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The Housing Market and Economic Inequality: An Investigation into New Zealand

A thesis
submitted in partial fulfilment
of the requirements for the degree
of
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Abstract

New Zealand has experienced unprecedented growth in house prices, rent prices, and net wealth per adult over the last three decades. This incredible growth has led to New Zealand political parties and media outlets arguing that the residential property market is driving economic inequality. Despite these claims, only a few studies have empirically tested the impact of house prices on income or wealth inequality using New Zealand data. This thesis contributes to those few studies, analysing the relationship using aggregated annual data from 1995 to 2020. This is the most extended period for any New Zealand analysis. The primary analysis approach is an autoregressive distributed lag (ARDL) model used in conjunction with a principal components analysis, both of which perform well with small sample sizes. An increase in house prices is found to decrease the wealth Gini coefficient and increase the income Gini coefficient in the short- and long-run; all else held constant.

The analysis gives evidence of heterogeneity in the relationship—different deciles experience varying changes in wealth or income share following a house price shock. Heterogeneity arises because housing-related assets are disproportionately allocated across the income and wealth distribution. The heterogeneity across deciles can lead to contrasting results for different inequality measures. Furthermore, the wealth inequality heterogeneity becomes accentuated during a negative house price shock in the short-run. This is driven by the differing ability of deciles to reshuffle their asset portfolios in response to a house price shock. However, the wealth inequality relationship becomes symmetric in the long-run, while for the income distribution, the heterogeneity is

always symmetric. A non-linear ARDL approach estimates potential asymmetries and separates the behaviours in the short- and long-run.

Previous research rarely analyses wealth and income inequality measures concurrently, while this thesis employs two strategies to do so. First, a seemingly unrelated regression is used, which has an efficiency gain when accounting for the joint disturbances. The efficiency gain yields more accurate model estimates with less variance. Second, a system of equations is utilised. Controlling for income inequality in the wealth inequality model lowers the impact of house prices on wealth inequality. However, when the simultaneity issue is mitigated, controlling for both inequality types concurrently makes minimal difference to the house price estimates. Finally, introducing loan-to-value ratio restrictions for residential property is found to have no significant impact on wealth inequality but increases the income Gini coefficient in the same period. Overall, this thesis provides valuable insights into the complex relationship between the New Zealand housing market and economic inequality.

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Disclaimer

Stats NZ has provided access to some of the data used in this study under conditions designed to give effect to the security and confidentiality provisions of the Data and Statistics Act 2022. The results presented in this study are the work of the author, not Stats NZ or individual data suppliers, nor are these results official statistics. They have been created for research purposes, with some results utilising data from the Integrated Data Infrastructure (IDI), which Stats NZ carefully manages. For more information about the IDI, please visit <https://www.stats.govt.nz/integrated-data/>.

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List of Abbreviations

Abbreviation	Definition
2SLS	Two-Stage Least-Squares Regression
AR	Autoregressive
ARDL	Autoregressive Distributed Lag
CECM	Conditional Error-Correction Model
CPI	Consumer Price Index
DL	Distributed Lag
DoF	Degrees of Freedom
ECM	Error-Correction Model
ECT	Error-Correction Term
GDP	Gross Domestic Product
GFC	Global Financial Crisis
Gini	Gini coefficient
HPI	House Price Index
IMF	International Monetary Fund
IV	Instrumental Variable
LCH	Life-Cycle Hypothesis
LR	Likelihood Ratio
LVR	Loan-to-Value Ratio
MHUD	Ministry of Housing and Urban Development
MIDAS	Mixed Data Sampling

Abbreviation	Definition
NARDL	Non-linear Autoregressive Distributed Lag
NZ	New Zealand
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PC	Principal Component
PCA	Principal Components Analysis
RBNZ	Reserve Bank of New Zealand
RDD	Regression Discontinuity Design
RDiT	Regression Discontinuity in Time
SIC	Schwarz Information Criterion
SPAR	Sales-Price Appraisal Ratio
UN	United Nations
VAR	Vector Auto Regression
WID	World Inequality Database

