***	0.180**
	(0.0527)	(0.0523)	(0.0768)
Log GDP per capita at destination	0.160	0.164	0.327**
	(0.131)	(0.132)	(0.163)
Log GDP per capita at origin	0.164	0.166	0.339*
	(0.121)	(0.121)	(0.176)
Unemployment rate at destination	-0.0152***	-0.0151***	-0.0223***
	(0.00562)	(0.00579)	(0.00664)
Unemployment rate at origin	-0.0147**	-0.0147**	-0.0143**
	(0.00593)	(0.00607)	(0.00669)
Share of 40-64 labour force at destination	-0.00676	-0.00705	-0.0178*
	(0.00800)	(0.00798)	(0.0102)
Share of 40-64 labour force at origin	-0.0269***	-0.0267***	-0.0210**
	(0.00784)	(0.00777)	(0.0101)
Annual GDP growth rate	0.0327***	0.0327***	0.0199***
	(0.00222)	(0.00223)	(0.00371)
Expected GDP growth rate over the next 12 months	0.0465***	0.0466***	0.0584***
	(0.00551)	(0.00550)	(0.00923)
Constant	-16.88***	-15.66***	-24.85***
	(2.064)	(1.980)	(3.541)
Observations	4,800	4,800	4,800
Over-dispersion parameter			0.0668***
Number of fixed effects	240	32	240
Squared correlation	0.986	0.908	0.982

Notes:
1. Standard errors in parentheses.
2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
3. Fixed effects are not displayed due to space constraints.

When compared to evidence from other advanced economies, New Zealand's findings are not unique. Cavalleri et al. (2021) investigated the role of housing factors in shaping inter-regional migration flows across 14 OECD countries and found that high housing costs consistently act as a significant barrier to internal migration. Many economies demonstrated clear 'push' and 'pull' effects related to housing prices – higher house prices in origin regions increased outward migration, while higher prices in destination regions reduced inflows. New Zealand's results align with countries such as Canada, Italy, the UK, and the US, both in terms of the signs and statistical significance of house price variables (Cavalleri et al., 2021). This international consistency underscores the broader relevance of housing affordability as a key determinant of regional mobility, highlighting that New Zealand's experience is part of a broader global pattern.

For other variables in the NegBin gravity model, the effects of standard gravity variables are all in line with findings from the literature. As expected, the coefficients on population size at both origin and destination regions are positive, indicating larger inter-regional job-to-job flows in more-populated regions. The negative coefficient on the travel distance variable and the positive coefficient on the 'same island' dummy variable highlight that many workers prefer to make shorter migrations to neighbouring regions or within the same island. Short-distance migration entails lower transportation costs and other opportunity costs (e.g., being closer to family and relatives etc.).

The gravity model also yields the following statistically significant findings on the importance of labour market conditions and macroeconomic factors to inter-regional job-to-job transitions:

- First, higher unemployment is significantly associated with fewer inter-regional job-to-job flows. Higher regional unemployment rates indicate unfavourable economic conditions, discouraging both inflows and outflows of workers. When unemployment is high, some workers may perceive the risks of moving as too great if other regions also have weak job markets. Yagan (2014) found that during the Great Recession in 2007, workers in high-unemployment regions were less likely to move due to increased risk aversion and uncertainty about finding better opportunities elsewhere. Therefore, workers become more cautious about making job changes during economic downturns.

- Second, higher GDP per capita at destination and origin regions is significantly associated with more worker mobility. Higher regional labour productivity is often translated into higher average earnings for individuals and households. Higher incomes at destination regions contribute to mobility by attracting workers from other regions.

- Third, regions with higher shares of the older-age workforce are associated with less worker mobility. Negative effects on both origin and destination regions suggest that a region with a large proportion of the older workforce is expected to have lower inflows and outflows of workers. This suggests either that older workers tend to be less mobile or regions with large shares of older workers are less attractive to workers from other regions.

- Fourth, higher actual and anticipated GDP growth are associated with higher regional worker flows. This relationship reflects that pro-cyclical nature of labour market dynamics, where inter-regional job-to-job flows follow business cycles. When economic conditions remain subdued in the near term, inter-regional worker movements will slow down due to weak demands on products and jobs. During economic expansions, workers become more active in seeking new job opportunities, which causes higher worker churn.

The extended gravity models (Equation 5) follow similar estimation methods and emphasise the heterogeneous effects of housing costs between large and small regions. Recall that these extended models incorporate interaction terms between house prices and region size (large vs. small) in order to test whether the impact of house prices on inter-regional worker flows varies between large and small regions.

Table 10 presents the regression results of the extended gravity models. Similar to findings in Table 9, regression estimates from Poisson and NegBin methods are considerably different. Coefficients for house price variables are notably different between Poisson and NegBin methods, highlighting the sensitivity of the results to the choice of estimation method.

In the Poisson estimation method, the interaction between log house price at origin and region size shows a strong positive effect. For large regions, a 1% increase in origin house prices is associated with a 0.236% increase in inter-regional job-to-job transitions (significant at the 1% level), while for small regions, the effect is smaller but still significant (0.133%, significant at the 5% level). This suggests that higher house prices in the region of origin encourage the out-migration of workers. Notably, the effect is larger for large regions (Auckland, Wellington, and Canterbury) than for small regions (the rest of New Zealand), which may reflect more significant outflows of workers in large and expensive housing markets. In contrast, the Negative Binomial method shows weaker effects. The coefficient for large regions drops to 0.165 (significant at the 10% level), while the coefficient for small regions increases slightly to 0.182 (significant at the 5% level). The effect of house prices at origin is more balanced between large and small regions.

For house prices at destination regions, the results are less consistent across methods. In the Poisson method, the interactions between house price and region size are mixed and insignificant for both large and small regions, suggesting that house prices do not strongly influence regional worker movements. However, in the NegBin method, the coefficients become more negative (-0.14 for large regions and -0.132 for small regions), though they remain statistically insignificant. This shift may indicate higher house prices in the destination region have only a weak effect on slowing inflows of workers, as high house costs could deter workers moving from other regions.

The Poisson method emphasises the role of house prices at the origin in driving inter-regional worker movements, while the NegBin method offers a more balanced view, with weaker effects from house prices at the origin and potential deterrent effects from the destination region. These differences underscore the importance of controlling for overdispersion, as the NegBin method finds a sign of violation of equidispersion (the over-dispersion parameter in NegBin is positive and statistically significant at the 1% level).

A statistical hypothesis test was applied to test the difference between the coefficient on house prices in small origin regions and the coefficient on house prices in large origin regions and returned a *p*-value of 0.8252. A similar result was found when applied to house price variables in large and small destination regions. These results do not support for the idea that small and large regions show materially different effects on inter-regional job-to-job transitions.

Table 10 Regression results from extended gravity models

Variables	(1) Poisson	(2) NegBin
Log population at destination	0.715***	0.983***
	(0.211)	(0.356)
Log population at origin	0.990***	1.327***
	(0.192)	(0.363)
Log travel time	0.592	-0.451
	(0.788)	(1.295)
Dummy for same island	2.777***	2.165*
	(0.786)	(1.284)
Log HP at destination x large region	0.0278	-0.140
	(0.0552)	(0.0944)
Log HP at destination x small region	-0.0271	-0.132
	(0.0504)	(0.0807)
Log HP at origin x large region	0.236***	0.165*
	(0.0582)	(0.0979)
Log HP at origin x small region	0.113**	0.182**
	(0.0526)	(0.0782)
Log GDP per capita at destination	0.186	0.325*
	(0.129)	(0.167)
Log GDP per capita at origin	0.204	0.335*
	(0.126)	(0.177)
Unemployment rate at destination	-0.0144***	-0.0224***
	(0.00530)	(0.00676)
Unemployment rate at origin	-0.0153***	-0.0144**
	(0.00576)	(0.00673)
Share of 40-64 labour force at destination	-0.00683	-0.0177*
	(0.00797)	(0.0102)
Share of 40-64 labour force at origin	-0.0261***	-0.0210**
	(0.00769)	(0.0101)
Annual GDP growth rate	0.0307***	0.0200***
	(0.00230)	(0.00368)
Expected GDP growth rate over the next 12 months	0.0496***	0.0581***
Constant	-25.50***	-23.34*
	(7.826)	(12.18)
Observations	4,800	4,800
Over-dispersion parameter		0.0668***
# fixed effects	240	240
Squared correlation	0.986	0.982

Notes:
1. Standard errors in parentheses.
2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The next sections present results from the baseline and extended gravity models by age (section 5.3.2), gender (section 5.3.3), and ethnicity (section 5.3.4). The aim is to highlight heterogeneous mobility responses to house prices. Only the results on the effects of house prices on inter-regional worker transition from the preferred specification (Negative Binomial model) are presented, but full regression results are available in Appendix 2.

5.3.2 Age

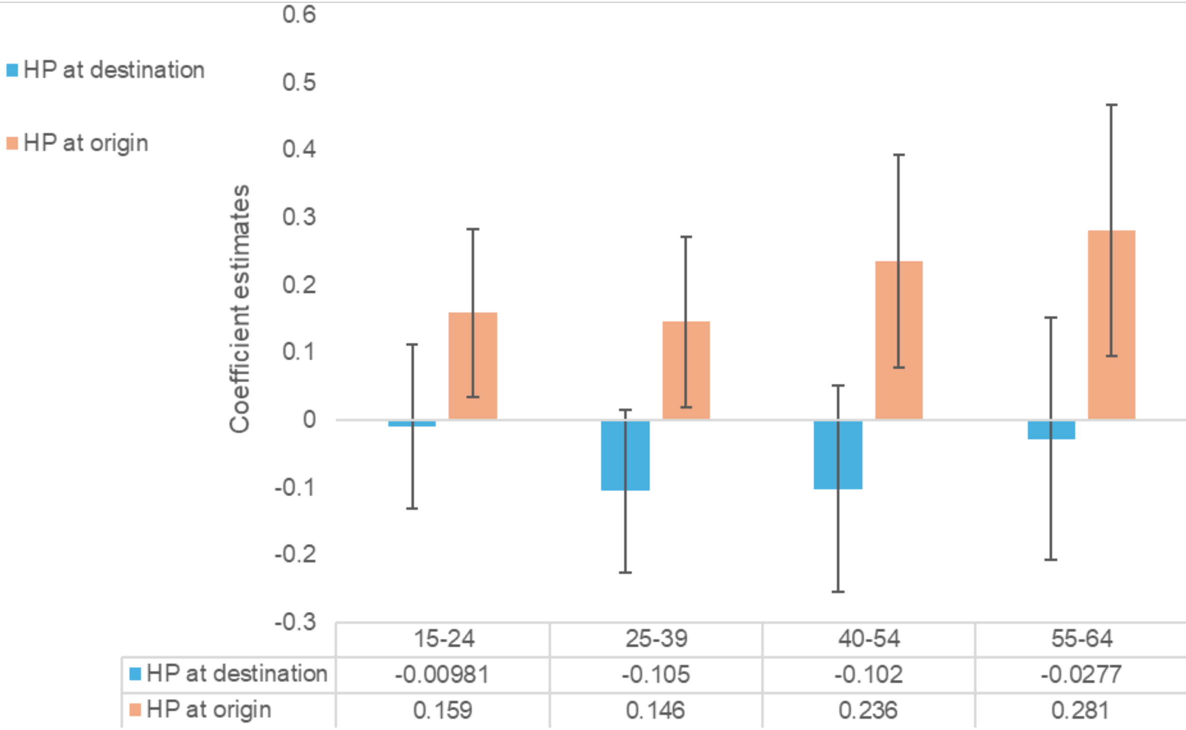
Figure 13 presents the coefficients on log median house prices in both origin and destination regions, along with their 95% confidence intervals, across four broad age groups. The results reveal distinct patterns in how house prices influence inter-regional worker flows depending on whether they are in the origin and destination region and the age group of the workers.

For origin regions, the coefficients on house prices are positive and statistically significant across all age groups, indicating that higher house prices act as a strong push factor driving workers to move out of their current job location. This effect is particularly pronounced for older age cohorts. Specifically, a 1% increase in median house prices is associated with a 0.24% increase in outflows for the 40-54 cohort. For the 55-64 cohort, the effect appears to be even stronger, with a 0.28% increase in outflows for the same 1% rise in house prices. In contrast, the push effects are nearly halved for younger cohorts. A 1% increase in house prices is associated with a 0.16% increase in outflows for the 15-24 cohort. A similar increase is also observed for the 25-39 cohort.

These findings suggest that older workers are more responsive to rising house prices. One possible answer is that they have greater equity in their homes and are more likely to capitalize on higher property values to fund migration. Younger workers, who may have less equity or face higher barriers to relocation, are less affected by changes in house prices.

On the destination side, the impact of house prices is much weaker and generally statistically insignificant. However, there is one notable exception: the 25-39 cohort appears to experience a small (and significant at the 10% level) negative pull effect from higher house prices. A 1% increase in median house prices in the destination region is associated with a 0.11% reduction in inflows of 25 to 39-year-old workers from other regions.

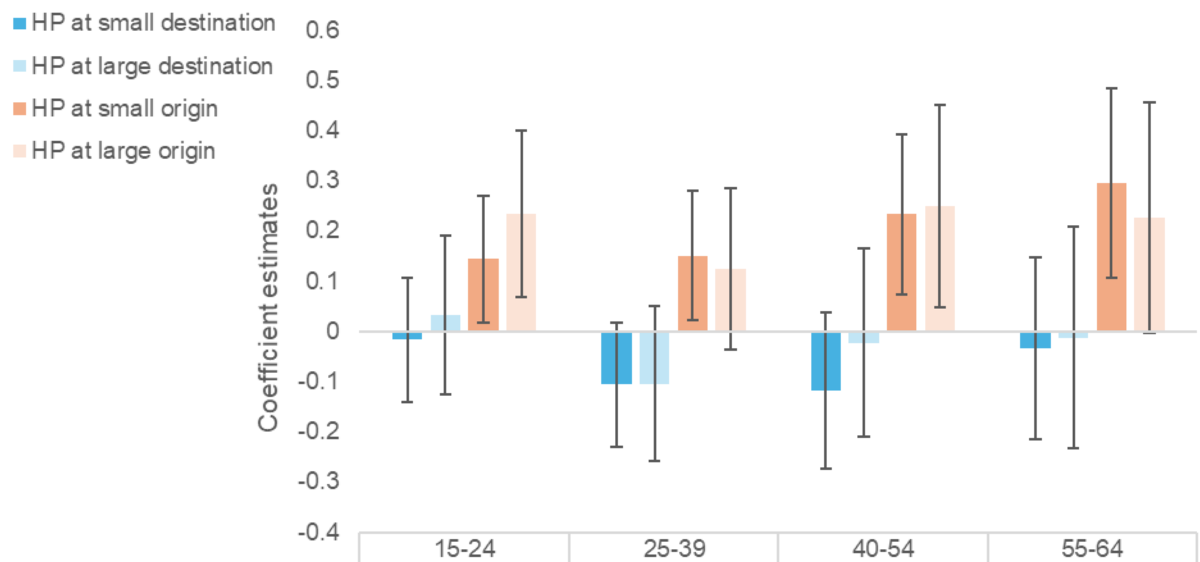
Figure 12 Coefficients on log median house price variables from baseline gravity model, by age group



Source: Author’s calculations using IDI data.
Notes:
1. Estimated coefficients on house price variables are shown in bars and the data table.
2. Vertical lines are 95% confidence intervals for corresponding estimated coefficients.

Figure 14 extends the analysis by presenting separate estimates for house prices in small and large regions based on the extended gravity model. Statistical tests were conducted to assess whether the effects of house prices differ significantly between small and large regions. The results indicate that these differences are hardly significant, implying that workers in both small and large regions experience similar push and pull effects from changes in house prices. This finding underscores the universal nature of housing market dynamics in influencing workers’ mobility, regardless of the size of the region.

Figure 13 Coefficients on interaction terms between log median house prices and region size from extended gravity model, by age group



	15-24	25-39	40-54	55-64
HP at small destination	-0.0171	-0.106	-0.118	-0.0331
HP at large destination	0.0325	-0.104	-0.0228	-0.0124
HP at small origin	0.144	0.151	0.234	0.296
HP at large origin	0.235	0.125	0.25	0.227

Source: Author's calculations using IDI data.
Notes:
1. Estimated coefficients on house price variables are shown in bars and the data table.
2. Vertical lines are 95% confidence intervals for corresponding estimated coefficients.

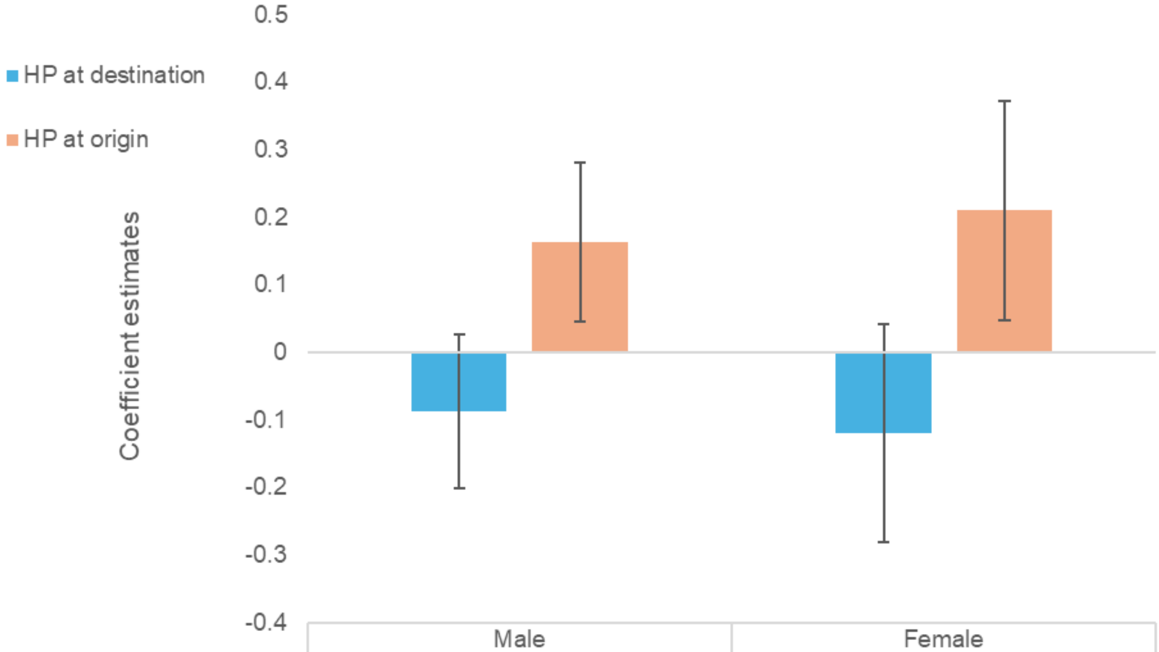
5.3.3 Gender

Figure 15 presents the coefficients on house prices in both origin and destination regions for male and female workers. The results reveal that both male and female workers experience significant push effects from higher house prices in their current work location, though the magnitude of these effects differs slightly between genders. When local house prices increase by 1%, the results indicate an expected 0.16% increase in outflows for male workers and 0.21% increase in outflows for female workers. While the push effect appears to be stronger for female workers, this difference is unlikely to be statistically significant, as the 95% confidence intervals for the house price coefficients largely overlap between genders.

Figure 16 gives separate estimates for house prices in small and large regions by gender. There are a couple of interesting patterns. On the origin side, male workers experience similar push effects from house prices in small and large regions, indicating that men are equally likely to move out of their current location regardless of the size of the region. For females, the push effect is particularly strong in small regions. This could reflect the unique challenges women face in smaller labour markets, such as limited job opportunities.

On the destination side, female workers are more sensitive to higher house prices in large regions, where a 1% increase in house prices significantly reduces inflows by 0.2%. In contrast, male workers appear unresponsive to house prices in destination regions.

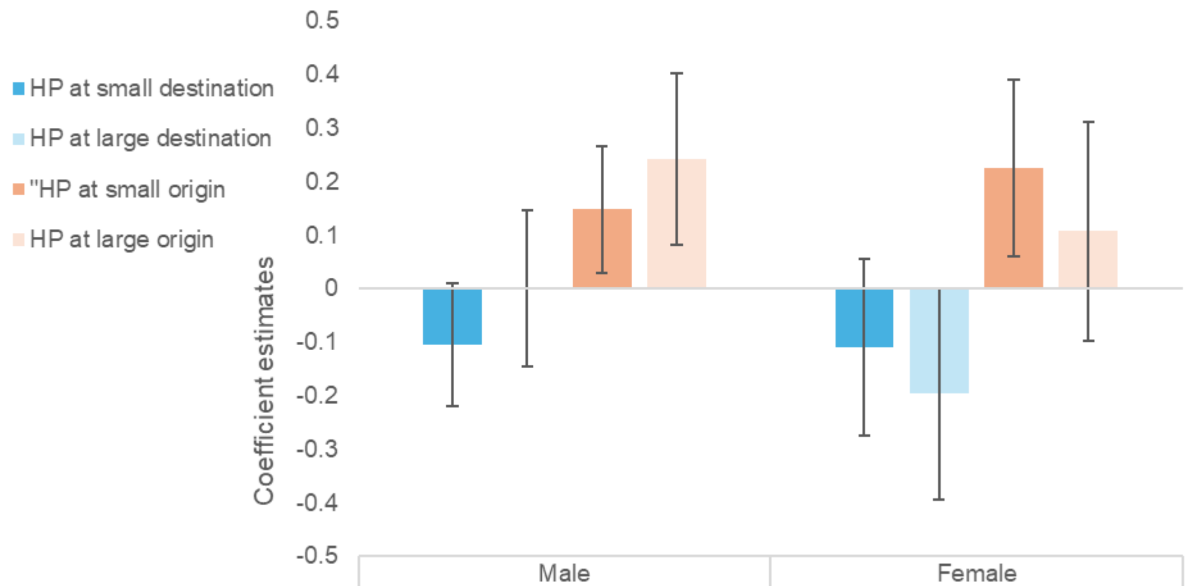
Figure 14 Coefficients on log median house price variables from baseline gravity model, by gender



	Male	Female
HP at destination	-0.0881	-0.12
HP at origin	0.163	0.21

Source: Author’s calculations using IDI data.
Notes:
1. Estimated coefficients on house price variables are shown in bars and the data table.
2. Vertical lines are 95% confidence intervals for corresponding estimated coefficients.

Figure 15 Coefficients on interaction terms between log median house prices and region size from extended gravity model, by gender



	Male	Female
HP at small destination	-0.104	-0.108
HP at large destination	0.000713	-0.196
"HP at small origin	0.149	0.226
HP at large origin	0.243	0.108

Source: Author's calculations using IDI data.
Notes:
1. Estimated coefficients on house price variables are shown in bars and the data table.
2. Vertical lines are 95% confidence intervals for corresponding estimated coefficients.

5.3.4 Ethnicity

The regression results in Figure 17 show how house prices at origin and destination regions influence inter-regional job flows across four ethnic groups: European, Māori, Pacific, and Asian and others. Each ethnic group presents distinct insights.

1. Europeans exhibit the highest sensitivity to house prices. Higher housing costs at the origin push them to seek job opportunities elsewhere, while higher costs at the destination deter them from moving. This 'dual' effect suggests that Europeans are responsive to changes in housing market dynamics.

2. Māori show moderate sensitivity to house prices, particularly at the origin. A 1% increase in house prices at the origin region will see an additional 0.13% outflow of Māori workers. Higher housing costs in their current region encourage or force them to move, but they are less influenced by housing costs at potential destinations. This indicates that Māori are more likely to be pushed

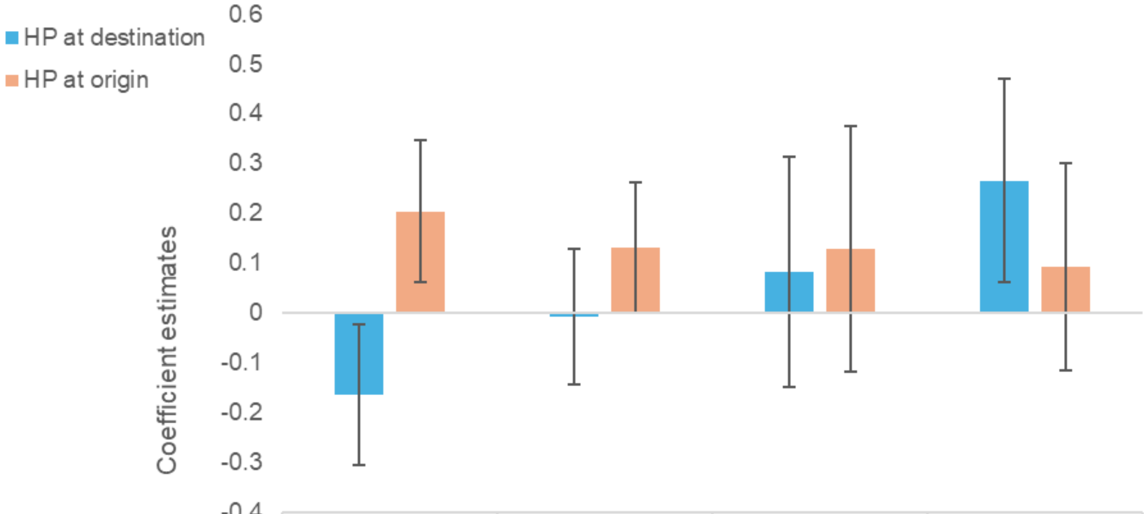
by local housing market conditions rather than pulled by opportunities elsewhere.