Chapter 1: Introduction

From 2000 to 2020, New Zealand (NZ) witnessed the highest increase in house prices among all Organisation for Economic Co-operation and Development (OECD) countries (Perry, 2021). Throughout the same period, wealth per person increased substantially; from 2015 to 2021 alone, the median net wealth per household increased by 39 per cent (Stats NZ - Tatauranga Aotearoa, 2022b). Furthermore, wealth per adult increased by 32 per cent from 2019 to 2020, approximately 60 per cent of which is attributed to rising house prices (Davies et al., 2022). Because of the high association between house prices and net wealth, media outlets and political parties regularly proposition that rising house prices are worsening wealth inequality in NZ (*Affordable housing and rent*, 2022; Corlett, 2022; Gaynor, 2016; McClure, 2021; Rashbrooke, 2014; Sabour, 2021). However, a limited amount of research directly explores this question. It remains unclear whether house prices negatively impact wealth distributions or if housing is the primary way NZers grow their net wealth.

Similar arguments are made around house prices and income inequality. From 2000 to 2020, rent prices increased by 49 per cent (OECD, 2023a), increasing housing costs for renters and revenue for landlords. Housing costs are a critical factor in NZ as 60 per cent of renters spend more than 40 per cent of their income on housing - the highest in the OECD. Because rent prices are closely related to house prices in the long-run Field (Gallin, 2008; Zhai et al., 2018), many hypothesise that rising house prices drive income inequality. However, given that income inequality has experienced relatively little change since the 1990s (Creedy et al., 2018; Perry, 2016; Wilkinson & Jeram, 2016), while house prices have experienced considerable growth, what extent is the impact of house prices on income inequality?

Income and wealth inequality are essential considerations for policymakers. Income inequality has a demonstrated association with several undesirable outcomes, such as decreased economic growth (Cingano, 2014), increased costs for the middle-class (Frank, 2007), increased rates of depression (Tibber et al., 2021), worse health outcomes (Coburn, 2015), lower happiness (Alesina et al., 2004), higher mortality rates (Smith, 1996), and a multitude of other negative impacts. Similarly, a less equitable wealth distribution is argued to impact the health and academic ability of low-income children (Bradley & Corwyn, 2002), disproportionately impact life expectancy (Montez & Zajacova, 2013; Olshansky et al., 2012), increase crime rates (Fajnzylber et al., 2002), undermine social cohesion (Goubin, 2018), and lead to a range of other negative factors (Pfeffer & Schoeni, 2016). Overall, economic inequality has many consequences for all nations; therefore, understanding its determinants is essential in mitigating inequality.

1.1 Summary of the Literature

Despite the claims of media outlets and political figures, all NZ-based research has found that house prices are negatively associated with wealth inequality. However, the number of NZ studies is scarce. Symes (2022) is the foremost analysis to examine the relationship using NZ data. Utilising the 2018 wealth distribution and a scenario-based approach, Symes finds that rising house prices lower wealth inequality. Similarly, Rashbrooke et al. (2017) found house prices to have a mildly equalising effect on asset distribution, although the authors did not explicitly consider wealth distributions. Other NZ studies have made reasonable hypotheses of housing's impact on the wealth distribution using postulates from research (Cheung, 2011; Scobie et al., 2007; Wilkinson & Jeram, 2016) but are yet to estimate these theories empirically.