3. Pacific peoples display the least sensitivity to house prices, with no statistically significant effects on job transitions. On the face of these results, this suggests that other factors, such as incomes, may play a more significant role in their mobility decisions compared to housing costs.

4. Asians and others stand out as the only group more likely to move to regions with higher house prices. Figure 18 illustrates the proportion of workers moving between different types of regions, comparing Asians and other ethnic groups with European, Māori and Pacific. Asians and others show a higher proportion of moves between large regions (29.0%) compared to the rest of the population (18.9%). This suggests that Asians are more likely to relocate within large urban areas, possibly due to better job opportunities or local amenities.

   Taking a closer examination of the systemic differences in house price effects between small and large regions (Figure 19), the results do not provide strong evidence that large regions exert particularly significant push or pull effects on worker mobility compared to small regions.

Figure 16 Coefficients on log median house prices from baseline gravity model, by ethnicity

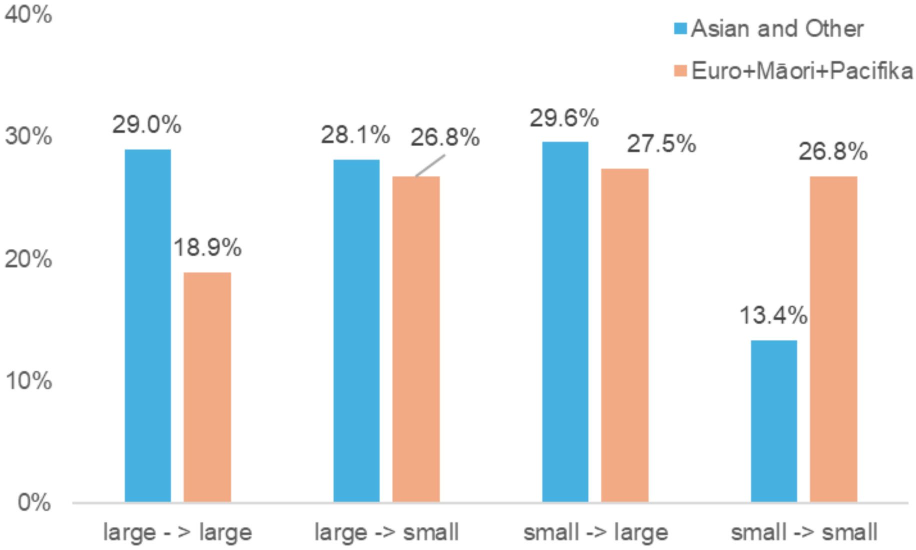


	European	Maori	Pacific	Asians and others
HP at destination	-0.163	-0.00705	0.0833	0.266
HP at origin	0.204	0.131	0.128	0.0929

Source: Author's calculations using IDI data.

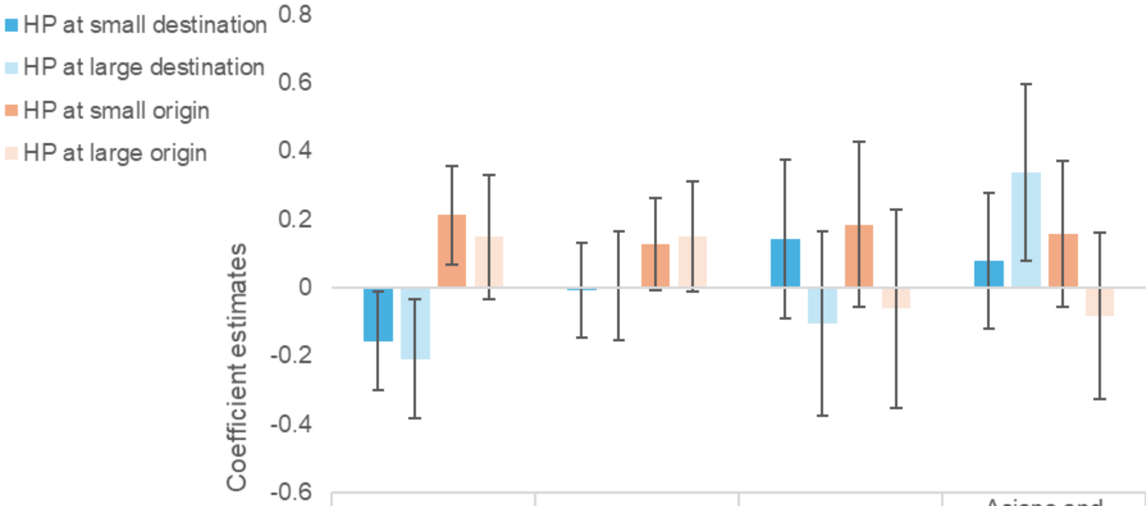
Notes:
1. Estimated coefficients on house price variables are shown in bars and the data table.
2. Vertical lines are 95% confidence intervals for corresponding estimated coefficients.

Figure 17 Region-to-region worker flows, average 2000-2020



Source: Author's calculations using IDI data.
Notes:
1. Large regions include Auckland, Wellington and Canterbury. Small regions are all other regions.
2. 'large->large', 'large->small', 'small->large', and 'small->small' are worker movements between large regions, from large to small, from small to large, and between small regions.

Figure 18 Coefficients on interaction terms between log median house prices and region size from extended gravity model, by ethnicity



	European	Maori	Pacific	Asians and others
HP at small destination	-0.156	-0.00866	0.143	0.0788
HP at large destination	-0.209	0.00397	-0.105	0.336
HP at small origin	0.212	0.127	0.185	0.156
HP at large origin	0.149	0.15	-0.0613	-0.0824

Source: Author’s calculations using IDI data.
Notes:
1. Estimated coefficients on house price variables are shown in bars and the data table.
2. Vertical lines are 95% confidence intervals for corresponding estimated coefficients.

Chapter 6: Estimating the impact of inter-regional worker flows on earnings

This chapter analyses the relationship between inter-regional job-to-job transitions and changes in earnings in New Zealand. In particular, it focuses on investigating the impact of job location on short-term earnings growth, providing insights into how geographic mobility influences workers' economic outcomes.

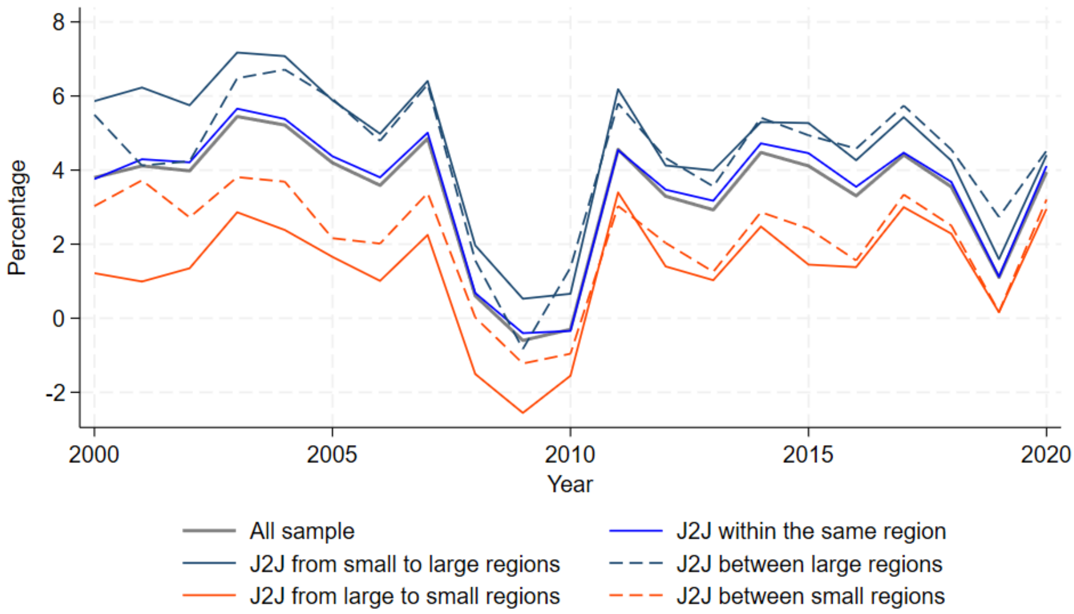
6.1 Exploratory analysis

This section presents a descriptive analysis of earnings dynamics of different types of job-to-job transition. The sample is all workers who experienced a job-to-job transition over the study period. Workers' monthly earnings are derived from EMS information on wages and salaries. An average is taken of workers' earnings over a five-month period centred on March (since using March earnings alone would be affected by differences among workers in the timing of pay and number of pay periods falling in March). If a person starts (exits) a job in March, an average of earnings is taken over the subsequent (previous) five months. Although hourly earnings would be preferrable for such an analysis, New Zealand's IDI does not have data on number of hours worked for the full population. However, on the basis of a set of plausible assumptions, it is possible to estimate workers' full-time equivalent (FTE) workload as a proxy for hours worked (Fabling & Maré, 2015). Such FTE estimates appear to improve accuracy and reduce variation/noise in labour-related measures such as income and labour productivity. Earnings were also adjusted for inflation using the Consumer Price Index for March quarters. Monthly earnings above the 99^{th} percentile or below the 1^{st} percentile were considered outliers and excluded from the analysis. The annual change in monthly earnings is then computed by subtracting log real monthly earnings in year t+1 from log real monthly earnings in year t and multiplying by 100. Figure 20 plots these earnings changes by five different job-to-job transitions, plus the earnings changes for the entire sample (all workers including stayers, entrants, and exiters), for the period 2001 to 2021.

Two noticeable features stand out. The first feature is the correlation of earnings with economic growth. When economic growth is booming (2001-2007 and 2013-2019), changes to earnings following a job-to-job transition tend to grow at a faster rate. During economic contractions or recessions (2008-2012), subdued growth in earnings is observed. This pattern is not unique to New Zealand and is observed in many advanced economies (Carrillo-Tudela et al., 2022; Deutscher, 2019; Hoffmann & Malacrino, 2019).

The second feature is heterogeneous earnings changes for different kinds of job-to-job transition. Workers who moved from small to large regions and between large regions experienced the highest growth in earnings. Over the full sample period, their earnings grew 7.0 and 6.4 per cent, respectively. Workers who changed jobs within the same region ("J2J within the same region") had earnings growth of 5.7 per cent. Growth in earnings for workers moving from large to small regions or between regions was the lowest, at 3.3 and 4.4 per cent, respectively. These findings may not be surprising. Large regions (Auckland, Wellington, and Canterbury) are generally more productive than other regions, offering a higher wage/earning premium for workers living there (Lewis & Stillman, 2007; Maré, 2017). In particular, workers from smaller regions tend to get extra income benefits. Conversely, workers leaving large regions tend to lose the benefits offered by the large regions but do not seem to get pay cuts.

Figure 19 Annual growth in real earnings by different job-to-job transitions



Source: Author's calculations using IDI data.

Figure 20 focuses only on averages of earnings growth and so does not provide a complete picture of distributional effects.

Figure 21 is a histogram-type line chart summarising the distribution of individual earnings growth over 12 discrete ranges (x-axis). Each discrete range presents a specific growth range. For example, [10%, 19%] includes earnings growth of at least 10% but less than 20%. These discrete ranges cover losses in earnings by 80 to 99% [-80%, -99%] to gains in earnings by 80 to 99% [80%, 99%]. The y-axis measures the proportion of workers whose earnings growth fell within the corresponding range.

Consistent with Figure 20, all earnings growth distributions peak between 0% and 9%. A plurality of job-to-job transitions involved relatively little change in earnings over a 12-month period, regardless of whether the job change was intra- or inter-regional or any change in region size.

Figure 21 also reveals some interesting patterns. Just over one in five workers who either move from large to small regions (20.8%) or move between small regions (20.1%) experienced pay cuts greater than 20% [-20%, -29%] and below. The percentage for workers moving from small to large regions is smaller, just over 17%.

It appears that moving to larger regions has on average a slight positive impact on earnings growth for job changers. Approximately 35.3% of workers who moved between large regions, and 34.5% of workers who relocated from small to large regions, experienced pay gains of more than 20%. These figures are marginally higher than the 33% and 32% for workers moving between small regions and those moving from large to small regions, respectively.

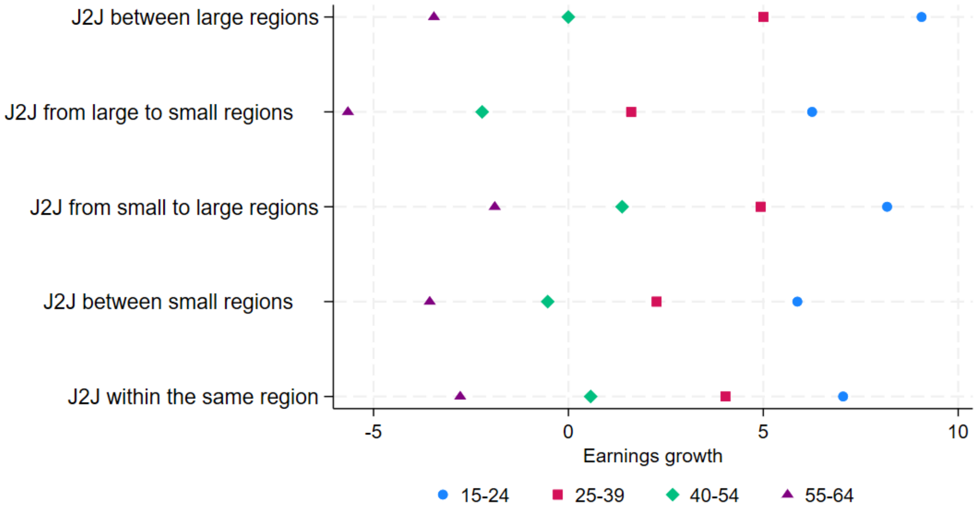
Figure 20 Earnings growth distributions by different job-to-job transitions

Source: Author's calculations using IDI data.
Notes:

1. Individual records of earnings growth are calculated as log changes of March-month earnings over two consecutive years, $[\ln(E_t) - \ln(E_{t-1})] \times 100\%$. Then they are allocated to one of the 14 mutually exclusive discrete ranges ("bins"). Each bin represents a growth range.
2. The y-axis measures the proportions of the selected group distributed over bins.

Figure 22, Figure 23, and Figure 24 take a closer look at average earnings growth patterns across age, gender, and ethnic groups. Figure 22 shows that younger workers in the age groups of 15-24 and 25-39, as well as older workers aged 40-54 and 55-64, display two distinct patterns of earnings. For younger workers, changing jobs leads to higher earnings growth compared to older workers. Since younger workers generally earn less than their older counterparts, a job switch is expected to have a more substantial impact on their earnings. However, the extent of wage promotions was not uniform across different regions and depended on where young workers left and where they headed to. Larger regions, which are usually major economic centres, often offer higher wages and salaries due to the urban labor productivity premium (Maré, 2016). Therefore, workers migrating to Auckland, Wellington, and Canterbury regions could expect to earn more. When workers leave these regions, they may still find good jobs but lose the urban wage premium. The results support this hypothesis, showing that workers changing jobs between large regions and from small to large regions experienced the highest earnings growth. On average, workers aged 35 to 39 years who relocated from small to large regions and between large regions earned 5.6% and 5.3% more than their previous jobs, respectively. However, for workers leaving large regions, their earnings growth was only 1.8%. This difference of roughly four percentage points suggests a moderate wage premium associated with larger region size.

Figure 21 Average earnings growth by job-to-job transition and age group

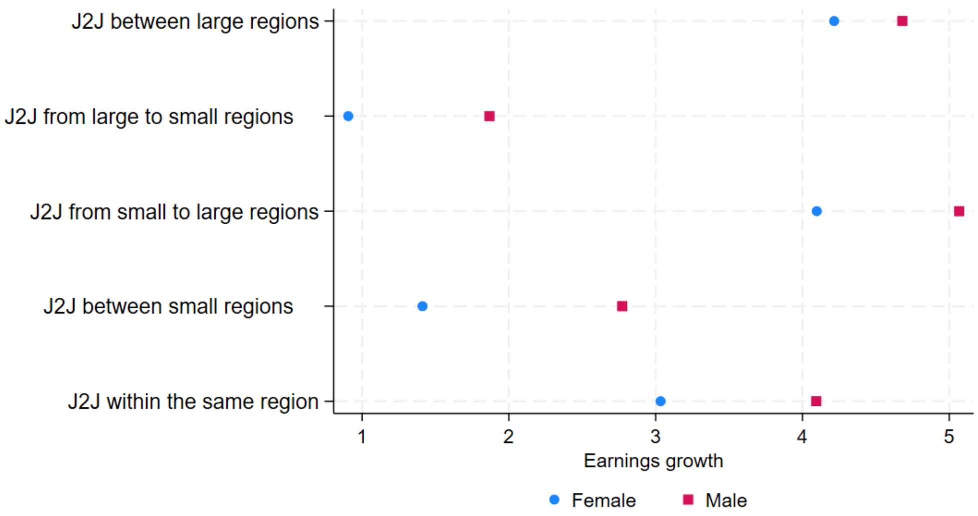


Source: Author's calculations using IDI data.

On the other hand, older workers do not seem to financially benefit from switching jobs. The average earnings growth across all job-to-job transitions for the oldest cohort (55-64) was negative. In particular, their earnings plummeted by more than 5% per year on average if they had left large regions.

Regarding gender, urban wage premia generally hold (Figure 23). However, a stark and persistent pattern emerges of a significant gender gap in earnings growth. Although women are just as mobile as men in changing jobs, they experience markedly lower average earnings growth. This gender gap may prevent women's earnings from closing in on men's earnings, resulting in substantial disparities in pay.

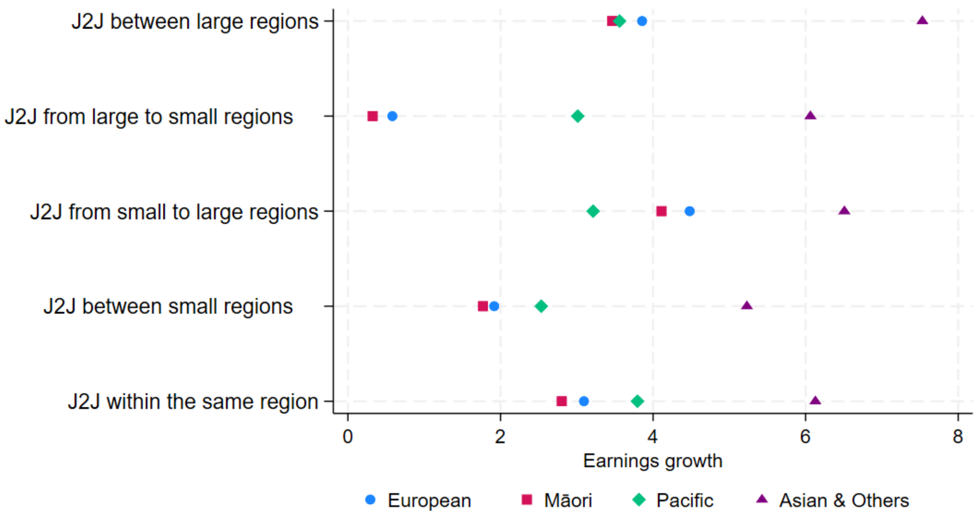
Figure 22 Average earnings growth by job-to-job transition and gender



Source: Author's calculations using IDI data.

Differences in earnings growth following job-to-job transitions are also apparent by ethnic group. Among all ethnic groups, Asian and other workers have the strongest growth rates in earnings. Moving between large regions had the most significant positive impact on their earnings, with an average increase of 7.2% per year. Earnings growth among Pacific workers has been relatively muted and roughly the same across all job-to-job transition types, which suggests that transitioning from one job to another does not lead to significant wage growth for Pacific workers. If Pacific workers do switch jobs, the highest gains are seen when they switch within the same region, with a rate of 3.9%. This is slightly more than the 3.7% rate for job-to-job transitions between large regions and the 3.4% rate for job-to-job transitions from small to large regions.

Figure 23 Average earnings growth by job-to-job transition and ethnicity



Source: Author's calculations using IDI data.

The earnings growth patterns for European and Māori workers vary depending on their migration directions. Moving to large regions generally leads to higher-earning jobs, while leaving large regions results in lower earnings growth. The most surprising finding is that there was almost no growth (only 0.3%) in earnings for job-to-job transitions from large to small regions, indicating that earnings in new jobs were almost the same as in old jobs for European and Māori workers.

6.2 Estimation method

To estimate the impact of geographic mobility on earnings, linear models are used to predict the percentage change in earnings from a job change as a function of the type of job-to-job transition and a set of explanatory variables. This is shown in Equation 6:

Equation 6 Earnings growth model

$$\Delta rw_{it} = \sum_{k} \alpha_k J2J_{it} + \pi \Delta FTE_{it} + \sum_{s} \gamma_s^o I_{ist-1}^o + \sum_{s} \gamma_s^d I_{ist}^d + \sum_{f} \rho_f^o I_{ift-1}^o + \sum_{f} \rho_f^d I_{ift}^d + \beta X_{it-1} + GDP_t + \theta_i + \mu + \varepsilon_{it}$$

where subscripts i and t represent worker and year respectively.

Equation 6 includes the following variables:

- The dependent variable $\Delta rw_{it} = \ln(rw_{it+1}^{d}) - \ln(rw_{it}^{o})$ which is the log difference in real earnings between the current period t+1 and the previous period t.

- $J2J_{it}$ is a set of five different job-to-job transition indicators, namely (1) job transitions within the same region, (2) between small regions, (3) from small to large regions, (4) from large to small regions, and (5) between large regions. Job-to-job transitions within the same region is set as the reference category.

- ΔFTE is changes in FTE, measuring changes in hours worked.

- $\sum_s \gamma_s^o I_{ist}^o$ and $\sum_s \gamma_s^d I_{ist+1}^d$ are each a set of 19 indicator variables for the industry of worker i's job at time t and $t+1$, respectively. Industries are coded to level 1 of the Australian and New Zealand Standard Industrial Classification (ANZSIC 2006) which has 19 categories: Agriculture, Mining, Manufacturing, Electricity, waste and water supply, Construction, Wholesale trade, Retail trade, Accommodation and food services, Transport and warehousing, Telecommunications, Finance and banking, Rental and real estate services, Professional services, Administrative business services, Central and local government, Education, Healthcare, Recreational services and Other services. The Other services are the reference category for origin and destination industries.

- $\sum_f \rho_f^o I_{ift}^o$ and $\sum_f \rho_f^d I_{ift+1}^d$ are sets of firm size indicators for origin and destination jobs for worker i. Firm size indicators cover seven categories: firms with less than 4 (FTE) employees, 5-9 employees, 10-19 employees, 20-49 employees, 50-99 employees, 100-249 employees and 250 or more employees. The smallest firm size serves as the reference category at both origin and destination firms.

- X_{it} are the workers' demographic characteristics, covering age, gender and ethnicity. For the age variable, both linear and quadratic terms are considered. However, gender and ethnicity are time-invariant at the personal level and are excluded in fixed-effect models.

- GDP_t is the annual GDP growth rate which controls for common economic shocks.

- θ_i are unobserved worker fixed effects, such as worker quality and experience.
- μ and ε_{it} are the intercept and residual terms. The residual term is normally distributed.

The key variables of interest are the job-to-job transition indicators $J2J_{it}$. The corresponding coefficients, α_k, measure the average earnings growth premia compared to those workers who change jobs and remain in the same region, conditional on factors such as industry, firm size, and worker characteristics. In other words, these coefficients indicate additional (positive or negative) earnings growth obtained when workers relocate to other regions.