When considering studies outside of NZ, it is regularly shown that rising house prices improve wealth inequality. These analyses have examined countries from the Euro area (Adam & Tzamourani, 2016; Carpentier et al., 2018), Ireland (Horan et al., 2021), Spain (Martínez-Toledano, 2020), the United States of America (US) (Bivens, 2015; Di, 2005; Kartashova & Zhou, 2021; Kuhn et al., 2020; Wolff, 2016), or a combination of developed nations (Arrigoni, 2022), and all found the same result. The aforementioned papers use various approaches but generally agree that rising house prices close the gap between the middle and top of the distribution. The relationship arises because of housing portfolio allocation across the distribution. Housing assets comprise a greater proportion of net wealth for those in the middle of the distribution than the bottom or top (Cribb et al., 2022; Rashbrooke et al., 2017; Symes, 2022).

Rising house prices simultaneously increase the gap between homeowners and non-homeowners, but not enough to offset the overall decrease in wealth inequality. Furthermore, when studies exclusively study the top and bottom of the distribution instead of an overall inequality measure, they generally find that positive house price shocks exacerbate wealth inequality (Di, 2007b; Liu & Bai, 2022; Travers et al., 2016). Therefore, alternative target groups typically result in contrasting literature findings. One question that needs greater attention in the literature is how decreasing house prices affect wealth inequality. Martínez-Toledano (2020) and Wolff (2012) are among the few studies to thoroughly compare the impacts of house prices based on the directionality of a shock. Martínez-Toledano contrasted the changes to wealth inequality following a housing boom and bust, while Wolff (2012) considered the impact of solely negative house price shocks.

Numerous studies have examined income inequality and house prices globally. Despite this, the relationship between house prices and income inequality is more contested than in papers examining wealth inequality. Furthermore, Dustmann et al. (2022) argue that the topic requires greater academic research. Only one study has utilised NZ data for the income inequality analysis, finding that the Gini coefficient and Palma ratio are more inequitable after housing costs are considered (Perry, 2016). No NZ study has used regression estimation for modelling the relationship. Outside of NZ, considerably more papers have examined the relationship using various approaches. These papers primarily argue that rising house prices exacerbate income inequality by disproportionately increasing housing-related costs across the income distribution. These include studies that focus on the US (Albouy et al., 2016), Iran (Gholipour et al., 2016), Germany (Dustmann et al., 2022), Singapore (Abeysinghe & Hao, 2014), and a panel of 57 countries (Vale & Camões, 2022).

Many other studies have considered the opposite direction of causality for the income inequality and house price relationship. Some papers have found that worsening income inequality positively affects house prices, arguing that rising income inequality will increase house prices when the housing supply is fixed in the short-run. This positive association has been demonstrated by studies using data from China (Zhang, 2015; Zhang et al., 2016) and a panel of countries (Awaworyi Churchill et al., 2023; Goda et al., 2019). However, there is a further dispute on the relationship amongst the studies that considered this direction of causality. Some studies have found income inequality: is negatively associated with house prices (Hailemariam et al., 2021; Özmen et al., 2019); is statistically unrelated to house prices (Hassani et al., 2019); has a contrasting relationship depending on the shape of the distribution (Määttänen & Terviö, 2014); or has an entirely ambiguous impact on house prices (Kim & Rhee, 2022). Ultimately, the

literature has no consensus on the mechanisms between house prices and income inequality.

Other papers have extended the housing and inequality relationship further and considered the effect of introducing/changing policies for residential properties. Specifically, some papers have examined loan-to-value ratios' (LVRs) role in economic inequality, finding conflicting results for wealth inequality (Carpantier et al., 2018; Park & Kim, 2022; Zhai et al., 2023). In contrast, three studies have examined the impact of LVRs on income inequality, all finding a positive association (Frost & van Stralen, 2018; Malovana et al., 2023; Ndou & Mokoena, 2019). Park and Kim (2022) utilise a unique regression discontinuity design (RDD) approach when considering wealth inequality and LVRs, as South Korea has a specific start date for LVR restrictions. Similarly, NZ has distinct start and stop dates for LVR restrictions, creating a unique opportunity to investigate LVRs and economic inequality using the same approach. Furthermore, studies have yet to analyse NZ solely when examining LVRs and economic inequality.

1.2 Contribution to the Literature

This thesis makes several contributions to the existing housing and inequality literature. First, it builds on the relatively small number of papers that have explored either relationship using NZ data. Additionally, it expands on the period of data utilised for any NZ analysis, specifically for house prices and wealth inequality, which have only been considered in NZ for a maximum of eight years thus far. In contrast, this study utilises data from at least 1995 to 2020. Furthermore, an autoregressive distributed lag (ARDL) approach is utilised in this thesis, which is infrequently done in the literature.

An ARDL model has the added benefit of potentially separating the relationship's short- and long-run dynamics.

Although house prices and wealth inequality have been studied in detail internationally, more attention should be paid to the impact of negative house price shocks. Therefore, this thesis contributes to a missing puzzle piece in the literature by considering asymmetries in both relationships utilising a non-linear autoregressive distributed lag (NARDL) model. Accounting for asymmetries in the short- and long-run is another advantage of using an ARDL approach. The impact of house prices on each decile is estimated across the distribution, solving the discrepancy in the literature that different target groups lead to contrasting analysis findings. Instead, the impacts for each decile are clearly shown so readers can holistically consider how house prices change each property of an inequality distribution.

This thesis also addresses a potential inconsistency in the housing and economic inequality literature. Most studies focus solely on one measure of inequality, i.e., wealth or income. However, a relationship likely exists between the two forms of inequality, especially in the long-run. Thus, rising house prices may decrease (increase) wealth inequality and increase (decrease) income inequality when considering each measure individually. However, examining the combined impact of housing may yield different results than considering them separately. Alternatively, the relationship between the two inequalities can be used for added information to the system by utilising a seemingly unrelated regression (SUR) approach. This added information can result in efficiency gains for the estimates, yielding more accurate results with decreased variance. Lastly, the implications of LVRs deserve to be explored further using the unique approach

outlined by Park and Kim (2022). Thus, the final contribution to the literature is considering how introducing LVRs affects wealth and income inequality in NZ.

Based on the previous literature and the most significant gaps in the current knowledge, the research questions this thesis aims to answer are: (i) what is the effect of house prices on income and wealth inequality in NZ? (ii) does the effect on economic inequality change for a positive or negative house price shock? (iii) what is the impact of rising (falling) house prices on each income/wealth distribution area? (iv) who are the biggest winners and losers from changing income/wealth share following a house price shock? (v) are the findings robust to concurrently considering two forms of inequality? (vi) can the estimates be improved by considering the relationship between each inequality? (vii) and, what is the impact of introducing an LVR restriction for residential properties on income and wealth inequality in NZ?