For example, suppose a positive coefficient for the 'job-to-job transition from small to large region' variable is observed. In that case, it suggests a higher wage premium for workers migrating to large regions compared to those changing jobs within the same region.

Furthermore, job-to-job transitions are expected to have varying effects on New Zealand's demographic subgroups. Therefore, equation 6.1 is estimated separately for all age (15-24, 25-39, 40-54 and 55-64), gender (male and female) and ethnic (European, Māori, Pacific, and Asian and other) groups.

Fixed Effects (FE) and Random Effects (RE) estimation methods were tested and applied in this study. In FE models, the θ_i are permitted to correlate with regressors on the right-hand of equation 6. 1. This allows for a form of endogeneity. In contrast, the RE model assumes that θ_i is purely random with respect to individual workers and is uncorrelated with regressors. Standard Hausman tests are commonly applied to pick the most appropriate model. Hausman tests compare two sets of estimates from FE and RE and require statistically significant results to reject the null hypothesis that worker effects, θ_i, are random. Under the assumption of the null hypothesis, both FE and RE return similar results, but RE estimates are more efficient in giving unbiased standard errors. When the null hypothesis is rejected, worker fixed effects are not randomly distributed, and FE estimates are unbiased due to mitigation of θ_i.

The Hausman test returned strong results (*p*-values are less than 5% statistical significance level) that rejected the null hypothesis for all models. This chapter presents only FE estimates; RE estimates are shown in Appendix 8. By default, FE models remove all time-invariant variables as they are absorbed in worker effects θ_i. Thus, gender and ethnicity variables are not estimated.

6.3 Regression results

6.3.1 Impact of job-to-job transitions on earnings growth

This section only focuses on a small subset of regression estimates from the FE models. Additional regression results on both FE and RE methods can be found in Appendix 3.

Table 11 presents estimated coefficients, α_k, on job-to-job transitions as well as coefficients on GDP growth and the intercept from the FE model for the full working-age population and for demographic subgroups. Results for age groups are presented in columns 2 to 5. Results for male and female workers are in columns 6 and 7. The last four columns present results for ethnic groups.

The positive coefficients on annual GDP growth shown in Table 11 suggest a strongly procyclical feature of wage growth related to job-to-job transitions. Changing jobs generally has more positive effects on wages during economic expansions compared to economic contractions. During the expansion period, jobs are more abundant, and workers have more choices to switch to better-paid jobs. In economic contractions, demand for workers is weak and wages offered to open positions may be lower, so workers may receive smaller wage growth from changing jobs.

The intercept term, μ, provides the estimated average earnings growth for the reference group – workers who change jobs in the same location. The α_k coefficients are the corresponding estimated coefficients for the other four types of job-to-job transition, indicating additional earnings premia. Summing μ and α_k, $(\mu + \alpha_k)$, returns the average earnings growth effects.

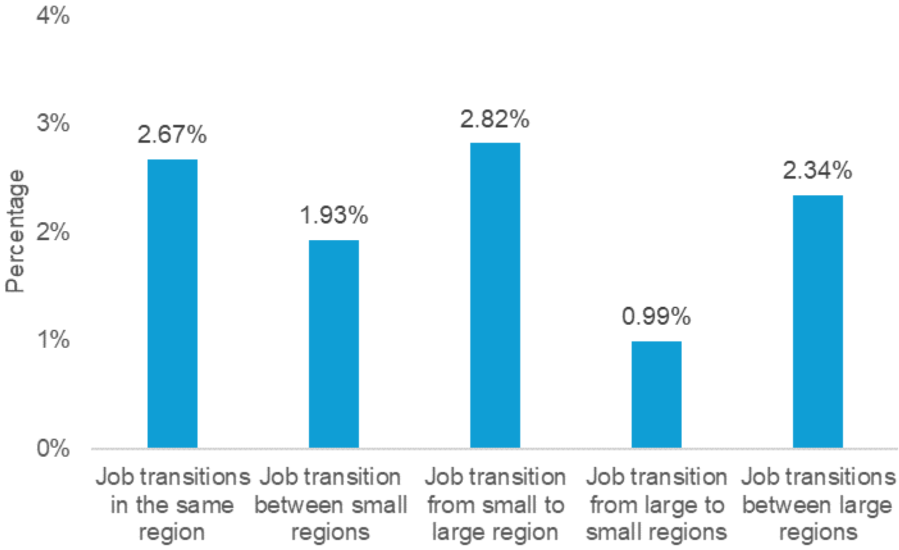
Table 11 Fixed effects regression results on earnings growth and job-to-job transitions

	(1) All workers	(2) Age: 15-24	(3) Age: 25-39	(4) Age: 40-54	(5) Age: 55-64	(6) Sex: Male	(7) Sex: Female	(8) Ethnicity: European	(9) Ethnicity: Māori	(10) Ethnicity: Pacific	(11) Ethnicity: Asian & Others
Job transition between small regions	-0.00742***	-0.00979***	-0.00870***	-0.00593***	-0.00940*	-0.00764***	-0.00688***	-0.00858***	-0.00661***	0.00700	-0.00381
	(0.000865)	(0.00209)	(0.00185)	(0.00215)	(0.00531)	(0.00117)	(0.00129)	(0.000959)	(0.00170)	(0.00464)	(0.00307)
Job transition from small to large region	0.00149*	-0.00474***	0.00282*	0.00199	-0.00551	0.00477***	-0.00141	0.00204**	0.000974	-0.00273	0.00220
	(0.000790)	(0.00181)	(0.00162)	(0.00200)	(0.00504)	(0.00110)	(0.00114)	(0.000892)	(0.00178)	(0.00322)	(0.00227)
Job transition from large to small region	-0.0168***	-0.00617***	-0.0187***	-0.0202***	-0.0231***	-0.0181***	-0.0160***	-0.0202***	-0.0175***	-0.00311	-0.00138
	(0.000806)	(0.00191)	(0.00163)	(0.00200)	(0.00501)	(0.00111)	(0.00117)	(0.000911)	(0.00183)	(0.00312)	(0.00230)
Job transition between large regions	-0.00333***	-0.000978	-0.00301	-0.00837***	-0.00976	-0.00223*	-0.00437***	-0.00469***	-0.00152	-0.00349	0.00217
	(0.000965)	(0.00240)	(0.00190)	(0.00256)	(0.00726)	(0.00135)	(0.00138)	(0.00110)	(0.00259)	(0.00328)	(0.00247)
Annual GDP growth	0.533***	0.572***	0.522***	0.539***	0.279***	0.634***	0.428***	0.572***	0.521***	0.595***	0.359***
	(0.0129)	(0.0326)	(0.0266)	(0.0317)	(0.0816)	(0.0179)	(0.0185)	(0.0147)	(0.0299)	(0.0482)	(0.0355)
Intercept	0.0267***	0.0378***	0.00340	-0.0110*	-0.0232	0.0317***	0.0224***	0.0259***	0.0154***	0.0252***	0.0432***
	(0.00218)	(0.00492)	(0.00473)	(0.00582)	(0.0169)	(0.00302)	(0.00313)	(0.00238)	(0.00517)	(0.00916)	(0.00674)
Observations	6,383,800	1,901,600	2,361,600	1,647,300	473,200	3,263,100	3,120,700	4,712,500	1,092,600	467,400	1,044,600
R^2	0.852	0.910	0.854	0.830	0.873	0.828	0.872	0.846	0.858	0.867	0.874

Notes:
1. Standard errors are clustered in person and appear in parentheses.
2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results in Table 11 show that transitioning from a job in a large region to a job in a small region negatively impacts earnings. Nine out of 11 models have statistically significant negative coefficients on job-to-job transitions from large to small regions. This signals that job relocations from large to small regions tend to immediately lower wage growth in the short run. For the full working-age population, the estimated wage growth for job relocation from large to small regions is 0.99% (=0.0267-0.0168)x100%, holding other factors constant. That is the slowest rate compared to others (Figure 25).

Figure 24 Estimated earnings growth rates by type of job-to-job transition



Source: Author's calculations using IDI data.

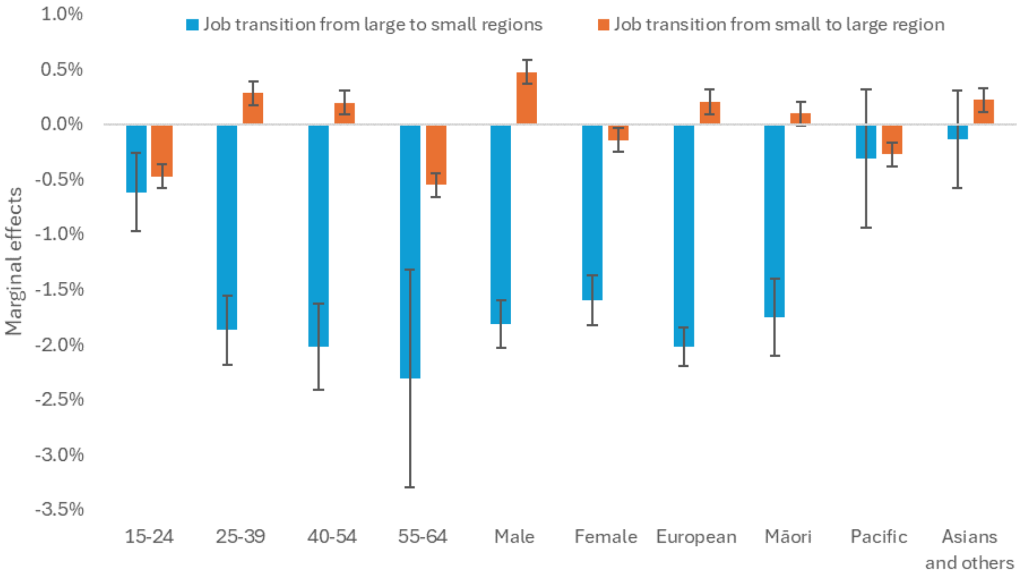
This finding may reflect the fact that New Zealand workers do not retain wage premia earned in large regions when they land in a new job elsewhere. Large regions, including Auckland, Wellington, and Canterbury, are the most urbanised and productive areas which offer broad economic benefits to businesses and workers. Duranton and Puga (2004) and Rosenthal and Strange (2004) pointed out that three major micro-economic drivers - efficient use of resources (e.g., infrastructure), greater knowledge spillovers, and improved skill matching to businesses - help boost productivity for businesses within urban areas. Maré (2016) showed that the three major regions were at least 13% more productive than rural regions and 2% more productive than other urban areas. In return, many businesses benefit from these factors to build economic strengths and are more willing to pay higher wages and salaries (as well as better training opportunities and work conditions) to attract workers from other areas or retain their employees (Lewis & Stillman, 2007). When leaving these major areas, businesses in other regions may not be able to offer comparable pay or emigrated workers might be willing to accept lower wages.

For workers who migrate from small to large regions, one may expect a larger pay-off given the urban productivity premia illustrated above. Regression results generally indicate these productivity premia spillover to individual’s wages and salaries, but the effects are very marginal. For the full working-age population, workers who make such moves gain another 0.15 percentage point premium on top of the reference group, so their earnings growth rate is 2.82% per annum. On average, workers migrating to large urban areas receive slightly more attractive pay and can expect to see the fastest pay increases compared to other workers.

Figure 26 focuses specifically on earnings outcomes among workers entering and leaving large regions, both overall and by demographic subgroup. It highlights the fact that the effects of job-to-job transitions on earnings are highly heterogenous across different groups of workers. Most workers migrating out of large regions experienced significantly slower growth in wages, except Pacific and Asian and other workers. Among those affected workers, those 25 years and older, male, European, and Māori were the most affected. For workers migrating into large regions, only five out of 12 groups experienced faster wage growth, including age 25-39, age 40-54, male, European and Asian and other groups. On the contrary, workers who are 15-24, 55-64, female, and Pacific, seem not to benefit from moving into large regions.

For job-to-job transitions between large regions and between small regions, estimated coefficients are negligible. Many of them are not statistically significant. Moving jobs between similar-sized regions does not bring additional wage benefits to workers.

Figure 25 Marginal effects on earnings growth of job-to-job transitions from large to small regions and from small to large regions



Source: Author's calculations using IDI data.
Notes:
1. Marginal effects are calculated as 100% x estimated coefficient on job transition from small to large region and job transition from large to small region in Table 9.

6.3.2 Impact of changes in firm size and industry on earnings growth

This section provides additional insights into the effects of switching industries and firm size on workers' earnings. This information is of interest because it reveals the extent of the wage gains from moving to or from a particular industry or firm when changing jobs. Equation 6 controls for both industry and firm-size fixed effects in both the current (t) and future (t+1) year. Fixed effects on year t show wage premia associated with leaving a specific industry or firm, while fixed effects on year t+1 show wage premia associated with joining a new industry or firm.

Table 12 and Table 13 show the effects on change in earnings of firm size in origin job (Table 12) and destination job (Table 13) for the full working-age population and by age, gender, and ethnic group. There are seven firm size categories: 1-4, 5-9, 10-19, 20-49, 50-99, 100-249, and 250 or more employees, with the smallest firm size category being the reference category. Estimates shown in both tables display additional wage gains and losses experienced by leaving and joining a specific firm size category.

Two critical patterns emerge. First, relative to leaving a job in a firm with 1 to 4 employees, leaving a job in a larger firm is associated with negative wage growth. This is why the figures in Table 12 relating to origin job are all negative. Conversely, relative to taking a new job in a firm with 1 to 4 employees, taking a new job in a firm of larger size is associated with positive wage growth. This is why the figures in Table 13 relating to destination job are all positive.

Table 12 Average impacts on earnings growth associated with firm size of origin job

	15-64	15-24	25-39	40-54	55-64	Male	Female	European	Māori	Pacific	Asians and others
Firm size 5-9 employees	-2.0%	-2.0%	-2.1%	-2.1%	-1.3%	-2.7%	-1.3%	-2.2%	-1.7%	-1.4%	-1.5%
Firm size 10-19 employees	-3.0%	-2.8%	-3.0%	-3.2%	-2.5%	-3.9%	-1.9%	-3.2%	-2.3%	-2.4%	-2.3%
Firm size 20-49 employees	-4.0%	-3.4%	-3.9%	-4.4%	-3.9%	-5.1%	-2.7%	-4.2%	-3.7%	-3.1%	-3.2%
Firm size 50-99 employees	-4.4%	-3.9%	-4.3%	-4.8%	-4.1%	-6.2%	-2.6%	-4.7%	-4.0%	-3.9%	-3.4%
Firm size 100-249 employees	-5.9%	-5.3%	-5.7%	-6.4%	-6.0%	-7.8%	-3.8%	-6.2%	-5.8%	-5.4%	-4.7%
Firm size 250+ employees	-7.1%	-5.8%	-6.8%	-8.1%	-8.2%	-9.2%	-5.0%	-7.3%	-7.5%	-7.2%	-5.6%

Source: Author's calculations using IDI data.
Notes:
1. Marginal effects = ρ_f^o x 100%.
2. Each marginal effect indicates a percentage point difference in the average wage of workers in a specific firm size (rows) over workers in the smallest firm size (1-4 employees).
3. Numbers are shaded from red for lower values to green for higher values (closer to zero).

Table 13 Average impacts of earnings growth associated with firm size or destination job

	15-64	15-24	25-39	40-54	55-64	Male	Female	European	Māori	Pacific	Asians and others
Firm size 5-9 employees	1.6%	1.2%	2.2%	1.1%	0.8%	2.5%	0.6%	1.7%	1.7%	1.5%	1.5%
Firm size 10-19 employees	2.4%	1.8%	3.0%	2.2%	1.1%	3.7%	0.9%	2.5%	2.3%	1.7%	2.8%
Firm size 20-49 employees	3.3%	2.0%	4.2%	3.3%	2.3%	5.0%	1.4%	3.4%	3.2%	3.0%	3.3%
Firm size 50-99 employees	3.7%	2.2%	4.8%	3.5%	2.3%	5.7%	1.6%	3.9%	3.8%	3.1%	3.4%
Firm size 100-249 employees	4.7%	3.6%	5.5%	4.3%	3.0%	6.9%	2.3%	5.0%	4.5%	4.3%	4.0%
Firm size 250+ employees	6.5%	5.4%	7.2%	6.4%	4.5%	8.9%	4.1%	6.5%	7.0%	7.0%	5.9%

Source: Author's calculations using IDI data.
Notes:
1. Marginal effects = ρ_f^d x 100%.
2. Each marginal effect indicates a percentage point difference in the average wage of workers in a specific firm size (rows) over workers in the smallest firm size (1-4 employees).
3. Numbers are shaded from red for higher values to green for lower values (closer to zero).

Second, wage growth decreases with firm size at t and increases with firm size at t+1. This implies that workers gain (lose) greater wage growth when climbing up (down) the firm size category. For example, workers who moved to (or left) the largest firm size category (250+ employees) on average gained (lost) 6.5 percentage points (7.1

percentage points)on their wages compared to workers who joined (left) the smallest firm category.

These results provide strong evidence of the wage ladder on firm size in New Zealand. Firm size is often used as an indicator of productivity, as large firms tend to be more productive in many countries (Berlingieri et al., 2018; Leung et al., 2008; Posti & Maiti, 2023). According to Allan and Maré (2021), workers in New Zealand tend to earn higher wages in high-performing firms. Workers can advance their careers by transitioning from low-productivity to high-productivity firms. Haltiwanger et al. (2018) found that many American workers, particularly younger ones, follow this pattern.

The relationship between wage progression and firm size seems to hold true across different subgroups. Some workers experience more significant changes in earnings as they move between firms of different sizes. Notably, changes in firm size led to more significant wage changes for workers in older age groups (25-39, 40-54, and 55-64), male workers, and those of European or Māori ethnicities.

Table 14 and Table 15 display wage growth for the industries of both origin and destination jobs relative to wage growth in the reference industry ‘Other services’. Industries such as mining, finance and banking services, and utilities show significantly higher wage premiums. For instance, relative to getting a job in the ‘Other services’ industry, getting a new job in the mining industry pays wages that are 17.2 percentage points higher. Conversely, relative to leaving a job in the ‘Other services’ industry, leaving a job in the mining industry reduces wages by 17.5 percentage points. Similarly, getting a new job in the finance industry or in the utilities industry increases wages by 6.0 percentage points and 5.8 percentage points (relative to getting a new job in the ‘Other services’ industry), respectively. When workers leave these industries, they immediately lose these wage premiums at a similar scale. Conversely, several service industries offer minimal wage premiums, including administrative and support services, retail trade, accommodation and food services, education, and healthcare services. These findings align with industry-level productivity in New Zealand, implying that higher productivity industries generally offer better wages (Conway & Meehan, 2013).

Table 14 Average impacts on earnings growth associated with industry of origin job

	15-64	15-24	25-39	40-54	55-64	Male	Female	European	Māori	Pacific	Asians and others
Agriculture	-1.8%	-3.1%	-0.9%	-1.0%	0.2%	-2.4%	-1.1%	-1.9%	-1.4%	-2.3%	-2.6%
Mining	-17.5%	-19.1%	-18.1%	-16.5%	-15.3%	-18.6%	-11.6%	-16.9%	-20.6%	-25.7%	-12.7%
Manufacturing	-3.8%	-2.5%	-3.4%	-4.5%	-5.4%	-3.9%	-3.1%	-3.7%	-4.0%	-5.3%	-3.6%
Utilities	-5.0%	-1.3%	-4.6%	-7.0%	-7.0%	-4.7%	-5.4%	-5.4%	-4.7%	-5.5%	-3.4%
Construction	-1.9%	-1.2%	-1.6%	-2.6%	-4.1%	-2.1%	-1.3%	-1.6%	-2.9%	-3.1%	-1.5%
Wholesale	-2.8%	-0.7%	-2.7%	-3.8%	-4.2%	-2.5%	-3.0%	-2.9%	-2.3%	-2.8%	-2.6%
Retail trade	-2.7%	-5.6%	-0.5%	0.6%	0.0%	-1.9%	-3.2%	-2.9%	-1.9%	-2.5%	-2.8%
Hospitality	-3.3%	-4.3%	-1.6%	-1.4%	-1.8%	-2.6%	-3.4%	-3.5%	-3.0%	-1.6%	-3.3%
Transport	-2.6%	-0.8%	-2.9%	-3.5%	-3.6%	-3.1%	-1.5%	-2.5%	-3.5%	-3.4%	-1.9%
Telecom	-0.2%	7.4%	-2.6%	-4.6%	-3.3%	0.4%	-0.7%	-0.5%	1.1%	-2.1%	1.0%
Finance	-5.3%	-3.1%	-5.2%	-7.2%	-7.1%	-4.6%	-5.7%	-5.4%	-4.2%	-6.2%	-5.1%
Rental serv	-2.4%	-2.9%	-1.9%	-1.9%	-1.7%	-2.6%	-2.1%	-2.6%	-2.0%	-1.9%	-2.0%
Professional serv	-1.0%	2.5%	-1.8%	-3.1%	-3.3%	-1.7%	-0.4%	-1.1%	-1.3%	-0.9%	-0.2%
Administrative serv	5.7%	3.8%	6.3%	6.8%	7.7%	6.5%	5.0%	5.9%	5.3%	6.1%	4.6%
Government	-1.2%	1.9%	-1.4%	-2.5%	-3.5%	-1.0%	-1.4%	-1.1%	-1.0%	-1.6%	-1.1%
Education	1.5%	6.1%	0.8%	-0.5%	-3.1%	5.6%	-0.2%	1.5%	0.8%	1.0%	3.1%
Healthcare	1.1%	0.4%	0.9%	1.5%	1.3%	1.7%	0.5%	1.2%	1.4%	0.2%	0.4%
Recreational serv	1.3%	1.3%	1.5%	1.9%	0.8%	1.0%	1.6%	1.3%	1.4%	0.7%	0.3%

Source: Author's calculations using IDI data.
Notes:
1. Marginal effects = γ_s^o x 100%.
2. Each marginal effect indicates a percentage point difference in the average wage of workers in a specific industry (rows) over workers in the 'Other services' industry.
3. Numbers are shaded from red for lower values to green for higher values.

Table 15 Average impacts on earnings growth associated with industry of destination job

	15-64	15-24	25-39	40-54	55-64	Male	Female	European	Māori	Pacific	Asians and others
Agriculture	1.7%	2.8%	1.4%	0.9%	-0.5%	1.9%	1.3%	2.0%	1.2%	0.4%	1.7%
Mining	17.2%	20.3%	18.1%	14.9%	17.1%	17.1%	15.4%	16.9%	18.6%	17.1%	14.7%
Manufacturing	3.9%	3.4%	3.7%	3.8%	4.1%	3.3%	4.1%	4.0%	3.2%	3.7%	3.3%
Utilities	5.8%	4.2%	5.3%	6.6%	7.4%	5.1%	6.5%	5.6%	5.5%	5.2%	5.6%
Construction	3.3%	1.9%	3.3%	4.4%	5.2%	2.9%	3.0%	3.0%	3.7%	3.6%	3.7%
Wholesale	3.5%	2.4%	3.6%	4.2%	3.5%	2.6%	4.4%	3.6%	2.9%	2.2%	3.2%
Retail trade	0.6%	2.1%	-0.6%	-0.5%	-0.7%	-0.5%	1.6%	0.8%	-0.1%	-0.2%	-0.2%
Hospitality	1.4%	2.7%	0.3%	0.7%	1.4%	-0.7%	2.5%	1.9%	1.3%	-0.8%	0.3%
Transport	4.2%	3.6%	4.4%	4.6%	4.5%	4.2%	3.2%	4.1%	4.3%	3.2%	4.1%
Telecom	4.2%	3.9%	4.1%	5.0%	3.0%	4.2%	4.4%	4.5%	3.0%	2.1%	3.7%
Finance	6.0%	5.9%	5.3%	6.4%	5.6%	5.2%	6.7%	6.4%	5.1%	4.5%	5.0%
Rental serv	2.6%	1.8%	2.9%	3.2%	3.0%	2.0%	3.1%	2.9%	2.3%	1.4%	2.2%
Professional serv	3.4%	1.7%	3.8%	3.8%	4.1%	3.6%	3.3%	3.4%	2.8%	1.9%	3.1%
Administrative serv	-4.6%	-3.2%	-5.2%	-5.7%	-4.7%	-6.4%	-2.8%	-4.4%	-4.5%	-6.9%	-4.4%
Government	3.6%	3.2%	3.4%	3.3%	3.6%	1.4%	5.6%	3.6%	2.9%	3.3%	3.1%
Education	-0.6%	-3.3%	0.0%	0.3%	3.3%	-4.0%	1.4%	-0.4%	-0.4%	-1.4%	-2.5%
Healthcare	-0.1%	0.5%	0.1%	-0.9%	-0.3%	-0.7%	0.9%	-0.2%	-0.4%	-0.9%	0.5%
Recreational serv	-1.4%	-0.9%	-1.8%	-2.0%	0.5%	-2.3%	-0.7%	-1.3%	-1.2%	-1.0%	-2.2%

Source: Author's calculations using IDI data.
Notes:
1. Marginal effects = γ_s^d x 100%.
2. Each marginal effect indicates a percentage point difference in the average wage of workers in a specific industry (rows) over workers in the 'Other services' industry.
3. Numbers are shaded from red for higher values to green for lower values.

Chapter 7: Conclusions

This thesis has explored the intricate relationship between house prices, inter-regional worker mobility, and earnings growth in New Zealand. By leveraging comprehensive data from Statistics New Zealand's Integrated Data Infrastructure (IDI) and employing advanced econometric techniques, the study has provided valuable insights into how housing market dynamics influence worker mobility and the subsequent impact on individual earnings. The findings contribute to the broader literature on labour market dynamics and offer important policy implications for addressing housing affordability and labour market efficiency in New Zealand.

7.1 Summary of key findings

At the national level, worker mobility marginally increased over the 2000-2020 period. This trend contrasts with declining mobility rates observed in other advanced economies (Biswas et al., 2009; Cavalleri et al., 2021; Hyatt & McEntarfer, 2012). This divergence highlights the need to examine contextual drivers of mobility, including housing markets and labour market structures.

Mobility behaviour is highly heterogenous across demographics and locations. Worker mobility rates are usually higher in smaller regions, where limited job opportunities may incentivize workers to see employment elsewhere.

Age also plays a pivotal role in mobility patterns. Younger workers (below 40 years of age) are generally more mobile compared with older cohorts. This reflects that workers in the early stages of their careers may be less constrained by housing costs and more motivated to relocate to where better job opportunities are located. In contrast, older workers may not have the same motivations and find it more difficult to move due to higher opportunity costs (e.g. selling their homes, enrolling their children in new schools).

The thesis reveals that house prices play a significant role in shaping inter-regional worker mobility in New Zealand. Higher housing prices in the origin region act as a 'push' factor, encouraging workers to relocate to other regions in search of more affordable living conditions. Conversely, higher house prices in the destination region discourage flows of workers into the region. This dual effect is consistent with findings from other advanced economies, such as the U.S., Canada, and the U.K., where housing affordability has been identified as a critical barrier to worker mobility (Causa et al., 2021).

This thesis has also highlighted that the impact of house prices on worker mobility varies across demographic groups. Older workers (aged 40-64) are more sensitive to house price changes compared to younger workers (aged 15-24), likely due to their greater equity in homes and higher financial stakes in the housing market. Additionally, female workers exhibit a stronger push effect from rising housing prices, particularly in smaller regions, suggesting that women may face unique challenges in smaller labour markets, such as limited job opportunities.

Furthermore, the thesis examines the short-term impact of inter-regional job-to-job transitions on earnings growth. The findings indicate that workers who move from smaller to larger regions experience modest earnings growth, reflecting the urban wage premium associated with more productive and economically vibrant regions. However, workers who move from larger to smaller regions tend to experience slower earnings growth, as they lose the wage benefits associated with urban areas.

The analysis further reveals that the impact of job-to-job transitions on earnings varies across demographic groups. Younger workers (aged 15-39) tend to benefit more from job changes, particularly when moving to larger regions, while older workers (aged 55-64) often experience slower earnings growth or even wage losses when relocating. Male workers and those of European or Asian ethnicity are more likely to benefit from job transitions, while female and Pacific workers experience smaller earnings gains, highlighting persistent gender and ethnic disparities in the labour market.

7.2 Limitations and future research

While this thesis provides valuable insights into the relationship between house prices, worker mobility, and earnings growth, it is not without limitations. The study focuses on short-term earnings outcomes following job transitions, so future research could explore the long-term effects of mobility on career progression and income trajectories. Additionally, the analysis is limited to New Zealand, and comparative studies in other countries could provide further insights into the role of housing markets in shaping labour market dynamics.

Future research could also explore the role of other factors, such as social networks, family ties, and local amenities, in influencing worker mobility decisions. Furthermore, the impact of technological advancements, such as remote work, on inter-regional mobility and housing markets warrants further investigation, particularly in the context of the COVID-19 pandemic and its long-term effects on work patterns.

More careful tests of endogeneity between house prices and worker mobility are needed. Using lagged house prices in regression models may be practically reasonable in applied gravity analyses. However, it imposes a strong assumption on the time-lag structure and does not guarantee its credibility if this assumption is violated. Some instrumental variables suggested in the literature review may offer future opportunities to validate the findings.

Analysing aggregate worker mobility is a macro-level approach which offers a 'top-down' view of the broader picture of workers' decisions on inter-regional migration and preferences for job locations. Such an approach assumes that all workers act as an 'average' person in the population and take identical actions in response to changes in house prices. The micro-level approach is a 'bottom-up' approach which highlights the complexity of the migration decision-making process among different people and households. For instance, Rabe and Taylor (2010) demonstrated that housing tenure significantly influenced migration propensity among British households. Households living in relatively cheap areas were less likely to move due to credit constraints. However, those in more expensive housing areas were more mobile as they could afford to relocate by selling their homes. Additionally, tenants in social houses exhibited limited responsiveness to house prices since many remained in rented accommodation. Similarly, Whelan and Parkinson (2017) found that homeowners with mortgages were less likely to migrate compared to renters in private and social accommodation in Australia. This thesis has not explored analyses using the micro-level approach. Future studies should bring in IDI data at both the person-level (e.g. qualification, migration status) and the household-level (e.g. household income, number of dependent child(ren) and housing tenure) and test thoroughly the relationship between individual circumstances, housing markets, and mobility behaviours.

Another limitation of this study is that it does not account for international migration. International migration is a significant component of New Zealand's workforce and population and may interact with internal mobility patterns and housing dynamics. According to the New Zealand Productivity Commission's *Immigration by the numbers* report (2022), international migrants are, on average, relatively young, well-educated, active in employment and make a positive contribution to productivity. The same report noted that migrant workers (especially recent migrants who had been in New Zealand for 5 years or less) often exhibited higher mobility rates and were disproportionately represented in high-growth or urbanised areas, such as Auckland. In seeking employment, these migrants may be more responsive to local housing market conditions due to lower housing equity or tenure security.

Consequently, the absence of this factor from the gravity model means that the influence of international migrant inflows and outflows on regional housing demand and internal migration patterns remains unexamined. For instance, high levels of international migration into Auckland could further increase house prices, potentially ‘pushing’ domestic residents to other regions – an effect not captured in the current study. Future research should therefore seek to integrate international migrant status into the framework of housing-mobility analysis. Using IDI data, it would be valuable to distinguish between different migrant categories (e.g., work visa holders, recent residents, and long-term residents) and examine how their mobility decisions respond to regional house price differentials. This approach would not only provide a more complete picture of labour market fluidity but also help policymakers design more nuanced housing and immigration policies that account for the interplay between international and internal migration.

7.3 Policy implications

The findings of this thesis have several important policy implications. First, the strong link between house prices and worker mobility suggests that addressing housing affordability is crucial for maintaining labour market fluidity and economic efficiency. Policymakers should consider measures to increase housing supply, particularly in high-demand regions, to reduce the barriers to worker mobility. This could include land use regulation reforms, housing development incentives, and better urban planning.

The “Using land for housing” Inquiry report prepared by the New Zealand Productivity Commission (2015) suggested “*the planning systems and land use regulation imposed by central, regional and local governments affect the speed and efficiency with which land is made available for residential development*”. For example, regulations such as urban limits (which restrict the outward expansion of cities), housing density limits, and building height restrictions can severely constrain development capacity. As a result, housing supply in many cities and regions has failed to keep pace with population growth, exacerbating housing affordability issues. To address these challenges, the report recommended adopting more effective development tools that evaluate different planning options and demonstrate how specific changes to planning controls could enhance development capacity. By implementing such tools, policymakers could better balance regulatory constraints with the need to increase housing supply, ultimately improving housing affordability and meeting the demands of a growing population.

Second, the study highlights the need for policies supporting workers making job transitions. This could involve targeted training programmes, subsidies for relocation, and initiatives to improve job matching in the labour market. In Australia, Commonwealth Rent Assistance (CRA) is a flexible housing subsidy that enables private renters to relocate to areas with better employment opportunities (Whelan & Parkinson, 2017). These authors advocated allowing region-specific rent subsidies to incentivise more efficient geographic mobility by capturing significant differences in housing costs and employment opportunities by regions.

Finally, the findings underscore the importance of monitoring and addressing regional disparities in economic opportunities. Policymakers should focus on promoting economic development in smaller regions to reduce the reliance on large urban centres and provide more balanced opportunities for workers across the country.

In conclusion, this thesis has demonstrated that house prices are a critical determinant of worker mobility in New Zealand, with significant implications for earnings growth and labour market efficiency. The findings highlight the need for targeted policies to address housing affordability, support worker transitions, and reduce regional and demographic disparities in economic opportunities. By addressing these challenges, policymakers can foster a more dynamic and inclusive labour market, ultimately contributing to broader economic growth and social well-being in New Zealand.

References

Allan, C., & Maré, D. C. (2021). Do workers share in firm success? Pass-through estimates for New Zealand. *Pass-Through Estimates for New Zealand (September 1, 2021)*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3954537

Aschhoff, B., & Schmidt, T. (2008). Empirical Evidence on the Success of R&D Cooperation—Happy Together? *Review of Industrial Organization*, *33*(1), 41–62. https://doi.org/10.1007/s11151-008-9179-7

Azzopardi, D., Fareed, F., Hermansen, M., Lenain, P., & Sutherland, D. (2020). *The decline in labour mobility in the United States: Insights from new administrative data*.

Ball, C., Groshenny, N., Karagedikli, Ö., Ozbilgin, M., & Robinson, F. (2020). *Low wage growth and job-to-job transitions: Evidence from administrative data in New Zealand*.

Bang, J. T., & MacDermott, R. (2019). Does FDI Attract Immigrants? An Empirical Gravity Model Approach. *International Migration Review*, *53*(1), 237–253. https://doi.org/10.1177/0197918318768554

Bansak, C., Morin, N., & Starr, M. (2007). Technology, Capital Spending, and Capacity Utilization. *Economic Inquiry*, *45*(3), 631–645. https://doi.org/10.1111/j.1465-7295.2007.00019.x

Baseler, T. (2023). Hidden income and the perceived returns to migration. *American Economic Journal: Applied Economics*, *15*(4), 321–352.

Bayoumi, M. T., & Barkema, J. (2019). *Stranded! How rising inequality suppressed US migration and hurt those left behind*. International Monetary Fund. https://books.google.com/books?hl=en&lr=&id=aKcZEAAAQBAJ&oi=fnd&pg=PP2&dq=Stranded!+How+Rising+Inequality+Suppressed+US+Migration+and

+Hurt+Those+Left+Behind&ots=tG7N85Dzsd&sig=jU8z8mbFJENBQk3zAWPfW7lVrGY

Beegle, K., De Weerdt, J., & Dercon, S. (2011). Migration and economic mobility in Tanzania: Evidence from a tracking survey. *Review of Economics and Statistics*, *93*(3), 1010–1033.

Benz, M., & Frey, B. S. (2008). Being Independent is a Great Thing: Subjective Evaluations of Self-Employment and Hierarchy. *Economica*, *75*(298), 362–383. https://doi.org/10.1111/j.1468-0335.2007.00594.x

Berlingieri, G., Calligaris, S., & Criscuolo, C. (2018). The Productivity-Wage Premium: Does Size Still Matter in a Service Economy? *AEA Papers and Proceedings*, *108*, 328–333. https://doi.org/10.1257/pandp.20181068

Biswas, T., McHardy, J., & Nolan, M. A. (2009, September). *Inter-regional Migration: The UK experience* [Monograph]. Department of Economics, University of Sheffield. http://www.shef.ac.uk/economics/research/serps/year.html

Blackburn, M. L. (2015). The Relative Performance of Poisson and Negative Binomial Regression Estimators. *Oxford Bulletin of Economics and Statistics*, *77*(4), 605–616. https://doi.org/10.1111/obes.12074

Bonifazi, C., Heins, F., Licari, F., & Tucci, E. (2021). The regional dynamics of internal migration intensities in Italy. *Population, Space and Place*, *27*(7), e2331. https://doi.org/10.1002/psp.2331

Borjas, G. J. (2013). *Labor economics* (Sixth edition). New York: McGraw-Hill.

Bosquet, C., & Boulhol, H. (2010). *Scale-dependence of the negative binomial pseudo-maximum likelihood estimator*. https://shs.hal.science/halshs-00535594/

Burger, M., van Oort, F., & Linders, G.-J. (2009). On the Specification of the Gravity Model of Trade: Zeros, Excess Zeros and Zero-inflated Estimation. *Spatial Economic Analysis*, *4*(2), 167–190. https://doi.org/10.1080/17421770902834327

Cameron, A. C., & Trivedi, P. K. (1986). Econometric models based on count data. Comparisons and applications of some estimators and tests. *Journal of Applied Econometrics*, *1*(1), 29–53.

Cameron, A. C., & Trivedi, P. K. (2010). *Microeconometrics using stata* (Vol. 2). Stata press College Station, TX. https://www.stata-press.com/books/preview/mus2-preview.pdf

Carrillo-Tudela, C., Visschers, L., & Wiczer, D. (2022). *Cyclical Earnings, Career and Employment Transitions*.

Causa, O., Abendschein, M., Luu, N., & Cavalleri, M. C. (2022). *Getting on the job ladder: The policy drivers of hiring transitions*. https://www.oecd-ilibrary.org/economics/getting-on-the-job-ladder-the-policy-drivers-of-hiring-transitions_0304c673-en

Causa, O., Luu, N., & Abendschein, M. (2021). *Labour market transitions across OECD countries: Stylised facts*.

Cavalleri, M. C., Luu, N., & Causa, O. (2021). *Migration, housing and regional disparities: A gravity model of inter-regional migration with an application to selected OECD countries*. https://www.oecd-ilibrary.org/economics/migration-housing-and-regional-disparities-a-gravity-model-of-inter-regional-migration-with-an-application-to-selected-oecd-countries_421bf4aa-en

Champion, T. (2001). Urbanisation, sub-urbanisation, des-urbanisation and re-urbanisation. *Handbook of Urban Studies*, 141–161.

Champion, T., & Shuttleworth, I. (2017). Is Longer-Distance Migration Slowing? An Analysis of the Annual Record for England and Wales since the 1970s. *Population, Space and Place*, *23*(3), e2024. https://doi.org/10.1002/psp.2024

Chi, Guanghua, Lin, F., Chi, Guangqing, & Blumenstock, J. (2020). A general approach to detecting migration events in digital trace data. *PLoS ONE*, *15*(10), e0239408. https://doi.org/10.1371/journal.pone.0239408

Cochrane, W., & Poot, J. (2021). Effects of Immigration on Local Housing Markets. In K. Kourtit, B. Newbold, P. Nijkamp, & M. Partridge (Eds), *The Economic Geography of Cross-Border Migration* (pp. 269–292). Springer International Publishing. https://doi.org/10.1007/978-3-030-48291-6_12

Coleman, A., & Zheng, G. (2019). New jobs, old jobs and the evolution of work in regional New Zealand. *New Zealand Productivity Commission, Research Note*.

Coleman, A., & Zheng, G. (2020). *Job-to-job transitions and the regional job ladder*.

Conway, P., & Meehant, L. (2013). *Productivity by the numbers: The New Zealand experience*. New Zealand Productivity Commission, Te Kōmihana Whai Hua o Aotearoa.

Coulombe, S. (2006). Internal Migration, Asymmetric Shocks, and Interprovincial Economic Adjustments in Canada. *International Regional Science Review*, *29*(2), 199–223. https://doi.org/10.1177/0160017606286357

Coulson, N. E., & Grieco, P. L. (2013). Mobility and mortgages: Evidence from the PSID. *Regional Science and Urban Economics*, *43*(1), 1–7.

Coulter, R., & Van Ham, M. (2013). Following People Through Time: An Analysis of Individual Residential Mobility Biographies. *Housing Studies*, *28*(7), 1037–1055. https://doi.org/10.1080/02673037.2013.783903

Cushing, B., & Poot, J. (2004). Crossing boundaries and borders: Regional science advances in migration modelling. *Papers in Regional Science*, *83*(1), 317–338. https://doi.org/10.1007/s10110-003-0188-5

Davies, B., & Maré, D. (2020). *Delineating functional labour market areas with estimable classification stabilities* [Working paper]. https://www.motu.nz/our-research/urban-and-regional/regions/delineating-functional-labour-market-areas-with-estimable-classification-stabilities

Deutscher, N. (2019). *Job-to-job transitions and the wages of Australian workers*. Treasury Working Paper.

Fabling, R., & Maré, D. C. (2015). *Addressing the absence of hours information in linked employer-employee data*.

Fernainy, P., Cohen, A. A., Murray, E., Losina, E., Lamontagne, F., & Sourial, N. (2024). Rethinking the pros and cons of randomized controlled trials and observational studies in the era of big data and advanced methods: A panel discussion. *BMC Proceedings*, *18*(2), 1. https://doi.org/10.1186/s12919-023-00285-8

Fleming, D., Grimes, A., Lebreton, L., Maré, D., & Nunns, P. (2018). Valuing sunshine. *Regional Science and Urban Economics*, *68*, 268–276. https://doi.org/10.1016/j.regsciurbeco.2017.11.008

Foster, T. B., Fiorio, L., & Ellis, M. (2024). *Internal Migration in the US During the COVID-19 Pandemic*. https://www.researchgate.net/profile/Thomas-Foster-4/publication/384500911_Internal_Migration_in_the_US_during_the_COVID-19_Pandemic/links/66fbf9869e6e82486ffcf470/Internal-Migration-in-the-US-during-the-COVID-19-Pandemic.pdf

Gale, R. P., Zhang, M.-J., & Lazarus, H. M. (2023). The role of randomized controlled trials, registries, observational databases in evaluating new interventions. *Best Practice & Research Clinical Haematology*, *36*(4), 101523. https://doi.org/10.1016/j.beha.2023.101523

Glaeser, E. L. (1999). Learning in cities. *Journal of Urban Economics*, *46*(2), 254–277.

Glaeser, E. L., & Maré, D. C. (2001). Cities and Skills. *Journal of Labor Economics*, *19*(2), 316–342. JSTOR. https://doi.org/10.1086/319563

Golan, A., Lane, J., & McENTARFER, E. (2007). The Dynamics of Worker Reallocation within and across Industries. *Economica*, *74*(293), 1–20. https://doi.org/10.1111/j.1468-0335.2006.00527.x

Greene, W. H. (1994). *Accounting for excess zeros and sample selection in Poisson and negative binomial regression models*.

Greenwood, M. J. (1997). Internal migration in developed countries. *Handbook of Population and Family Economics*, *1*, 647–720.

Grimes, A., Mare, D., Preston, K., & Donovan, S. (2018). *Amenities and the attractiveness of New Zealand cities*. AgEcon Search. https://ageconsearch.umn.edu/record/290497

Grimes, A., Preston, K., Maré, D. C., Badenhorst, S., & Donovan, S. (2019). The contrasting importance of quality of life and quality of business for domestic and international migrants. *Available at SSRN 3477058*.

Gyourko, J., Saiz, A., & Summers, A. (2008). A New Measure of the Local Regulatory Environment for Housing Markets: The Wharton Residential Land Use Regulatory Index. *Urban Studies*, *45*(3), 693–729. https://doi.org/10.1177/0042098007087341

Hall, M. (2023). *Measuring internal migration: Retrospective self-report*. Springer.

Haltiwanger, J., Hyatt, H., & McEntarfer, E. (2018). Who moves up the job ladder? *Journal of Labor Economics*, *36*(S1), S301–S336.

Hoffmann, E. B., & Malacrino, D. (2019). Employment time and the cyclicality of earnings growth. *Journal of Public Economics*, *169*, 160–171.

Housing affordability inquiry. (2012). https://www.treasury.govt.nz/sites/default/files/2024-05/pc-inq-ha-final-report-v5.pdf

Hyatt, H. R., & McEntarfer, E. (2012). Job-to-job Flows and the Business Cycle. *US Census Bureau Center for Economic Studies Paper No. CES-WP-12-04*.

Hyatt, H. R., & Spletzer, J. R. (2013). The recent decline in employment dynamics. *IZA Journal of Labor Economics*, *2*(1), 5. https://doi.org/10.1186/2193-8997-2-5

Hyslop, D., & Maré, D. C. (2009). Job mobility, and wage dynamics. *Statistics New Zealand LEED Research Paper*.

Imbens, G. W., & Rubin, D. B. (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge university press. https://books.google.com/books?hl=en&lr=&id=Bf1tBwAAQBAJ&oi=fnd&pg=PR17&dq=Imbens,+G.+W.,+%26+Rubin,+D.+B.+(2015).+Causal+Inference+for+Statistics,+Social,+and+Biomedical+Sciences:+An+Introduction&ots=jfYJ5fYWBE&sig=Zu-sfWKkG2M7_G8H9T2tavPVZZo

Joshi, H. (2016). Why do we need longitudinal survey data? *IZA World of Labor*. https://doi.org/10.15185/izawol.308

Karagedikli, Ö. (2018). *Job-to-job flows and inflation: Evidence from administrative data in New Zealand*. https://www.rbnz.govt.nz/-/media/project/sites/rbnz/files/publications/analytical-notes/2018/an2018-09.pdf

Kennedy, P. (2008). *A guide to econometrics*. John Wiley & Sons. https://books.google.com/books?hl=en&lr=&id=69MDEAAAQBAJ&oi=fnd&pg=PR10&dq=a+guide+to+econometrics+&ots=VRL_FGSZpa&sig=cv2OdqLyHnW1mVKO_gdtxeEI_k4

Kirchberger, M. (2021). Measuring internal migration. *Regional Science and Urban Economics*, *91*, 103714.

Kristman, V. L., Manno, M., & Côté, P. (2005). Methods to Account for Attrition in Longitudinal Data: Do They Work? A Simulation Study. *European Journal of Epidemiology*, *20*(8), 657–662.

Krugman, P. (1991). Increasing Returns and Economic Geography. *Journal of Political Economy*, *99*(3), 483–499. https://doi.org/10.1086/261763

Lehmer, F., & Ludsteck, J. (2011). The returns to job mobility and inter-regional migration: Evidence from Germany. *Papers in Regional Science*, *90*(3), 549–571. https://doi.org/10.1111/j.1435-5957.2010.00326.x

Leung, D., Meh, C., & Terajima, Y. (2008). *Firm size and productivity*. Bank of Canada. https://www.bankofcanada.ca/2008/11/working-paper-2008-45/?theme_mode=light

Lewis, G., & Stillman, S. (2007). Regional economic performance in New Zealand: How does Auckland compare? *New Zealand Economic Papers*, *41*(1), 29–68. https://doi.org/10.1080/00779950709558498

Linnemann, H. (1966). *An econometric study of international trade flows*. Amsterdam, North-Holland.

Liu, L. Q. (2018). *Regional labor mobility in Spain*. International Monetary Fund.

Maré, D. (2017). *Urban Productivity Estimation with Heterogeneous Prices and Labour*. Motu working papers. https://www.motu.nz/our-research/productivity-and-innovation/firm-productivity-and-performance/urban-productivity-estimation-with-heterogeneous-prices-and-labour/

Maré, D. C. (2016). *Urban productivity estimation with heterogeneous prices and labour*.

Maré, D. C., Morten, M., & Stillman, S. (2007). Settlement patterns and the geographic mobility of recent migrants to New Zealand*. *New Zealand Economic Papers*, *41*(2), 163–195. https://doi.org/10.1080/00779950709558508

Mayda, A. M. (2005). *International migration: A panel data analysis of economic and non-economic determinants*. IZA Discussion Papers. https://www.econstor.eu/handle/10419/33295

McKenzie, D., Gibson, J., & Stillman, S. (2013). A land of milk and honey with streets paved with gold: Do emigrants have over-optimistic expectations about incomes abroad? *Journal of Development Economics*, *102*, 116–127.

McLeod, K. (2018). *Where we come from, where we go—Describing population change in New Zealand*. New Zealand Treasury.

Meehan, L. (2020). Productivity in New Zealand: The role of resource allocation among firms. *New Zealand Economic Papers*, *54*(1), 39–66. https://doi.org/10.1080/00779954.2019.1573846

Melitz, M. J., & Polanec, S. (2015). Dynamic Olley-Pakes productivity decomposition with entry and exit. *The RAND Journal of Economics*, *46*(2), 362–375. https://doi.org/10.1111/1756-2171.12088

Mnasri, A., & Nechi, S. (2019, April 6). *New Approach to Estimating Gravity Models with Heteroscedasticity and Zero Trade Values* [MPRA Paper]. https://mpra.ub.uni-muenchen.de/93426/

Molloy, R., Trezzi, R., Smith, C. L., & Wozniak, A. (2016). Understanding declining fluidity in the US labor market. *Brookings Papers on Economic Activity*, *2016*(1), 183–259.

New Zealand Productivity Commission. (2015). *Using land for housing*. https://www.treasury.govt.nz/publications/using-land-housing-productivity-commission-inquiry-material-2014-2015

New Zealand Productivity Commission. (2022). *Immigration by the numbers*. https://www.treasury.govt.nz/sites/default/files/2024-05/pc-inq-is-immigration-by-the-numbers.pdf#:~:text=The%20number,labour%20market.

OECD. (2020). *OECD Regions and Cities at a Glance 2020*. OECD. https://doi.org/10.1787/959d5ba0-en

Osborne, A. J., Broadbent, J. M., Morton, S. M. B., Boden, J. M., & Poulton, R. (2023). What have we learned from longitudinal studies in Aotearoa New Zealand? *Journal of the Royal Society of New Zealand*, *53*(4), 425–428. https://doi.org/10.1080/03036758.2023.2208778

Pardede, E. L., McCann, P., & Venhorst, V. A. (2020). Internal migration in Indonesia: New insights from longitudinal data. *Asian Population Studies*, *16*(3), 287–309. https://doi.org/10.1080/17441730.2020.1774139

Petrin, A., & Sivadasan, J. (2011). *Estimating Lost Output from Allocative Inefficiency, with an Application to Chile and Firing Costs* (No. W17373). National Bureau of Economic Research. https://doi.org/10.3386/w17373

Poghosyan, T. (2018). *Regional Labor Mobility in Finland*. IMF. https://www.elibrary.imf.org/view/journals/001/2018/252/001.2018.issue-252-en.xml

Poot, J., Alimi, O., Cameron, M. P., & Maré, D. C. (2016a). *The Gravity Model of Migration: The Successful Comeback of an Ageing Superstar in Regional Science* (SSRN Scholarly Paper No. 2864830). https://doi.org/10.2139/ssrn.2864830

Poot, J., Alimi, O., Cameron, M. P., & Maré, D. C. (2016b). *The gravity model of migration: The successful comeback of an ageing superstar in regional science*. (36), 63–86.

Posti, L., & Maiti, A. (2023). Firm Size and Productivity in the Informal Sector: Evidence from India. *The Indian Economic Journal*, 00194662231202088. https://doi.org/10.1177/00194662231202088

Potepan, M. J. (1994). Intermetropolitan Migration and Housing Prices: Simultaneously Determined? *Journal of Housing Economics*, *3*(2), 77–91. https://doi.org/10.1006/jhec.1994.1001

Rabe, B., & Taylor, M. P. (2010). *Differences in opportunities? Wage, unemployment and house-price effects on migration*. https://doi.org/10.1111/j.1468-0084.2011.00682.x

Ramos, R. (2016). Gravity models: A tool for migration analysis. *IZA World of Labor*. https://doi.org/10.15185/izawol.239

Ramos, R., & Suriñach, J. (2017). A gravity model of migration between the ENC and the EU. *Tijdschrift Voor Economische En Sociale Geografie*, *108*(1), 21–35.

Rampazzo, F., Bijak, J., Vitali, A., Weber, I., & Zagheni, E. (2024). Assessing Timely Migration Trends Through Digital Traces: A Case Study of the UK Before

Brexit. *International Migration Review*, 01979183241247009. https://doi.org/10.1177/01979183241247009

Ravenstein, E. G. (1885). The laws of migration. *Journal of the Royal Statistical Society*, *48*, 167–235.

Ravenstein, E. G. (1889). The laws of migration. *Journal of the Royal Statistical Society*, *52*, 241–305.

Reed, W. R. (2015). On the Practice of Lagging Variables to Avoid Simultaneity. *Oxford Bulletin of Economics and Statistics*, *77*(6), 897–905. https://doi.org/10.1111/obes.12088

Silva, J. M. C., & Tenreyro, S. (2022). The log of gravity at 15. *Portuguese Economic Journal*, 1–15.

Silva, J. S., & Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, *88*(4), 641–658.

Silva, & Tenreyro. (2011). Further simulation evidence on the performance of the Poisson pseudo-maximum likelihood estimator. *Economics Letters*, *112*(2), 220–222. https://doi.org/10.1016/j.econlet.2011.05.008

Sjaastad, L. A. (1962). The Costs and Returns of Human Migration. *Journal of Political Economy*, *70*(5, Part 2), 80–93. https://doi.org/10.1086/258726

Smith, J. P., & Thomas, D. (2003). Remembrances of things past: Test–retest reliability of retrospective migration histories. *Journal of the Royal Statistical Society Series A: Statistics in Society*, *166*(1), 23–49.

Stawarz, N., Sander, N., & Sulak, H. (2021). Internal migration and housing costs—A panel analysis for Germany. *Population, Space and Place*, *27*(4), e2412. https://doi.org/10.1002/psp.2412

Stillwell, J. (2009). Inter-regional migration modelling: A review. *Migration and Human Capital*, 29–48.

Sukanuntathum, A. (2012). Robust Estimation of Gravity Models under Heteroskedasticity and Data Censoring. *Procedia - Social and Behavioral*

Sciences, ASIA PACIFIC BUSINESS INNOVATION AND TECHNOLOGY MANAGEMENT SOCIETY, *40*, 731–735. https://doi.org/10.1016/j.sbspro.2012.03.257

United Nations. (1970). *Methods of Measuring Internal Migration*.

Whelan, S., & Parkinson, S. (2017). *Housing tenure, mobility and labour market behaviour*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2979102

Yagan, D. (2014). Moving to opportunity? Migratory insurance over the Great Recession. *Job Market Paper*. https://eml.berkeley.edu/~yagan/MigratoryInsurance.pdf

Yang, Z., Hardin, J. W., & Addy, C. L. (2009). A score test for overdispersion in Poisson regression based on the generalized Poisson-2 model. *Journal of Statistical Planning and Inference*, *139*(4), 1514–1521. https://doi.org/10.1016/j.jspi.2008.08.018

Zheng, G., Duy, H. M., & Pacheco, G. (2021). Benchmarking the productivity performance of New Zealand's frontier firms. *International Productivity Monitor*, *40*, 27–55.

Zheng, G., & Sing, M. (2023). Sectoral reallocation and income growth in the labour market during the COVID-19 pandemic. A review of the New Zealand labour market during COVID-19. *Reserve Bank of New Zealand Analytical Notes Series*, (AN2023/01). https://ideas.repec.org/p/nzb/nzbans/2023-01.html

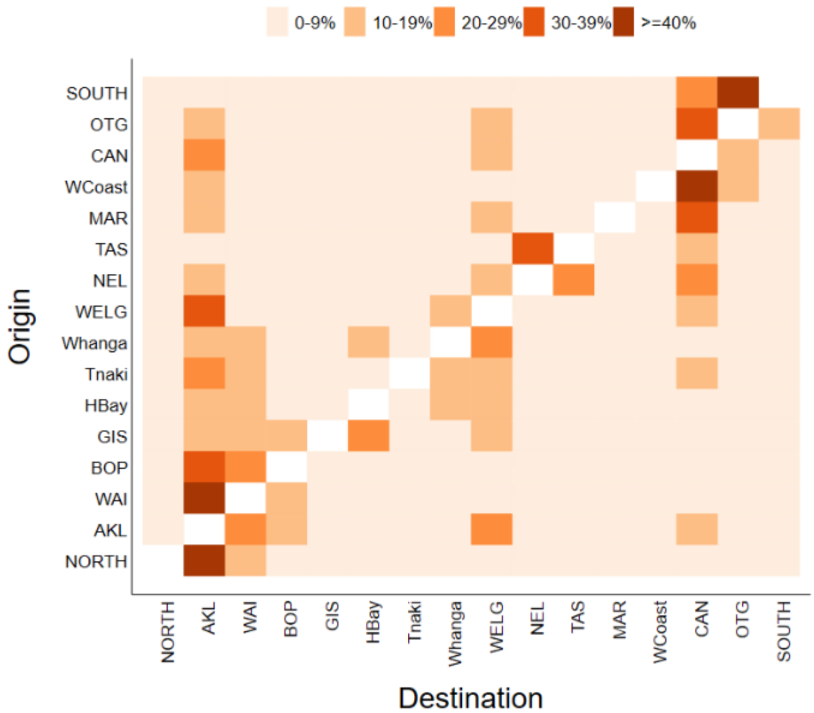
Appendices

1. Additional charts on region-to-region movements arising from inter-regional job-to-job transitions

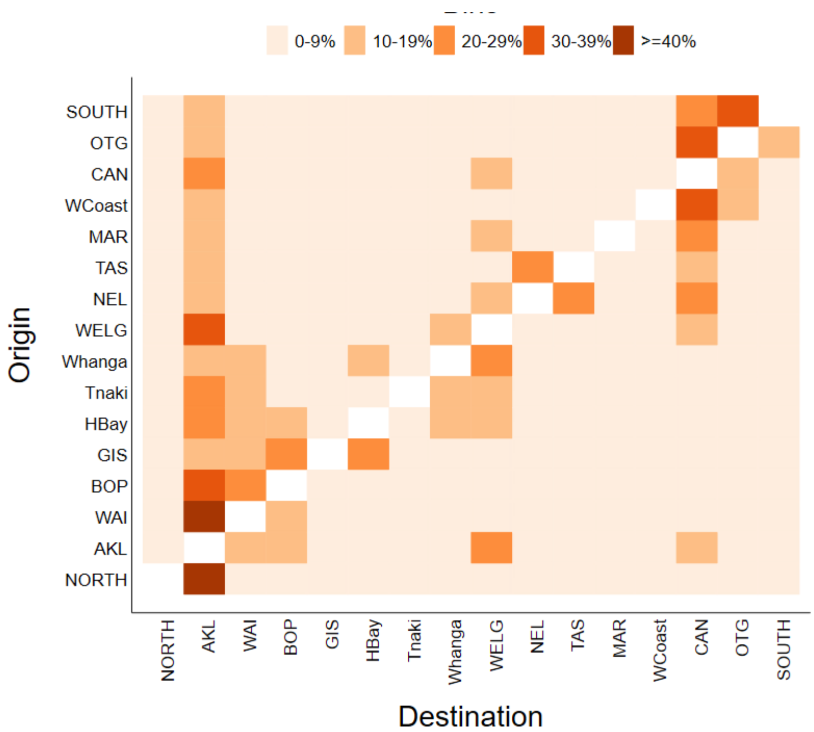
Appendix Figure 1 follows a similar setup to Figure 6 and presents different region-to-region movements by age group (15-24, 25-39, 40-54 and 55-64), gender (male and female) and ethnic group (European, Māori, Pacific, and Asian and Others).

Appendix Figure 1: Region-to-region movements arising from inter-regional job-to-job transitions by demographic groups

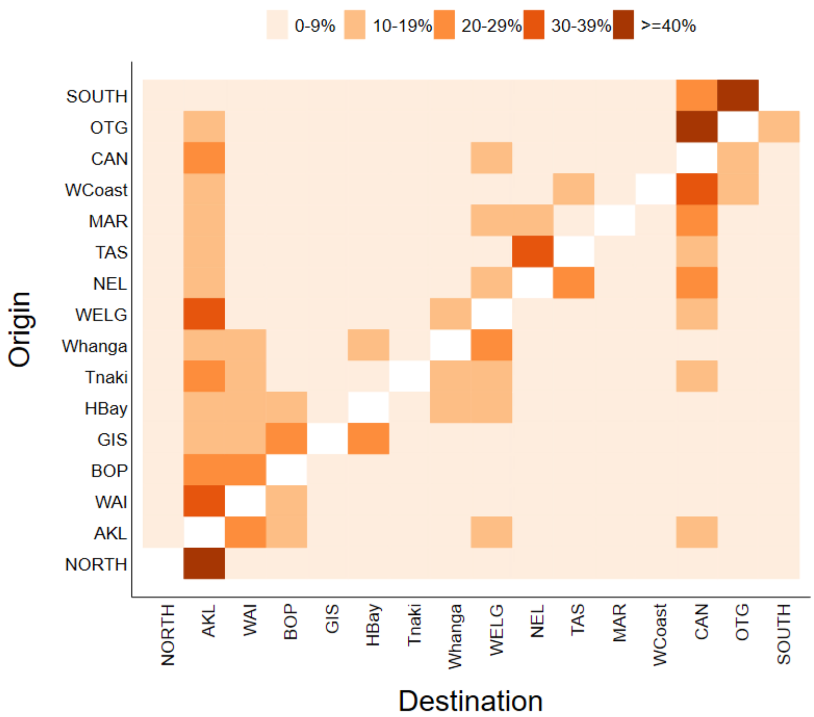
15-24 age group



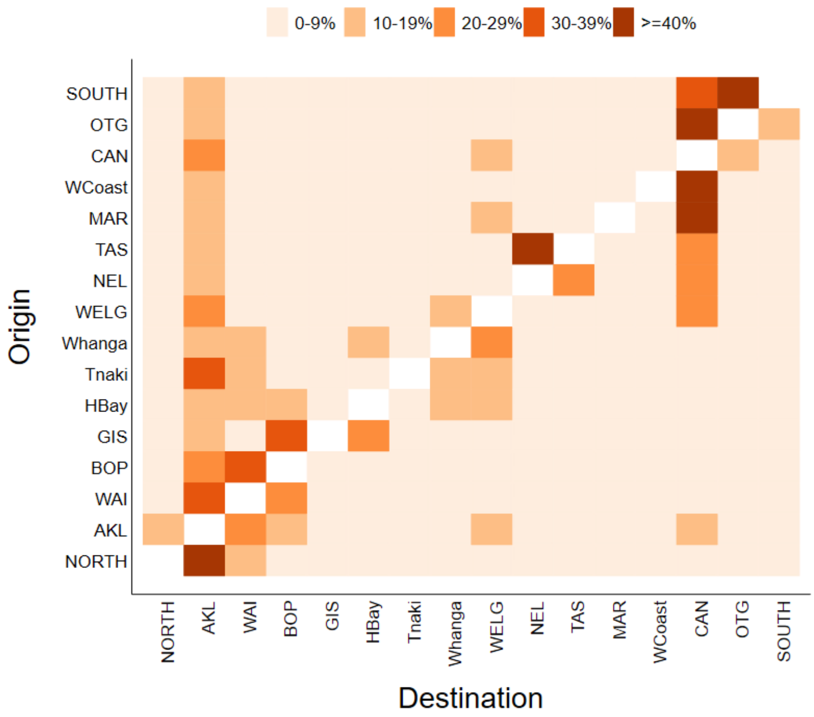
25-39 age group



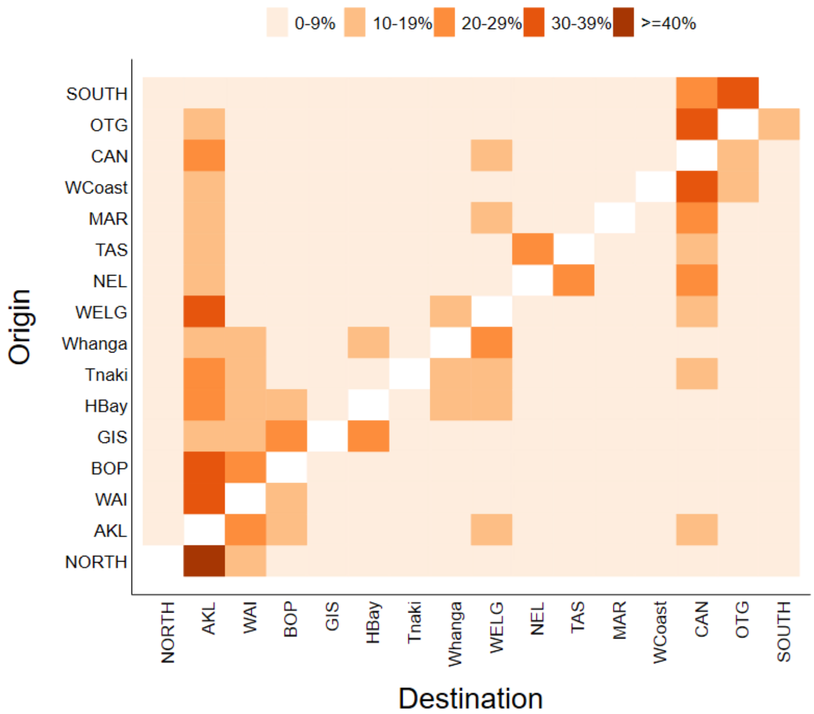
40-54 age group



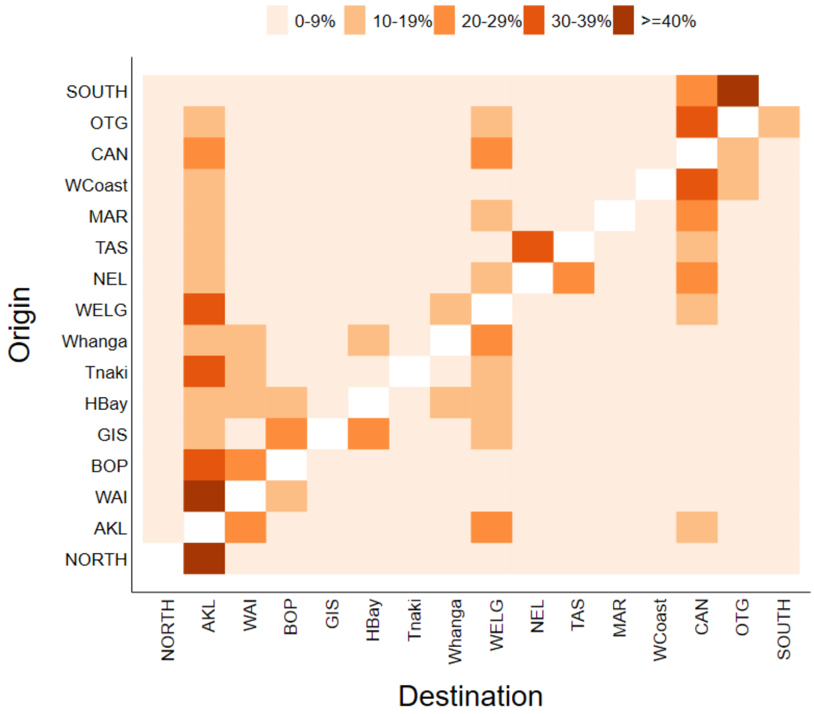
55-64 age group



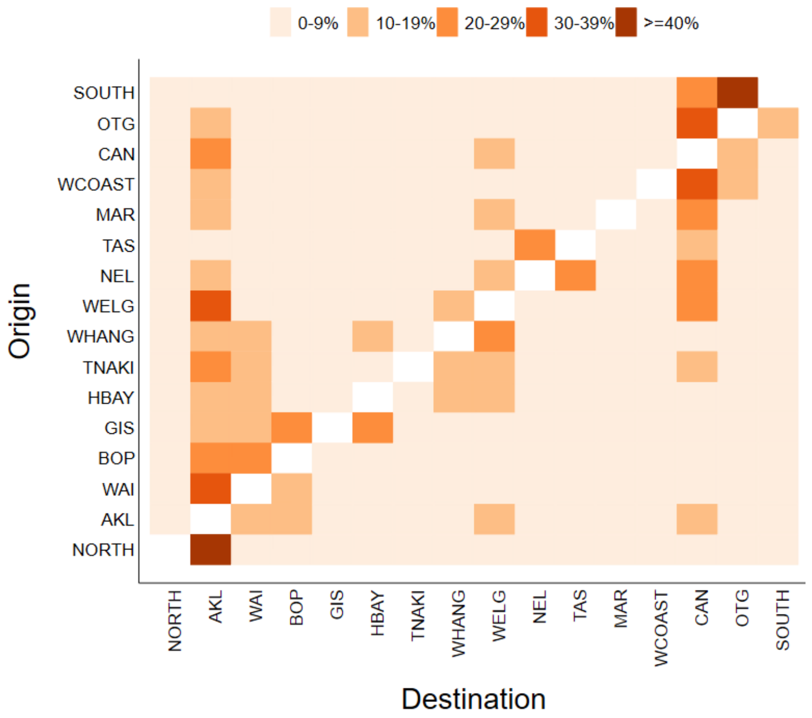
Male



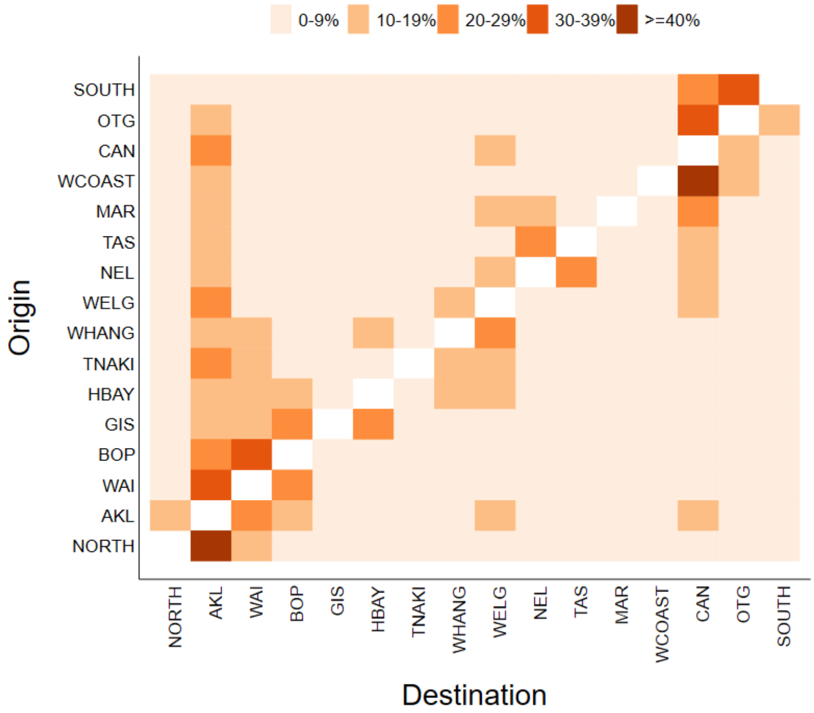
Female



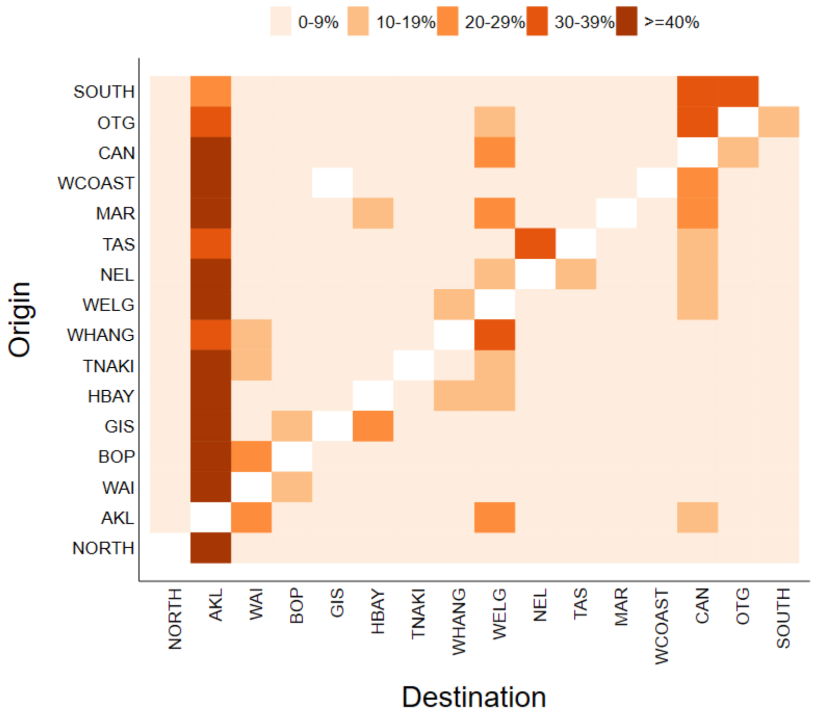
European



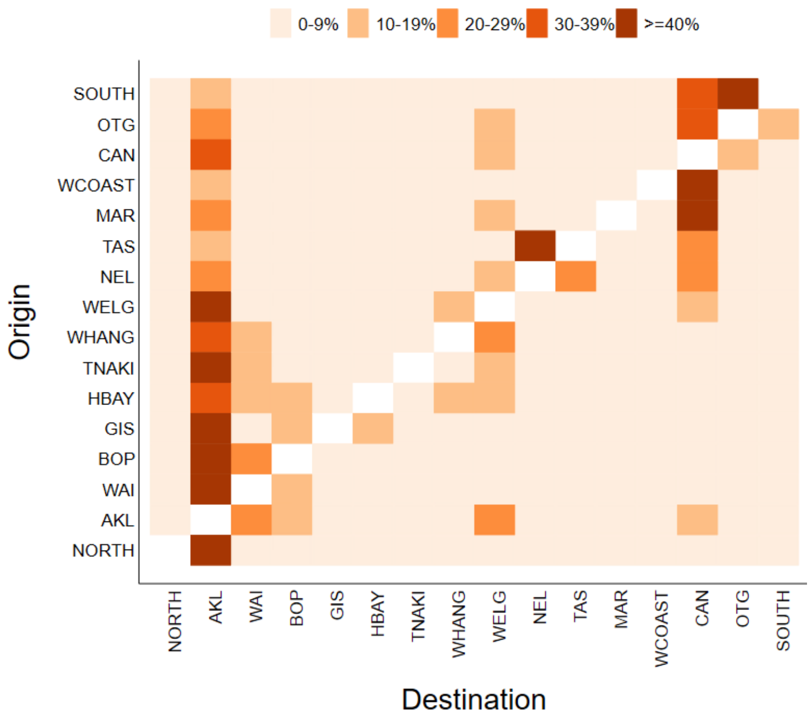
Māori



Pacific



Asians and others



Note: NORTH=Northland, AKL=Auckland, WAI= Waikato, BOP= Bay of Plenty, GIS=Gisborne, HBAY=Hawke's Bay, TNAKI=Taranaki, WHANG=Manawatu-Whanganui, WELG=Wellington, NEL=Nelson, TAS=Tasman, MAR=Marlborough, WCOAST=West Coast, CAN=Canterbury, OTG=Otago and SOUTH=Southland.

2. Additional gravity regression results

Appendix Table 1: Baseline gravity models by age groups

	15-24		25-39		40-54		55-64	
VARIABLES	Poisson	Negative Binomial	Poisson	Negative Binomial	Poisson	Negative Binomial	Poisson	Negative Binomial
Log population at destination location	0.806***	0.832***	1.022***	1.344***	0.273	0.402	0.800***	1.042***
	(0.202)	(0.256)	(0.178)	(0.248)	(0.256)	(0.311)	(0.282)	(0.345)
Log population at origin location	1.175***	1.165***	1.443***	1.567***	0.859***	0.955***	0.945***	1.379***
	(0.179)	(0.244)	(0.158)	(0.244)	(0.239)	(0.307)	(0.287)	(0.334)
Log travel time	-0.563***	-0.544***	-0.403***	-0.332***	-0.404***	-0.343***	-0.0539	0.00173
	(0.0743)	(0.0772)	(0.0599)	(0.0752)	(0.0771)	(0.0964)	(0.0945)	(0.112)
Dummy for same island	1.690***	1.767***	2.158***	2.940***	0.793	1.149	2.199***	2.819***
	(0.486)	(0.620)	(0.429)	(0.603)	(0.607)	(0.757)	(0.678)	(0.841)
Log median house price at destination location	0.00532	-0.00981	-0.0752*	-0.105*	0.0229	-0.102	0.0669	-0.0277
	(0.0658)	(0.0618)	(0.0443)	(0.0617)	(0.0581)	(0.0781)	(0.0772)	(0.0915)
Log median house price at origin location	0.141**	0.159**	0.151***	0.146**	0.191***	0.236***	0.289***	0.281***
	(0.0644)	(0.0632)	(0.0523)	(0.0643)	(0.0644)	(0.0802)	(0.0820)	(0.0952)
Log GDP per capita at destination location	-0.0340	0.0106	0.246**	0.253*	0.121	0.234	0.538***	0.591***
	(0.145)	(0.139)	(0.115)	(0.137)	(0.152)	(0.166)	(0.193)	(0.208)
Log GDP per capita at origin location	-0.126	-0.0604	0.277**	0.295*	0.153	0.249	0.495***	0.529***
	(0.128)	(0.153)	(0.123)	(0.153)	(0.129)	(0.159)	(0.169)	(0.199)
Unemployment rate at destination location	-0.0270***	-0.0259***	-0.00841	-0.0130**	-0.0101	-0.0209***	-0.0162*	-0.0298***
	(0.00686)	(0.00623)	(0.00521)	(0.00605)	(0.00789)	(0.00740)	(0.00903)	(0.0102)

Unemployment rate at origin location	-0.0268***	-0.0262***	-0.00239	-0.00164	-0.0161**	-0.0173**	-0.0203***	-0.0167*
	(0.00693)	(0.00641)	(0.00546)	(0.00660)	(0.00796)	(0.00741)	(0.00761)	(0.00958)
Share of the 40-64 workforce at destination location	-0.00862	-0.0166*	-0.0187**	-0.0245***	0.00312	-0.00779	0.0207*	0.0117
	(0.00879)	(0.00948)	(0.00746)	(0.00846)	(0.00910)	(0.0105)	(0.0116)	(0.0128)
Share of the 40-64 workforce at origin location	-0.0273***	-0.0254***	-0.0373***	-0.0359***	-0.0157*	-0.00582	-0.00563	0.00329
	(0.00883)	(0.00946)	(0.00729)	(0.00826)	(0.00864)	(0.0101)	(0.0109)	(0.0124)
Annual percentage changes in GDP	0.0377***	0.0297***	0.0290***	0.0173***	0.0350***	0.0296***	0.0315***	0.0243***
	(0.00325)	(0.00327)	(0.00231)	(0.00354)	(0.00268)	(0.00393)	(0.00358)	(0.00508)
Expected percentage changes in GDP, next year	0.0652***	0.0657***	0.0575***	0.0593***	0.0145*	0.0238**	0.00822	0.0200
	(0.00561)	(0.00686)	(0.00531)	(0.00750)	(0.00827)	(0.0106)	(0.0106)	(0.0128)
Constant	-12.15***	-13.53***	-24.71***	-30.52***	-10.19***	-14.68***	-33.90***	-41.78***
	(2.429)	(2.856)	(1.980)	(2.829)	(2.345)	(3.364)	(2.950)	(3.838)
Observations	4800	4800	4800	4800	4800	4800	4800	4800
# fixed effects	240	240	240	240	240	240	240	240
Over-dispersion parameter		0.0656***		0.0729***		0.154***		0.724***
Squared correlation	0.982	0.980	0.988	0.984	0.978	0.976	0.958	0.953

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix Table 2: Extended gravity models by age groups

	15-24		25-39		40-54		55-64	
VARIABLES	Poisson	Negative Binomial	Poisson	Negative Binomial	Poisson	Negative Binomial	Poisson	Negative Binomial
Log population at destination location	0.789***	0.809***	1.013***	1.330***	0.0925	0.290	0.763**	0.980**
	(0.212)	(0.292)	(0.208)	(0.281)	(0.263)	(0.348)	(0.298)	(0.385)
Log population at origin location	0.915***	1.068***	1.351***	1.603***	0.654***	0.976***	0.897***	1.480***
	(0.185)	(0.282)	(0.197)	(0.280)	(0.236)	(0.348)	(0.302)	(0.370)
Log travel time	0.642	0.355	0.0270	-0.304	2.569***	1.368	0.767	0.367
	(0.870)	(1.205)	(0.817)	(1.112)	(0.831)	(1.243)	(1.060)	(1.434)
Dummy for same island	3.061***	2.763**	2.641***	2.943***	3.874***	2.902**	3.076**	3.110**
	(0.884)	(1.213)	(0.880)	(1.132)	(0.816)	(1.254)	(1.198)	(1.475)
Log median house price x other destination	-0.00433	-0.0171	-0.0791*	-0.106*	-0.0306	-0.118	0.0513	-0.0331
	(0.0622)	(0.0630)	(0.0461)	(0.0631)	(0.0569)	(0.0796)	(0.0766)	(0.0924)
Log median house price x large destination	0.0615	0.0325	-0.0556	-0.104	0.134**	-0.0228	0.0966	-0.0124
	(0.0683)	(0.0808)	(0.0541)	(0.0787)	(0.0642)	(0.0953)	(0.0897)	(0.113)
Log median house price x other origin	0.0752	0.144**	0.126**	0.151**	0.131**	0.234***	0.271***	0.296***
	(0.0624)	(0.0641)	(0.0554)	(0.0659)	(0.0627)	(0.0814)	(0.0877)	(0.0966)
Log median house price x large origin	0.244***	0.235***	0.185***	0.125	0.304***	0.250**	0.321***	0.227*
	(0.0694)	(0.0845)	(0.0594)	(0.0823)	(0.0714)	(0.103)	(0.0890)	(0.117)
Log GDP per capita at destination location	0.00150	0.0222	0.259**	0.253*	0.176	0.257	0.551***	0.596***
	(0.143)	(0.144)	(0.115)	(0.140)	(0.150)	(0.169)	(0.193)	(0.209)
Log GDP per capita at origin location	-0.0757	-0.0397	0.298**	0.289*	0.213	0.252	0.511***	0.512**

	(0.139)	(0.157)	(0.125)	(0.155)	(0.131)	(0.162)	(0.173)	(0.202)
Unemployment rate at destination location	-0.0258***	-0.0256***	-0.00801	-0.0131**	-0.00991	-0.0210***	-0.0161*	-0.0302***
	(0.00631)	(0.00622)	(0.00517)	(0.00611)	(0.00697)	(0.00744)	(0.00899)	(0.0103)
Unemployment rate at origin location	-0.0277***	-0.0261***	-0.00273	-0.00159	-0.0159**	-0.0170**	-0.0202***	-0.0167*
	(0.00659)	(0.00640)	(0.00548)	(0.00662)	(0.00708)	(0.00741)	(0.00753)	(0.00957)
Share of the 40-64 workforce at destination location	-0.00848	-0.0169*	-0.0187**	-0.0242***	0.00369	-0.00698	0.0207*	0.0125
	(0.00886)	(0.00957)	(0.00743)	(0.00849)	(0.00901)	(0.0105)	(0.0116)	(0.0127)
Share of the 40-64 workforce at origin location	-0.0265***	-0.0249***	-0.0369***	-0.0361***	-0.0146*	-0.00639	-0.00533	0.00247
	(0.00873)	(0.00953)	(0.00723)	(0.00830)	(0.00847)	(0.0101)	(0.0109)	(0.0124)
Annual percentage changes in GDP	0.0354***	0.0288***	0.0281***	0.0175***	0.0315***	0.0290***	0.0304***	0.0246***
	(0.00317)	(0.00334)	(0.00250)	(0.00354)	(0.00278)	(0.00399)	(0.00352)	(0.00513)
Expected percentage changes in GDP, next year	0.0693***	0.0675***	0.0590***	0.0590***	0.0201**	0.0251**	0.00936	0.0194
	(0.00540)	(0.00702)	(0.00537)	(0.00759)	(0.00813)	(0.0107)	(0.0106)	(0.0129)
Constant	-22.34**	-22.03*	-28.32***	-30.99***	-37.79***	-32.02***	-41.68***	-45.96***
	(9.037)	(11.93)	(8.015)	(10.71)	(7.972)	(11.55)	(10.20)	(13.51)
Observations	4800	4800	4800	4800	4800	4800	4800	4800
# fixed effects	240	240	240	240	240	240	240	240
Over-dispersion parameter		0.0654***		0.0729***		0.154***		0.710***
Squared correlation	0.992	0.991	0.994	0.992	0.989	0.988	0.979	0.976

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix Table 3: Baseline gravity models by gender

	Male		Female	
VARIABLES	Poisson	Negative Binomial	Poisson	Negative Binomial
Log population at destination location	0.749***	0.772***	0.714***	1.187***
	(0.201)	(0.236)	(0.196)	(0.349)
Log population at origin location	1.126***	1.156***	1.231***	1.505***
	(0.192)	(0.230)	(0.174)	(0.349)
Log travel time	0.0341	0.0672	-0.928***	-0.786***
	(0.0625)	(0.0683)	(0.0738)	(0.109)
Dummy for same island	2.029***	2.115***	1.268***	2.494***
	(0.475)	(0.566)	(0.476)	(0.858)
Log median house price at destination location	-0.0364	-0.0881	-0.000381	-0.120
	(0.0496)	(0.0582)	(0.0596)	(0.0824)
Log median house price at origin location	0.146***	0.163***	0.195***	0.210**
	(0.0552)	(0.0601)	(0.0633)	(0.0825)
Log GDP per capita at destination location	0.0833	0.156	0.265*	0.398**
	(0.129)	(0.129)	(0.145)	(0.176)
Log GDP per capita at origin location	0.249**	0.296**	0.0508	0.194
	(0.115)	(0.136)	(0.151)	(0.197)

Unemployment rate at destination location	-0.00936	-0.0162***	-0.0200***	-0.0246***
	(0.00610)	(0.00595)	(0.00589)	(0.00661)
Unemployment rate at origin location	-0.0123*	-0.00978	-0.0154***	-0.0178**
	(0.00699)	(0.00629)	(0.00592)	(0.00696)
Share of the 40-64 workforce at destination location	-0.00607	-0.0155*	-0.00915	-0.0188
	(0.00744)	(0.00827)	(0.00932)	(0.0114)
Share of the 40-64 workforce at origin location	-0.0220***	-0.0153*	-0.0318***	-0.0292**
	(0.00735)	(0.00806)	(0.00892)	(0.0114)
Annual percentage changes in GDP	0.0315***	0.0219***	0.0347***	0.0231***
	(0.00244)	(0.00304)	(0.00271)	(0.00436)
Expected percentage changes in GDP, next year	0.0550***	0.0560***	0.0344***	0.0448***
	(0.00573)	(0.00730)	(0.00699)	(0.0103)
Constant	-21.77***	-23.43***	-12.63***	-24.44***
	(1.995)	(2.649)	(2.399)	(3.806)
Observations	4800	4800	4800	4800
# fixed effects	240	240	240	240
Over-dispersion parameter		0.0560***		0.115***
Squared correlation	0.992	0.991	0.992	0.988

*** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 4: Extended gravity models by gender

	Male		Female	
VARIABLES	Poisson	Negative Binomial	Poisson	Negative Binomial
Log population at destination location	0.620***	0.684***	0.770***	1.246***
	(0.216)	(0.264)	(0.225)	(0.392)
Log population at origin location	0.876***	1.080***	1.151***	1.613***
	(0.190)	(0.260)	(0.214)	(0.399)
Log travel time	2.544***	1.953*	-1.271	-2.386*
	(0.774)	(1.064)	(0.875)	(1.411)
Dummy for same island	4.678***	4.122***	0.988	0.760
	(0.757)	(1.075)	(0.918)	(1.418)
Log median house price x other destination	-0.0755*	-0.104*	0.0126	-0.108
	(0.0458)	(0.0591)	(0.0619)	(0.0843)
Log median house price x large destination	0.0633	0.000713	-0.00704	-0.196*
	(0.0518)	(0.0746)	(0.0664)	(0.101)
Log median house price x other origin	0.0764	0.149**	0.175***	0.226***
	(0.0504)	(0.0606)	(0.0669)	(0.0839)
Log median house price x large origin	0.265***	0.243***	0.215***	0.108
	(0.0572)	(0.0820)	(0.0698)	(0.104)
Log GDP per capita at destination location	0.137	0.181	0.262*	0.376**
	(0.124)	(0.132)	(0.147)	(0.178)
Log GDP per capita at origin location	0.312***	0.319**	0.0624	0.167
	(0.118)	(0.140)	(0.155)	(0.198)

Unemployment rate at destination location	-0.00870	-0.0159***	-0.0195***	-0.0250***
	(0.00540)	(0.00596)	(0.00592)	(0.00675)
Unemployment rate at origin location	-0.0126**	-0.00951	-0.0160***	-0.0181***
	(0.00619)	(0.00628)	(0.00602)	(0.00698)
Share of the 40-64 workforce at destination location	-0.00560	-0.0152*	-0.00953	-0.0186
	(0.00723)	(0.00831)	(0.00933)	(0.0114)
Share of the 40-64 workforce at origin location	-0.0209***	-0.0152*	-0.0313***	-0.0296***
	(0.00703)	(0.00808)	(0.00890)	(0.0114)
Annual percentage changes in GDP	0.0280***	0.0207***	0.0345***	0.0242***
	(0.00241)	(0.00304)	(0.00284)	(0.00440)
Expected percentage changes in GDP, next year	0.0606***	0.0584***	0.0348***	0.0423***
	(0.00558)	(0.00738)	(0.00684)	(0.0103)
Constant	-44.62***	-42.05***	-8.846	-8.829
	(7.630)	(10.23)	(8.742)	(13.29)
Observations	4800	4800	4800	4800
# fixed effects	240	240	240	240
Over-dispersion parameter		0.0557***		0.115***
Squared correlation	0.993	0.992	0.992	0.989

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix Table 5: Baseline gravity models by ethnic groups

	European		Māori		Pacific		Asian and others	
VARIABLES	Poisson	Negative Binomial	Poisson	Negative Binomial	Poisson	Negative Binomial	Poisson	Negative Binomial
Log population at destination location	0.381**	0.653**	0.477**	0.792***	0.763**	1.392***	1.775***	1.889***
	(0.175)	(0.285)	(0.190)	(0.263)	(0.339)	(0.352)	(0.395)	(0.363)
Log population at origin location	0.731***	0.949***	0.775***	1.048***	0.714**	1.312***	3.249***	3.413***
	(0.156)	(0.289)	(0.203)	(0.247)	(0.295)	(0.330)	(0.457)	(0.391)
Log travel time	-0.514***	-0.405***	0.00267	0.00721	-0.260**	-0.201	-0.122	-0.136
	(0.0656)	(0.0887)	(0.0748)	(0.0845)	(0.126)	(0.124)	(0.148)	(0.120)
Dummy for same island	0.898**	1.623**	1.165**	1.852***	1.048	2.458***	3.308***	3.492***
	(0.421)	(0.697)	(0.469)	(0.643)	(0.842)	(0.873)	(0.976)	(0.875)
Log median house price at destination location	-0.0553	-0.163**	0.0569	-0.00705	0.0770	0.0833	-0.0758	0.266**
	(0.0492)	(0.0721)	(0.0559)	(0.0692)	(0.101)	(0.118)	(0.0950)	(0.104)
Log median house price at origin location	0.170***	0.204***	0.0773	0.131*	0.00917	0.128	0.0479	0.0929
	(0.0537)	(0.0731)	(0.0568)	(0.0671)	(0.113)	(0.126)	(0.0932)	(0.106)
Log GDP per capita at destination location	0.168	0.319**	0.316**	0.221	0.569**	0.390*	1.366***	1.065***
	(0.131)	(0.151)	(0.145)	(0.154)	(0.224)	(0.226)	(0.292)	(0.240)
Log GDP per capita at origin location	0.107	0.253	0.368**	0.228	1.283***	0.999***	1.406***	1.340***
	(0.119)	(0.158)	(0.154)	(0.170)	(0.316)	(0.337)	(0.259)	(0.214)
Unemployment rate at destination location	-0.0108**	-0.0186***	-0.0293***	-0.0309***	-0.0336***	-0.0302**	-0.0333**	-0.0170
	(0.00538)	(0.00586)	(0.00527)	(0.00626)	(0.0117)	(0.0127)	(0.0133)	(0.0112)
Unemployment rate at origin location	-0.0167***	-0.0140**	-0.0254***	-0.0259***	-0.00274	-0.00731	0.00142	0.00970
	(0.00529)	(0.00587)	(0.00634)	(0.00643)	(0.0142)	(0.0146)	(0.0115)	(0.0117)

Share of the 40-64 workforce at destination location	-0.00790	-0.0180*	-0.00535	-0.0103	-0.00263	-0.0124	0.0387***	0.0274**
	(0.00778)	(0.00959)	(0.00800)	(0.00921)	(0.0105)	(0.0117)	(0.0144)	(0.0120)
Share of the 40-64 workforce at origin location	-0.0217***	-0.0184*	-0.0307***	-0.0263***	-0.0197*	-0.0172	0.00111	0.00667
	(0.00750)	(0.00942)	(0.00790)	(0.00914)	(0.0111)	(0.0123)	(0.0139)	(0.0115)
Annual percentage changes in GDP	0.0294***	0.0197***	0.0408***	0.0369***	0.0184***	0.0223***	0.0231***	0.00993**
	(0.00231)	(0.00336)	(0.00300)	(0.00366)	(0.00494)	(0.00726)	(0.00480)	(0.00503)
Expected percentage changes in GDP, next year	0.0338***	0.0443***	0.0727***	0.0671***	0.116***	0.104***	0.111***	0.133***
	(0.00565)	(0.00839)	(0.00741)	(0.00878)	(0.0112)	(0.0133)	(0.0109)	(0.0117)
Constant	-5.997***	-14.86***	-19.18***	-23.41***	-33.97***	-45.15***	-85.81***	-89.73***
	(2.143)	(3.234)	(2.126)	(2.993)	(3.611)	(4.073)	(3.769)	(3.831)
Observations	4800	4800	4800	4800	4800	4800	4800	4800
# fixed effects	240	240	240	240	240	240	240	240
Over-dispersion parameter		0.0678***		0.154***		0.714***		0.621***
Squared correlation	0.986	0.980	0.978	0.976	0.968	0.953	0.980	0.966

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix Table 6: Extended gravity models by ethnic groups

	European		Māori		Pacific		Asian	
VARIABLES	Poisson	Negative Binomial	Poisson	Negative Binomial	Poisson	Negative Binomial	Poisson	Negative Binomial
Log population at destination location	0.390*	0.690**	0.448**	0.786***	1.073***	1.589***	2.075***	2.059***
	(0.206)	(0.321)	(0.215)	(0.301)	(0.320)	(0.386)	(0.372)	(0.364)
Log population at origin location	0.637***	1.006***	0.635***	1.024***	0.837***	1.504***	3.211***	3.558***
	(0.190)	(0.329)	(0.229)	(0.284)	(0.275)	(0.364)	(0.425)	(0.391)
Log travel time	-0.246	-1.349	0.997	0.236	-4.948***	-4.692***	-6.108***	-4.820***
	(0.806)	(1.218)	(0.825)	(1.073)	(1.190)	(1.643)	(1.705)	(1.773)
Dummy for same island	1.229	0.605	2.263***	2.106**	-3.756***	-2.352	-3.040	-1.603
	(0.819)	(1.225)	(0.827)	(1.047)	(1.243)	(1.796)	(1.917)	(2.026)
Log median house price x other destination	-0.0561	-0.156**	0.0486	-0.00866	0.206**	0.143	0.130	0.336***
	(0.0505)	(0.0734)	(0.0593)	(0.0711)	(0.0985)	(0.119)	(0.119)	(0.102)
Log median house price x large destination	-0.0417	-0.209**	0.103*	0.00397	-0.0541	-0.105	-0.202**	0.0788
	(0.0576)	(0.0891)	(0.0602)	(0.0812)	(0.109)	(0.137)	(0.0968)	(0.132)
Log median house price x other origin	0.149***	0.212***	0.0381	0.127*	0.0822	0.185	0.0680	0.156
	(0.0561)	(0.0740)	(0.0578)	(0.0688)	(0.103)	(0.124)	(0.116)	(0.109)
Log median house price x large origin	0.205***	0.149	0.144**	0.150*	-0.0959	-0.0613	-0.0239	-0.0824
	(0.0605)	(0.0930)	(0.0636)	(0.0829)	(0.115)	(0.148)	(0.0928)	(0.125)
Log GDP per capita at destination location	0.178	0.306**	0.338**	0.224	0.486**	0.335	1.283***	1.012***
	(0.133)	(0.154)	(0.143)	(0.156)	(0.206)	(0.222)	(0.281)	(0.238)
Log GDP per capita at origin location	0.124	0.238	0.403**	0.233	1.219***	0.943***	1.390***	1.296***
	(0.122)	(0.159)	(0.157)	(0.173)	(0.299)	(0.326)	(0.249)	(0.211)

Unemployment rate at destination location	-0.0104**	-0.0188***	-0.0285***	-0.0308***	-0.0329**	-0.0308**	-0.0328**	-0.0182*
	(0.00531)	(0.00598)	(0.00506)	(0.00631)	(0.0129)	(0.0127)	(0.0137)	(0.0110)
Unemployment rate at origin location	-0.0170***	-0.0142**	-0.0262***	-0.0259***	-0.00387	-0.00795	-0.000153	0.00853
	(0.00524)	(0.00593)	(0.00627)	(0.00647)	(0.0147)	(0.0144)	(0.0114)	(0.0113)
Share of the 40-64 workforce at destination location	-0.00802	-0.0179*	-0.00543	-0.0103	-0.00471	-0.0123	0.0357***	0.0275**
	(0.00784)	(0.00962)	(0.00783)	(0.00926)	(0.0107)	(0.0115)	(0.0136)	(0.0118)
Share of the 40-64 workforce at origin location	-0.0213***	-0.0186**	-0.0299***	-0.0262***	-0.0194*	-0.0176	0.00308	0.00720
	(0.00752)	(0.00945)	(0.00771)	(0.00920)	(0.0112)	(0.0122)	(0.0135)	(0.0112)
Annual percentage changes in GDP	0.0286***	0.0203***	0.0391***	0.0367***	0.0233***	0.0260***	0.0280***	0.0143***
	(0.00249)	(0.00340)	(0.00306)	(0.00377)	(0.00467)	(0.00692)	(0.00478)	(0.00508)
Expected percentage changes in GDP, next year	0.0351***	0.0429***	0.0752***	0.0675***	0.110***	0.0977***	0.109***	0.127***
	(0.00557)	(0.00847)	(0.00732)	(0.00888)	(0.0119)	(0.0134)	(0.0110)	(0.0117)
Constant	-8.044	-5.608	-28.19***	-25.59**	10.53	-1.370	-26.40	-43.46**
	(8.084)	(11.55)	(8.242)	(10.11)	(11.21)	(15.96)	(17.95)	(18.26)
Observations	4800	4800	4800	4800	4800	4800	4800	4800
# fixed effects	240	240	240	240	240	240	240	240
		0.0677***		0.154***		0.697***		0.578***
Squared correlation	0.993	0.991	0.989	0.988	0.985	0.981	0.991	0.984

*** *p*<0.01, ** *p*<0.05, * *p*<0.1.

3. Additional earnings regression results

Appendix Table 7: Fixed-effects panel regressions

	All workers	15-24	25-39	40-54	55-64	Male	Female	European	Māori	Pacific	Asian
Changes in FTE (employment)	2.298***	2.247***	2.329***	2.348***	2.356***	2.296***	2.302***	2.317***	2.285***	2.230***	2.248***
	(0.000923)	(0.00160)	(0.00203)	(0.00268)	(0.00616)	(0.00140)	(0.00123)	(0.00107)	(0.00201)	(0.00327)	(0.00247)
Migrate from rural to rural region	-0.00742***	-0.00979***	-0.00870***	-0.00593***	-0.00940*	-0.00764***	-0.00688***	-0.00858***	-0.00661***	0.00700	-0.00381
	(0.000865)	(0.00209)	(0.00185)	(0.00215)	(0.00531)	(0.00117)	(0.00129)	(0.000959)	(0.00170)	(0.00464)	(0.00307)
Migration from rural to urban region	0.00149*	-0.00474***	0.00282*	0.00199	-0.00551	0.00477***	-0.00141	0.00204**	0.000974	-0.00273	0.00220
	(0.000790)	(0.00181)	(0.00162)	(0.00200)	(0.00504)	(0.00110)	(0.00114)	(0.000892)	(0.00178)	(0.00322)	(0.00227)
Migrate from urban to rural region	-0.0168***	-0.00617***	-0.0187***	-0.0202***	-0.0231***	-0.0181***	-0.0160***	-0.0202***	-0.0175***	-0.00311	-0.00138
	(0.000806)	(0.00191)	(0.00163)	(0.00200)	(0.00501)	(0.00111)	(0.00117)	(0.000911)	(0.00183)	(0.00312)	(0.00230)
Migrate from urban to urban region	-0.00333***	-0.000978	-0.00301	-0.00837***	-0.00976	-0.00223*	-0.00437***	-0.00469***	-0.00152	-0.00349	0.00217
	(0.000965)	(0.00240)	(0.00190)	(0.00256)	(0.00726)	(0.00135)	(0.00138)	(0.00110)	(0.00259)	(0.00328)	(0.00247)
Age group 25-39	-0.0185***					-0.0177***	-0.0193***	-0.0214***	-0.0120***	-0.0142***	-0.0113***
	(0.000675)					(0.000894)	(0.00103)	(0.000758)	(0.00151)	(0.00238)	(0.00197)
Age group 40-54	-0.0409***					-0.0453***	-0.0361***	-0.0435***	-0.0254***	-0.0291***	-0.0492***
	(0.00104)					(0.00140)	(0.00154)	(0.00117)	(0.00233)	(0.00386)	(0.00315)
Age group 55-64	-0.0586***					-0.0659***	-0.0512***	-0.0605***	-0.0404***	-0.0453***	-0.0759***
	(0.00152)					(0.00216)	(0.00214)	(0.00168)	(0.00366)	(0.00664)	(0.00516)
Agriculture at origin	-0.0178***	-0.0307***	-0.00866**	-0.0103**	0.00187	-0.0235***	-0.0112***	-0.0187***	-0.0143***	-0.0233***	-0.0259***
	(0.00184)	(0.00398)	(0.00392)	(0.00491)	(0.0134)	(0.00243)	(0.00289)	(0.00206)	(0.00412)	(0.00772)	(0.00573)

Mining at origin	-0.175***	-0.191***	-0.181***	-0.165***	-0.153***	-0.186***	-0.116***	-0.169***	-0.206***	-0.257***	-0.127***
	(0.00591)	(0.0191)	(0.0125)	(0.0129)	(0.0318)	(0.00662)	(0.0129)	(0.00621)	(0.0143)	(0.0386)	(0.0243)
Manufacturing at origin	-0.0381***	-0.0251***	-0.0335***	-0.0452***	-0.0536***	-0.0393***	-0.0312***	-0.0373***	-0.0398***	-0.0530***	-0.0356***
	(0.00162)	(0.00368)	(0.00344)	(0.00425)	(0.0120)	(0.00220)	(0.00243)	(0.00181)	(0.00387)	(0.00634)	(0.00492)
Utilities at origin	-0.0502***	-0.0126	-0.0459***	-0.0704***	-0.0702***	-0.0471***	-0.0535***	-0.0537***	-0.0469***	-0.0549***	-0.0337***
	(0.00332)	(0.00933)	(0.00664)	(0.00792)	(0.0231)	(0.00413)	(0.00570)	(0.00381)	(0.00696)	(0.0121)	(0.00997)
Construction at origin	-0.0190***	-0.0119***	-0.0160***	-0.0259***	-0.0411***	-0.0211***	-0.0129***	-0.0163***	-0.0286***	-0.0309***	-0.0148***
	(0.00174)	(0.00384)	(0.00370)	(0.00466)	(0.0128)	(0.00225)	(0.00325)	(0.00192)	(0.00404)	(0.00688)	(0.00553)
Wholesale at origin	-0.0279***	-0.00692	-0.0271***	-0.0376***	-0.0423***	-0.0254***	-0.0296***	-0.0291***	-0.0225***	-0.0280***	-0.0259***
	(0.00177)	(0.00421)	(0.00366)	(0.00460)	(0.0131)	(0.00237)	(0.00268)	(0.00196)	(0.00441)	(0.00693)	(0.00528)
Retail trade at origin	-0.0268***	-0.0557***	-0.00493	0.00603	0.000490	-0.0193***	-0.0324***	-0.0290***	-0.0185***	-0.0252***	-0.0283***
	(0.00158)	(0.00343)	(0.00343)	(0.00432)	(0.0119)	(0.00221)	(0.00224)	(0.00174)	(0.00389)	(0.00654)	(0.00472)
Hospitality at origin	-0.0325***	-0.0425***	-0.0163***	-0.0143***	-0.0175	-0.0259***	-0.0336***	-0.0345***	-0.0303***	-0.0163**	-0.0325***
	(0.00167)	(0.00351)	(0.00367)	(0.00481)	(0.0135)	(0.00250)	(0.00230)	(0.00187)	(0.00401)	(0.00686)	(0.00482)
Transport at origin	-0.0263***	-0.00779*	-0.0286***	-0.0350***	-0.0358***	-0.0306***	-0.0154***	-0.0249***	-0.0346***	-0.0340***	-0.0187***
	(0.00193)	(0.00463)	(0.00402)	(0.00495)	(0.0136)	(0.00253)	(0.00309)	(0.00219)	(0.00438)	(0.00697)	(0.00586)
Telecom at origin	-0.00209	0.0736***	-0.0262***	-0.0461***	-0.0332	0.00438	-0.00688*	-0.00524*	0.0111	-0.0213*	0.0103
	(0.00268)	(0.00644)	(0.00509)	(0.00778)	(0.0257)	(0.00392)	(0.00370)	(0.00301)	(0.00757)	(0.0110)	(0.00695)
Finance at origin	-0.0525***	-0.0308***	-0.0524***	-0.0716***	-0.0712***	-0.0460***	-0.0566***	-0.0537***	-0.0422***	-0.0615***	-0.0509***
	(0.00225)	(0.00538)	(0.00452)	(0.00613)	(0.0190)	(0.00351)	(0.00298)	(0.00252)	(0.00605)	(0.00890)	(0.00605)
Rental serv. at origin	-0.0241***	-0.0288***	-0.0188***	-0.0191***	-0.0168	-0.0262***	-0.0205***	-0.0261***	-0.0197***	-0.0189**	-0.0197***
	(0.00232)	(0.00529)	(0.00486)	(0.00605)	(0.0170)	(0.00334)	(0.00323)	(0.00256)	(0.00571)	(0.00959)	(0.00683)
Professional serv. at origin	-0.0102***	0.0248***	-0.0184***	-0.0308***	-0.0334**	-0.0166***	-0.00395	-0.0111***	-0.0132***	-0.00869	-0.00162
	(0.00182)	(0.00435)	(0.00376)	(0.00484)	(0.0141)	(0.00263)	(0.00253)	(0.00201)	(0.00481)	(0.00805)	(0.00523)

Administrative serv. at origin	0.0565***	0.0379***	0.0632***	0.0683***	0.0768***	0.0645***	0.0496***	0.0589***	0.0528***	0.0606***	0.0461***
	(0.00170)	(0.00387)	(0.00356)	(0.00442)	(0.0120)	(0.00236)	(0.00243)	(0.00195)	(0.00395)	(0.00627)	(0.00498)
Government at origin	-0.0117***	0.0192***	-0.0140***	-0.0246***	-0.0346**	- 0.00985***	-0.0140***	-0.0112***	-0.0100**	-0.0158**	-0.0110*
	(0.00206)	(0.00510)	(0.00420)	(0.00536)	(0.0154)	(0.00294)	(0.00289)	(0.00230)	(0.00488)	(0.00781)	(0.00612)
Education at origin	0.0154***	0.0606***	0.00806**	-0.00501	-0.0305**	0.0558***	-0.00194	0.0152***	0.00801*	0.0103	0.0309***
	(0.00191)	(0.00474)	(0.00402)	(0.00479)	(0.0132)	(0.00322)	(0.00250)	(0.00212)	(0.00444)	(0.00783)	(0.00586)
Healthcare at origin	0.0106***	0.00437	0.00942**	0.0153***	0.0134	0.0172***	0.00532**	0.0117***	0.0139***	0.00153	0.00419
	(0.00183)	(0.00460)	(0.00397)	(0.00449)	(0.0122)	(0.00360)	(0.00237)	(0.00204)	(0.00429)	(0.00730)	(0.00556)
Recreational serv. at origin	0.0126***	0.0128**	0.0150***	0.0192**	0.00840	0.0100***	0.0162***	0.0126***	0.0140**	0.00653	0.00330
	(0.00251)	(0.00523)	(0.00515)	(0.00754)	(0.0208)	(0.00373)	(0.00340)	(0.00278)	(0.00587)	(0.00985)	(0.00722)
Agriculture at destination	0.0173***	0.0279***	0.0142***	0.00879*	-0.00518	0.0187***	0.0131***	0.0196***	0.0121***	0.00357	0.0165***
	(0.00191)	(0.00408)	(0.00408)	(0.00504)	(0.0137)	(0.00253)	(0.00300)	(0.00214)	(0.00416)	(0.00809)	(0.00615)
Mining at destination	0.172***	0.203***	0.181***	0.149***	0.171***	0.171***	0.154***	0.169***	0.186***	0.171***	0.147***
	(0.00525)	(0.0146)	(0.0109)	(0.0122)	(0.0324)	(0.00594)	(0.0112)	(0.00560)	(0.0123)	(0.0279)	(0.0211)
Manufacturing at destination	0.0391***	0.0343***	0.0374***	0.0377***	0.0409***	0.0326***	0.0406***	0.0402***	0.0317***	0.0371***	0.0332***
	(0.00164)	(0.00363)	(0.00350)	(0.00430)	(0.0120)	(0.00224)	(0.00243)	(0.00183)	(0.00383)	(0.00631)	(0.00495)
Utilities at destination	0.0582***	0.0415***	0.0534***	0.0663***	0.0740***	0.0511***	0.0645***	0.0562***	0.0548***	0.0516***	0.0562***
	(0.00302)	(0.00813)	(0.00619)	(0.00737)	(0.0218)	(0.00382)	(0.00504)	(0.00347)	(0.00654)	(0.0107)	(0.00890)
Construction at destination	0.0329***	0.0187***	0.0329***	0.0443***	0.0515***	0.0291***	0.0303***	0.0295***	0.0370***	0.0357***	0.0369***
	(0.00174)	(0.00377)	(0.00374)	(0.00464)	(0.0128)	(0.00228)	(0.00313)	(0.00193)	(0.00398)	(0.00684)	(0.00550)
Wholesale at destination	0.0351***	0.0241***	0.0361***	0.0418***	0.0350***	0.0256***	0.0439***	0.0360***	0.0285***	0.0219***	0.0319***
	(0.00176)	(0.00402)	(0.00369)	(0.00464)	(0.0131)	(0.00239)	(0.00264)	(0.00196)	(0.00433)	(0.00677)	(0.00523)

Retail trade at destination	0.00583***	0.0211***	-0.00550	-0.00536	-0.00677	-0.00543**	0.0155***	0.00835***	-0.00113	-0.00205	-0.00225
	(0.00162)	(0.00343)	(0.00354)	(0.00439)	(0.0121)	(0.00230)	(0.00229)	(0.00179)	(0.00393)	(0.00665)	(0.00483)
Hospitality at destination	0.0142***	0.0271***	0.00309	0.00668	0.0141	-0.00669**	0.0251***	0.0185***	0.0132***	-0.00754	0.00285
	(0.00175)	(0.00356)	(0.00384)	(0.00498)	(0.0137)	(0.00266)	(0.00237)	(0.00196)	(0.00410)	(0.00716)	(0.00501)
Transport at destination	0.0418***	0.0362***	0.0435***	0.0463***	0.0448***	0.0421***	0.0315***	0.0405***	0.0429***	0.0315***	0.0411***
	(0.00193)	(0.00437)	(0.00407)	(0.00498)	(0.0137)	(0.00254)	(0.00306)	(0.00220)	(0.00433)	(0.00688)	(0.00576)
Telecom at destination	0.0422***	0.0386***	0.0411***	0.0499***	0.0304	0.0415***	0.0440***	0.0446***	0.0304***	0.0212*	0.0367***
	(0.00260)	(0.00578)	(0.00509)	(0.00806)	(0.0273)	(0.00374)	(0.00361)	(0.00292)	(0.00735)	(0.0109)	(0.00666)
Finance at destination	0.0598***	0.0586***	0.0530***	0.0639***	0.0563***	0.0524***	0.0674***	0.0636***	0.0512***	0.0445***	0.0503***
	(0.00215)	(0.00476)	(0.00444)	(0.00609)	(0.0182)	(0.00331)	(0.00287)	(0.00242)	(0.00556)	(0.00850)	(0.00582)
Rental serv. at destination	0.0264***	0.0178***	0.0292***	0.0316***	0.0296*	0.0198***	0.0309***	0.0285***	0.0227***	0.0143	0.0224***
	(0.00230)	(0.00509)	(0.00486)	(0.00606)	(0.0169)	(0.00332)	(0.00320)	(0.00255)	(0.00563)	(0.00926)	(0.00673)
Professional serv. at destination	0.0340***	0.0173***	0.0382***	0.0376***	0.0407***	0.0361***	0.0328***	0.0343***	0.0276***	0.0193**	0.0314***
	(0.00180)	(0.00405)	(0.00376)	(0.00483)	(0.0143)	(0.00260)	(0.00250)	(0.00199)	(0.00465)	(0.00792)	(0.00520)
Administrative serv. at destination	-0.0457***	-0.0318***	-0.0524***	-0.0569***	-0.0469***	-0.0644***	-0.0279***	-0.0436***	-0.0449***	-0.0694***	-0.0438***
	(0.00174)	(0.00384)	(0.00371)	(0.00451)	(0.0121)	(0.00244)	(0.00248)	(0.00201)	(0.00395)	(0.00631)	(0.00514)
Government at destination	0.0357***	0.0323***	0.0344***	0.0333***	0.0359**	0.0137***	0.0557***	0.0360***	0.0293***	0.0330***	0.0312***
	(0.00197)	(0.00453)	(0.00412)	(0.00519)	(0.0151)	(0.00285)	(0.00273)	(0.00220)	(0.00462)	(0.00738)	(0.00583)
Education at destination	- 0.00574***	-0.0330***	-0.000489	0.00336	0.0334**	-0.0397***	0.0141***	-0.00381*	-0.00373	-0.0142*	-0.0251***
	(0.00193)	(0.00454)	(0.00412)	(0.00486)	(0.0133)	(0.00330)	(0.00251)	(0.00214)	(0.00445)	(0.00780)	(0.00594)
Healthcare at destination	-0.00123	0.00533	0.000846	-0.00934**	-0.00292	-0.00719**	0.00860***	-0.00193	-0.00379	-0.00871	0.00464
	(0.00183)	(0.00441)	(0.00399)	(0.00446)	(0.0121)	(0.00354)	(0.00236)	(0.00204)	(0.00422)	(0.00718)	(0.00554)

Recreational serv. at destination	-0.0136***	-0.00947*	-0.0184***	-0.0200***	0.00514	-0.0225***	-0.00748**	-0.0127***	-0.0120**	-0.0104	-0.0217***
	(0.00256)	(0.00525)	(0.00528)	(0.00762)	(0.0215)	(0.00388)	(0.00343)	(0.00283)	(0.00603)	(0.0104)	(0.00734)
Firm size 5-9 employees at origin	-0.0201***	-0.0197***	-0.0207***	-0.0207***	-0.0131**	-0.0265***	-0.0126***	-0.0216***	-0.0168***	-0.0143***	-0.0148***
	(0.000858)	(0.00186)	(0.00177)	(0.00226)	(0.00596)	(0.00117)	(0.00126)	(0.000956)	(0.00202)	(0.00403)	(0.00238)
Firm size 10-19 employees at origin	-0.0298***	-0.0277***	-0.0300***	-0.0321***	-0.0246***	-0.0390***	-0.0191***	-0.0318***	-0.0234***	-0.0243***	-0.0233***
	(0.000872)	(0.00194)	(0.00181)	(0.00227)	(0.00596)	(0.00119)	(0.00128)	(0.000976)	(0.00202)	(0.00391)	(0.00246)
Firm size 20-49 employees at origin	-0.0397***	-0.0340***	-0.0386***	-0.0442***	-0.0388***	-0.0511***	-0.0266***	-0.0421***	-0.0368***	-0.0307***	-0.0319***
	(0.000849)	(0.00195)	(0.00177)	(0.00218)	(0.00566)	(0.00117)	(0.00124)	(0.000956)	(0.00199)	(0.00371)	(0.00237)
Firm size 50-99 employees at origin	-0.0443***	-0.0387***	-0.0428***	-0.0477***	-0.0414***	-0.0616***	-0.0258***	-0.0472***	-0.0397***	-0.0393***	-0.0339***
	(0.000956)	(0.00223)	(0.00199)	(0.00243)	(0.00621)	(0.00132)	(0.00139)	(0.00109)	(0.00221)	(0.00391)	(0.00265)
Firm size 100-249 employees at origin	-0.0587***	-0.0533***	-0.0567***	-0.0637***	-0.0599***	-0.0783***	-0.0384***	-0.0615***	-0.0580***	-0.0544***	-0.0472***
	(0.000935)	(0.00215)	(0.00195)	(0.00241)	(0.00629)	(0.00130)	(0.00135)	(0.00107)	(0.00219)	(0.00379)	(0.00253)
Firm size 250+ employees at origin	-0.0710***	-0.0584***	-0.0675***	-0.0805***	-0.0816***	-0.0924***	-0.0498***	-0.0728***	-0.0752***	-0.0724***	-0.0563***
	(0.000831)	(0.00185)	(0.00173)	(0.00220)	(0.00596)	(0.00116)	(0.00120)	(0.000943)	(0.00194)	(0.00353)	(0.00226)
Firm size 5-9 employees at destination	0.0163***	0.0120***	0.0222***	0.0107***	0.00762	0.0252***	0.00550***	0.0167***	0.0167***	0.0154***	0.0152***
	(0.000871)	(0.00189)	(0.00180)	(0.00231)	(0.00594)	(0.00117)	(0.00130)	(0.000971)	(0.00204)	(0.00401)	(0.00245)
Firm size 10-19 employees at destination	0.0243***	0.0176***	0.0298***	0.0216***	0.0110*	0.0369***	0.00928***	0.0246***	0.0234***	0.0174***	0.0281***
	(0.000878)	(0.00195)	(0.00182)	(0.00228)	(0.00590)	(0.00119)	(0.00130)	(0.000981)	(0.00203)	(0.00386)	(0.00252)

Firm size 20-49 employees at destination	0.0330***	0.0199***	0.0419***	0.0328***	0.0229***	0.0500***	0.0135***	0.0340***	0.0318***	0.0302***	0.0330***
	(0.000853)	(0.00195)	(0.00177)	(0.00218)	(0.00562)	(0.00116)	(0.00125)	(0.000959)	(0.00197)	(0.00363)	(0.00242)
Firm size 50-99 employees at destination	0.0373***	0.0224***	0.0476***	0.0345***	0.0231***	0.0570***	0.0157***	0.0387***	0.0382***	0.0305***	0.0339***
	(0.000957)	(0.00227)	(0.00198)	(0.00240)	(0.00616)	(0.00132)	(0.00139)	(0.00109)	(0.00222)	(0.00385)	(0.00267)
Firm size 100-249 employees at destination	0.0467***	0.0357***	0.0551***	0.0426***	0.0297***	0.0693***	0.0225***	0.0497***	0.0449***	0.0430***	0.0400***
	(0.000940)	(0.00219)	(0.00195)	(0.00239)	(0.00618)	(0.00131)	(0.00136)	(0.00107)	(0.00218)	(0.00378)	(0.00259)
Firm size 250+ employees at destination	0.0651***	0.0539***	0.0718***	0.0639***	0.0448***	0.0887***	0.0406***	0.0653***	0.0703***	0.0700***	0.0590***
	(0.000831)	(0.00187)	(0.00173)	(0.00218)	(0.00590)	(0.00115)	(0.00121)	(0.000943)	(0.00193)	(0.00345)	(0.00230)
Annual GDP growth	0.533***	0.572***	0.522***	0.539***	0.279***	0.634***	0.428***	0.572***	0.521***	0.595***	0.359***
	(0.0129)	(0.0326)	(0.0266)	(0.0317)	(0.0816)	(0.0179)	(0.0185)	(0.0147)	(0.0299)	(0.0482)	(0.0355)
Intercept	0.0267***	0.0378***	0.00340	-0.0110*	-0.0232	0.0317***	0.0224***	0.0259***	0.0154***	0.0252***	0.0432***
	(0.00218)	(0.00492)	(0.00473)	(0.00582)	(0.0169)	(0.00302)	(0.00313)	(0.00238)	(0.00517)	(0.00916)	(0.00674)
Observations	6,383,800	1,901,600	2,361,600	1,647,300	473,200	3,263,100	3,120,700	4,712,500	1,092,600	467,400	1,044,600
R^2	0.852	0.910	0.854	0.830	0.873	0.828	0.872	0.846	0.858	0.867	0.874

*** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 8: Linear regressions (random effects)

	All workers	15-24	25-39	40-54	55-64	Male	Female	European	Māori	Pacific	Asian
Changes in FTE (employment)	2.311***	2.272***	2.335***	2.365***	2.381***	2.304***	2.317***	2.334***	2.296***	2.241***	2.254***
	(0.000575)	(0.000820)	(0.00104)	(0.00142)	(0.00254)	(0.000874)	(0.000764)	(0.000685)	(0.00130)	(0.00197)	(0.00135)
Migrate from rural to rural region	-0.00803***	-0.0108***	-0.00946***	-0.00527***	-0.00167	-0.00715***	-0.00882***	-0.00886***	-0.00583***	0.000363	-0.00655***
	(0.000444)	(0.000817)	(0.000743)	(0.000869)	(0.00156)	(0.000604)	(0.000654)	(0.000503)	(0.000910)	(0.00220)	(0.00137)
Migration from rural to urban region	0.00367***	-0.00342***	0.00572***	0.00729***	0.00654***	0.00708***	0.000656	0.00468***	0.00344***	0.000200	0.00147
	(0.000457)	(0.000820)	(0.000741)	(0.000923)	(0.00172)	(0.000636)	(0.000656)	(0.000530)	(0.00108)	(0.00178)	(0.00114)
Migrate from urban to rural region	-0.0157***	-0.00587***	-0.0189***	-0.0196***	-0.0183***	-0.0170***	-0.0147***	-0.0185***	-0.0138***	-0.00311*	-0.00520***
	(0.000471)	(0.000870)	(0.000749)	(0.000947)	(0.00175)	(0.000652)	(0.000679)	(0.000549)	(0.00111)	(0.00173)	(0.00116)
Migrate from urban to urban region	0.000556	0.00289***	0.00208***	-0.00422***	-0.00446**	3.61e-05	0.000985	-0.000341	0.00268*	-0.00116	0.00287**
	(0.000504)	(0.000952)	(0.000768)	(0.00104)	(0.00214)	(0.000702)	(0.000723)	(0.000594)	(0.00142)	(0.00165)	(0.00113)
Binary variable in European	-0.00294***	0.0138***	-0.00353***	-0.00893***	-0.0118***	-0.00468***	-0.000987*		0.00372***	0.00382***	-0.0121***
	(0.000384)	(0.000703)	(0.000617)	(0.000818)	(0.00184)	(0.000510)	(0.000585)		(0.000557)	(0.00104)	(0.000769)
Binary variable in Māori	-0.00663***	-0.0134***	-0.00779***	0.000680	0.00642***	-0.00779***	-0.00554***	-0.00560***		-0.00407***	-0.0121***
	(0.000335)	(0.000574)	(0.000545)	(0.000743)	(0.00169)	(0.000456)	(0.000493)	(0.000398)		(0.00121)	(0.00161)
Binary variable in Pacific	-0.00932***	-0.0117***	-0.00976***	-0.00212*	0.00290	-0.00988***	-0.00842***	-0.00537***	-0.00205*		-0.00953***
	(0.000495)	(0.000850)	(0.000779)	(0.00113)	(0.00264)	(0.000655)	(0.000756)	(0.000875)	(0.00112)		(0.00166)
Binary variable in Asian and Others	0.0103***	0.00290***	0.0164***	0.0117***	0.00506**	0.0107***	0.0102***	0.00230***	-0.000895	0.00809***	
	(0.000429)	(0.000799)	(0.000679)	(0.000899)	(0.00200)	(0.000577)	(0.000644)	(0.000672)	(0.00153)	(0.00167)	

Binary variable in Female	-0.00746***	-0.00799***	-0.0152***	-0.00298***	0.00579***			-0.00700***	-0.00812***	-0.00796***	-0.00993***
	(0.000254)	(0.000483)	(0.000404)	(0.000516)	(0.00102)			(0.000298)	(0.000637)	(0.000933)	(0.000595)
Age group 25-39	-0.0178***					-0.0147***	-0.0218***	-0.0220***	-0.0134***	-0.0111***	-0.00541***
	(0.000293)					(0.000393)	(0.000442)	(0.000345)	(0.000673)	(0.000971)	(0.000719)
Age group 40-54	-0.0494***					-0.0522***	-0.0471***	-0.0545***	-0.0318***	-0.0334***	-0.0405***
	(0.000324)					(0.000454)	(0.000468)	(0.000375)	(0.000771)	(0.00120)	(0.000876)
Age group 55-64	-0.0779***					-0.0831***	-0.0730***	-0.0825***	-0.0508***	-0.0544***	-0.0736***
	(0.000497)					(0.000717)	(0.000693)	(0.000553)	(0.00132)	(0.00233)	(0.00164)
Agriculture at origin	-0.0155***	-0.0237***	-0.0100***	-0.00997***	0.00654	-0.0215***	-0.0101***	-0.0163***	-0.0131***	-0.0213***	-0.0190***
	(0.00100)	(0.00170)	(0.00164)	(0.00211)	(0.00408)	(0.00134)	(0.00157)	(0.00117)	(0.00232)	(0.00393)	(0.00266)
Mining at origin	-0.163***	-0.157***	-0.176***	-0.159***	-0.148***	-0.173***	-0.114***	-0.157***	-0.183***	-0.222***	-0.137***
	(0.00354)	(0.00927)	(0.00588)	(0.00577)	(0.0105)	(0.00397)	(0.00788)	(0.00381)	(0.00864)	(0.0233)	(0.0129)
Manufacturing at origin	-0.0408***	-0.0230***	-0.0399***	-0.0540***	-0.0578***	-0.0431***	-0.0317***	-0.0400***	-0.0411***	-0.0579***	-0.0319***
	(0.000884)	(0.00157)	(0.00141)	(0.00180)	(0.00357)	(0.00120)	(0.00133)	(0.00102)	(0.00218)	(0.00325)	(0.00228)
Utilities at origin	-0.0494***	-0.00569	-0.0466***	-0.0731***	-0.0815***	-0.0462***	-0.0534***	-0.0522***	-0.0444***	-0.0504***	-0.0281***
	(0.00191)	(0.00422)	(0.00293)	(0.00346)	(0.00737)	(0.00235)	(0.00337)	(0.00224)	(0.00413)	(0.00667)	(0.00506)
Construction at origin	-0.0167***	-0.00619***	-0.0153***	-0.0290***	-0.0322***	-0.0193***	-0.0128***	-0.0139***	-0.0250***	-0.0295***	-0.0103***
	(0.000945)	(0.00165)	(0.00152)	(0.00194)	(0.00378)	(0.00122)	(0.00183)	(0.00108)	(0.00226)	(0.00353)	(0.00256)
Wholesale at origin	-0.0308***	-0.00262	-0.0295***	-0.0498***	-0.0504***	-0.0297***	-0.0299***	-0.0313***	-0.0238***	-0.0337***	-0.0251***
	(0.000977)	(0.00181)	(0.00154)	(0.00196)	(0.00392)	(0.00131)	(0.00149)	(0.00112)	(0.00252)	(0.00358)	(0.00248)
Retail trade at origin	-0.0293***	-0.0507***	-0.0105***	-0.00287	0.00627*	-0.0229***	-0.0337***	-0.0320***	-0.0233***	-0.0286***	-0.0258***
	(0.000861)	(0.00147)	(0.00141)	(0.00183)	(0.00357)	(0.00121)	(0.00122)	(0.000982)	(0.00219)	(0.00335)	(0.00218)
Hospitality at origin	-0.0369***	-0.0444***	-0.0215***	-0.0218***	-0.0134***	-0.0304***	-0.0372***	-0.0384***	-0.0347***	-0.0222***	-0.0334***

	(0.000908)	(0.00150)	(0.00150)	(0.00206)	(0.00406)	(0.00135)	(0.00125)	(0.00105)	(0.00225)	(0.00351)	(0.00221)
Transport at origin	-0.0275***	-0.00524***	-0.0338***	-0.0381***	-0.0367***	-0.0316***	-0.0182***	-0.0258***	-0.0313***	-0.0358***	-0.0230***
	(0.00107)	(0.00202)	(0.00170)	(0.00213)	(0.00415)	(0.00141)	(0.00172)	(0.00126)	(0.00249)	(0.00363)	(0.00284)
Telecom at origin	0.00160	0.0830***	-0.0206***	-0.0551***	-0.0524***	0.00173	0.00246	-0.00310*	0.0175***	-0.00990	0.0237***
	(0.00154)	(0.00302)	(0.00217)	(0.00331)	(0.00788)	(0.00224)	(0.00213)	(0.00177)	(0.00461)	(0.00634)	(0.00353)
Finance at origin	-0.0566***	-0.0211***	-0.0542***	-0.0828***	-0.0867***	-0.0515***	-0.0594***	-0.0584***	-0.0467***	-0.0569***	-0.0462***
	(0.00125)	(0.00235)	(0.00189)	(0.00262)	(0.00561)	(0.00195)	(0.00166)	(0.00144)	(0.00352)	(0.00474)	(0.00295)
Rental serv. at origin	-0.0231***	-0.0216***	-0.0222***	-0.0270***	-0.0197***	-0.0243***	-0.0197***	-0.0252***	-0.0223***	-0.0195***	-0.0160***
	(0.00131)	(0.00235)	(0.00210)	(0.00265)	(0.00521)	(0.00189)	(0.00182)	(0.00148)	(0.00335)	(0.00509)	(0.00336)
Professional serv. at origin	0.000717	0.0382***	-0.00133	-0.0267***	-0.0360***	-0.00425***	0.00589***	-0.000937	-0.00104	7.55e-05	0.0147***
	(0.000985)	(0.00188)	(0.00151)	(0.00200)	(0.00411)	(0.00141)	(0.00138)	(0.00112)	(0.00275)	(0.00423)	(0.00242)
Administrative serv. at origin	0.0507***	0.0337***	0.0538***	0.0588***	0.0659***	0.0574***	0.0458***	0.0555***	0.0447***	0.0533***	0.0433***
	(0.000927)	(0.00165)	(0.00148)	(0.00189)	(0.00364)	(0.00129)	(0.00133)	(0.00111)	(0.00223)	(0.00321)	(0.00231)
Government at origin	-0.0143***	0.0192***	-0.0149***	-0.0331***	-0.0535***	-0.0151***	-0.0121***	-0.0129***	-0.0133***	-0.0162***	-0.00895***
	(0.00113)	(0.00222)	(0.00174)	(0.00224)	(0.00459)	(0.00162)	(0.00159)	(0.00130)	(0.00279)	(0.00413)	(0.00294)
Education at origin	0.0267***	0.0766***	0.0152***	0.00659***	-0.0176***	0.0624***	0.0108***	0.0266***	0.0166***	0.0197***	0.0485***
	(0.00104)	(0.00206)	(0.00165)	(0.00202)	(0.00403)	(0.00173)	(0.00136)	(0.00119)	(0.00250)	(0.00405)	(0.00274)
Healthcare at origin	0.0116***	0.00588***	0.00832***	0.0149***	0.0123***	0.0176***	0.00706***	0.0120***	0.0123***	0.000451	0.0121***
	(0.000987)	(0.00198)	(0.00160)	(0.00188)	(0.00358)	(0.00190)	(0.00128)	(0.00114)	(0.00240)	(0.00372)	(0.00253)
Recreational serv. at origin	0.0172***	0.0230***	0.0170***	0.0157***	0.00174	0.0152***	0.0210***	0.0169***	0.0192***	0.0179***	0.0112***
	(0.00141)	(0.00230)	(0.00222)	(0.00332)	(0.00658)	(0.00208)	(0.00191)	(0.00160)	(0.00340)	(0.00525)	(0.00358)
Agriculture at destination	0.0227***	0.0387***	0.0132***	0.0113***	0.0104**	0.0241***	0.0179***	0.0249***	0.0157***	0.00810**	0.0269***
	(0.00102)	(0.00167)	(0.00169)	(0.00218)	(0.00414)	(0.00136)	(0.00161)	(0.00118)	(0.00232)	(0.00407)	(0.00277)

Mining at destination	0.191***	0.237***	0.195***	0.165***	0.177***	0.192***	0.165***	0.188***	0.210***	0.222***	0.168***
	(0.00305)	(0.00697)	(0.00484)	(0.00531)	(0.00953)	(0.00345)	(0.00655)	(0.00330)	(0.00738)	(0.0176)	(0.0112)
Manufacturing at destination	0.0413***	0.0421***	0.0385***	0.0401***	0.0528***	0.0358***	0.0425***	0.0424***	0.0336***	0.0404***	0.0418***
	(0.000877)	(0.00148)	(0.00143)	(0.00183)	(0.00352)	(0.00120)	(0.00130)	(0.00101)	(0.00214)	(0.00321)	(0.00226)
Utilities at destination	0.0628***	0.0514***	0.0630***	0.0701***	0.0752***	0.0563***	0.0682***	0.0601***	0.0519***	0.0610***	0.0727***
	(0.00166)	(0.00334)	(0.00261)	(0.00312)	(0.00638)	(0.00209)	(0.00279)	(0.00195)	(0.00376)	(0.00566)	(0.00418)
Construction at destination	0.0354***	0.0249***	0.0338***	0.0460***	0.0558***	0.0323***	0.0318***	0.0305***	0.0387***	0.0425***	0.0441***
	(0.000928)	(0.00151)	(0.00153)	(0.00197)	(0.00378)	(0.00122)	(0.00173)	(0.00106)	(0.00221)	(0.00347)	(0.00250)
Wholesale at destination	0.0371***	0.0341***	0.0386***	0.0383***	0.0340***	0.0272***	0.0471***	0.0388***	0.0265***	0.0251***	0.0385***
	(0.000955)	(0.00166)	(0.00154)	(0.00197)	(0.00389)	(0.00129)	(0.00143)	(0.00109)	(0.00246)	(0.00349)	(0.00242)
Retail trade at destination	0.0118***	0.0358***	-0.00914***	-0.0105***	-0.00597*	-0.00273**	0.0241***	0.0162***	0.00456**	0.00398	0.00498**
	(0.000877)	(0.00143)	(0.00146)	(0.00188)	(0.00359)	(0.00125)	(0.00123)	(0.00100)	(0.00221)	(0.00343)	(0.00221)
Hospitality at destination	0.0182***	0.0322***	-0.000746	0.00691***	0.0213***	-0.00148	0.0293***	0.0241***	0.0188***	0.000353	0.00795***
	(0.000938)	(0.00148)	(0.00158)	(0.00215)	(0.00415)	(0.00142)	(0.00127)	(0.00109)	(0.00230)	(0.00365)	(0.00226)
Transport at destination	0.0411***	0.0393***	0.0400***	0.0425***	0.0484***	0.0423***	0.0290***	0.0394***	0.0439***	0.0313***	0.0449***
	(0.00105)	(0.00181)	(0.00169)	(0.00215)	(0.00408)	(0.00139)	(0.00164)	(0.00123)	(0.00244)	(0.00353)	(0.00269)
Telecom at destination	0.0442***	0.0325***	0.0565***	0.0561***	0.0435***	0.0386***	0.0493***	0.0469***	0.0264***	0.0374***	0.0405***
	(0.00141)	(0.00243)	(0.00210)	(0.00334)	(0.00787)	(0.00201)	(0.00199)	(0.00164)	(0.00425)	(0.00580)	(0.00314)
Finance at destination	0.0707***	0.0780***	0.0687***	0.0709***	0.0794***	0.0665***	0.0760***	0.0733***	0.0548***	0.0554***	0.0683***
	(0.00114)	(0.00191)	(0.00179)	(0.00252)	(0.00528)	(0.00175)	(0.00152)	(0.00133)	(0.00312)	(0.00426)	(0.00267)
Rental serv. at destination	0.0322***	0.0314***	0.0338***	0.0303***	0.0275***	0.0288***	0.0344***	0.0340***	0.0252***	0.0215***	0.0353***
	(0.00129)	(0.00220)	(0.00209)	(0.00267)	(0.00511)	(0.00187)	(0.00178)	(0.00146)	(0.00328)	(0.00493)	(0.00327)

Professional serv. at destination	0.0487***	0.0405***	0.0597***	0.0463***	0.0392***	0.0540***	0.0441***	0.0473***	0.0399***	0.0362***	0.0546***
	(0.000954)	(0.00163)	(0.00152)	(0.00202)	(0.00410)	(0.00137)	(0.00133)	(0.00108)	(0.00262)	(0.00410)	(0.00237)
Administrative serv. at destination	-0.0432***	-0.0307***	-0.0507***	-0.0510***	-0.0401***	-0.0618***	-0.0254***	-0.0420***	-0.0429***	-0.0613***	-0.0391***
	(0.000955)	(0.00162)	(0.00157)	(0.00199)	(0.00370)	(0.00135)	(0.00136)	(0.00114)	(0.00225)	(0.00326)	(0.00241)
Government at destination	0.0411***	0.0385***	0.0486***	0.0411***	0.0433***	0.0186***	0.0622***	0.0412***	0.0345***	0.0362***	0.0415***
	(0.00105)	(0.00183)	(0.00167)	(0.00216)	(0.00431)	(0.00152)	(0.00145)	(0.00120)	(0.00257)	(0.00380)	(0.00270)
Education at destination	-0.00203**	-0.0147***	-4.48e-05	0.00950***	0.0321***	-0.0401***	0.0193***	-2.83e-05	0.00243	-0.00448	-0.0211***
	(0.00102)	(0.00187)	(0.00166)	(0.00204)	(0.00399)	(0.00172)	(0.00133)	(0.00117)	(0.00245)	(0.00396)	(0.00273)
Healthcare at destination	0.00188*	0.0180***	0.00283*	-0.0108***	-0.00999***	-0.00627***	0.0118***	-0.000913	-0.00253	0.00242	0.0146***
	(0.000968)	(0.00178)	(0.00161)	(0.00189)	(0.00353)	(0.00186)	(0.00125)	(0.00112)	(0.00234)	(0.00363)	(0.00249)
Recreational serv. at destination	-0.00571***	0.00479**	-0.0110***	-0.0187***	0.00148	-0.0137***	0.000251	-0.00465***	-0.00695**	0.00413	-0.0137***
	(0.00142)	(0.00227)	(0.00228)	(0.00336)	(0.00654)	(0.00214)	(0.00191)	(0.00161)	(0.00350)	(0.00560)	(0.00357)
Firm size 5-9 employees at origin	-0.0198***	-0.0206***	-0.0187***	-0.0178***	-0.0167***	-0.0263***	-0.0125***	-0.0219***	-0.0185***	-0.0156***	-0.0120***
	(0.000498)	(0.000862)	(0.000812)	(0.00104)	(0.00197)	(0.000682)	(0.000729)	(0.000573)	(0.00122)	(0.00226)	(0.00119)
Firm size 10-19 employees at origin	-0.0290***	-0.0268***	-0.0269***	-0.0314***	-0.0292***	-0.0381***	-0.0186***	-0.0318***	-0.0253***	-0.0226***	-0.0196***
	(0.000502)	(0.000885)	(0.000815)	(0.00104)	(0.00196)	(0.000687)	(0.000734)	(0.000580)	(0.00122)	(0.00219)	(0.00122)
Firm size 20-49 employees at origin	-0.0387***	-0.0340***	-0.0363***	-0.0432***	-0.0398***	-0.0513***	-0.0246***	-0.0425***	-0.0357***	-0.0293***	-0.0271***
	(0.000486)	(0.000875)	(0.000792)	(0.000992)	(0.00186)	(0.000671)	(0.000705)	(0.000565)	(0.00119)	(0.00205)	(0.00117)
Firm size 50-99 employees at origin	-0.0439***	-0.0386***	-0.0401***	-0.0490***	-0.0479***	-0.0623***	-0.0246***	-0.0484***	-0.0401***	-0.0393***	-0.0281***

	(0.000548)	(0.000994)	(0.000893)	(0.00111)	(0.00206)	(0.000759)	(0.000791)	(0.000643)	(0.00132)	(0.00216)	(0.00131)
Firm size 100-249 employees at origin	-0.0591***	-0.0554***	-0.0522***	-0.0650***	-0.0641***	-0.0797***	-0.0379***	-0.0634***	-0.0593***	-0.0551***	-0.0428***
	(0.000530)	(0.000939)	(0.000864)	(0.00109)	(0.00207)	(0.000742)	(0.000758)	(0.000626)	(0.00130)	(0.00209)	(0.00123)
Firm size 250+ employees at origin	-0.0713***	-0.0563***	-0.0652***	-0.0843***	-0.0898***	-0.0935***	-0.0494***	-0.0747***	-0.0766***	-0.0732***	-0.0511***
	(0.000469)	(0.000819)	(0.000760)	(0.000979)	(0.00190)	(0.000655)	(0.000672)	(0.000549)	(0.00114)	(0.00195)	(0.00110)
Firm size 5-9 employees at destination	0.0169***	0.0143***	0.0226***	0.0138***	0.00501**	0.0258***	0.00624***	0.0169***	0.0153***	0.0134***	0.0187***
	(0.000511)	(0.000873)	(0.000831)	(0.00108)	(0.00205)	(0.000690)	(0.000758)	(0.000586)	(0.00125)	(0.00227)	(0.00124)
Firm size 10-19 employees at destination	0.0261***	0.0208***	0.0332***	0.0249***	0.0145***	0.0390***	0.0114***	0.0265***	0.0219***	0.0179***	0.0297***
	(0.000510)	(0.000889)	(0.000830)	(0.00107)	(0.00200)	(0.000695)	(0.000752)	(0.000588)	(0.00123)	(0.00218)	(0.00125)
Firm size 20-49 employees at destination	0.0358***	0.0253***	0.0453***	0.0365***	0.0262***	0.0514***	0.0182***	0.0367***	0.0315***	0.0293***	0.0373***
	(0.000491)	(0.000876)	(0.000799)	(0.00101)	(0.00189)	(0.000673)	(0.000718)	(0.000570)	(0.00119)	(0.00202)	(0.00119)
Firm size 50-99 employees at destination	0.0408***	0.0299***	0.0519***	0.0408***	0.0301***	0.0603***	0.0200***	0.0424***	0.0362***	0.0328***	0.0390***
	(0.000550)	(0.00101)	(0.000894)	(0.00110)	(0.00207)	(0.000762)	(0.000796)	(0.000645)	(0.00134)	(0.00214)	(0.00131)
Firm size 100-249 employees at destination	0.0507***	0.0438***	0.0605***	0.0494***	0.0376***	0.0725***	0.0280***	0.0536***	0.0448***	0.0448***	0.0463***
	(0.000535)	(0.000970)	(0.000866)	(0.00109)	(0.00204)	(0.000748)	(0.000769)	(0.000631)	(0.00130)	(0.00208)	(0.00125)
Firm size 250+ employees at destination	0.0698***	0.0625***	0.0795***	0.0699***	0.0586***	0.0924***	0.0470***	0.0696***	0.0701***	0.0705***	0.0686***
	(0.000464)	(0.000815)	(0.000750)	(0.000967)	(0.00187)	(0.000643)	(0.000672)	(0.000543)	(0.00113)	(0.00188)	(0.00109)
Annual GDP growth	0.499***	0.655***	0.415***	0.491***	0.319***	0.613***	0.384***	0.542***	0.548***	0.605***	0.328***

	(0.00742)	(0.0138)	(0.0119)	(0.0148)	(0.0271)	(0.0104)	(0.0106)	(0.00872)	(0.0178)	(0.0261)	(0.0179)
Intercept	0.0284***	0.0107***	0.00522***	-0.00605***	-0.0260***	0.0319***	0.0174***	0.0280***	0.0162***	0.0221***	0.0252***
	(0.000937)	(0.00162)	(0.00147)	(0.00195)	(0.00389)	(0.00127)	(0.00136)	(0.000960)	(0.00222)	(0.00354)	(0.00216)
Observations	6,383,800	1,901,600	2,361,700	1,647,300	473,200	3,263,100	3,120,700	4,712,500	1,092,500	467,400	1,044,700
R^2	0.774	0.832	0.739	0.699	0.710	0.741	0.800	0.769	0.794	0.791	0.782

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.