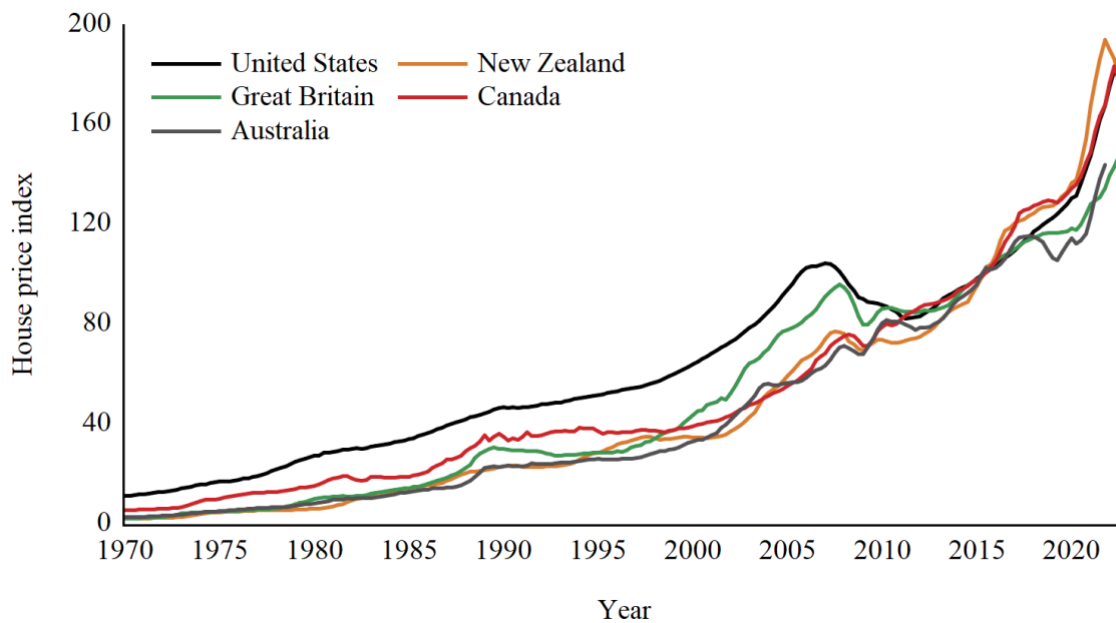
The results of this analysis are generalisable to many other nations, mainly developed countries. In 2020, NZ income inequality was highly comparable to Australia, Spain, and Switzerland (OECD, 2023c) but has historically had similar properties to Canada's income inequality (Ministry of Social Development - Te Manatū Whakahiato Ora, 2016). NZ wealth inequality over time is very similar to countries in the Euro area, Australia, and Great Britain (Ventura, 2022; *World Inequality Database*, 2023). In nominal and real terms, NZ house prices are akin to most developed nations, especially the US, Australia, Great Britain, and Canada (OECD, 2023a). This is represented in Figure 1.1, where it can be seen that NZ house prices followed a similar growth pattern from 1970 to 2022. However, house price inflation has grown the fastest in NZ compared to all these countries. Many of these countries are now experiencing a

housing downturn like NZ, which also gives the asymmetry analysis value for other nations.

The NZ housing and rental market resembles many developed countries but differs in some fundamental ways. First, compared to countries like Singapore, France, Sweden, and Germany, there is relatively limited government intervention, a greater government focus on outright ownership of housing, and relatively less regulation of the rental sector (Börsch-Supan, 1994; Holmqvist & Turner, 2014; Laferrère & Le Blanc, 2006; Murphy, 2004; Phang & Helble, 2016).

Second, property tax is mostly less stringent than in other developed countries. For instance, unlike Australia, Canada, and England, there is no capital gains or inheritance tax on owner-occupied properties (Bell, 2022b). Some argue that tax benefits are why NZers prioritise housing over other asset classes (Cheung, 2011). This potentially contributes to NZ's relatively high but decreasing homeownership rate at around 60 per cent (Stats NZ - Tatauranga Aotearoa, 2020). This homeownership rate is higher than in many other developed nations. However, despite the relatively high homeownership rates, housing affordability remains a priority, similar to many other developed countries (OECD, 2023b). Third, private landlords dominate the rental market in NZ more than in other developed countries, accounting for 85 per cent of available rental properties (Bell, 2022a). Lastly, NZ has fewer dwellings per inhabitant than the OECD average, representing a relatively low housing density (Fitchett & Jacob, 2017).

Figure 1.1: New Zealand house prices relative to four other developed nations from 1970 to 2022



Note: Data is sourced from (OECD, 2023a).

1.3 Executive Summary of Findings

House prices are demonstrated to have a statistically significant and negative impact on wealth inequality. A ten per cent increase in house prices will lead to an approximately 0.19 per cent decrease in the wealth Gini coefficient on average; all else held constant. This is robust to a wide range of different approaches and specifications. House prices lower the gap in wealth share between the top ten and bottom 40 per cent of the wealth distribution. The relationship is more complicated for the top and bottom 20 per cent of the wealth distribution. Both experience a loss in wealth share following a house price increase, but the top 20 per cent experiences a more substantial loss.

The 60 to 70 per cent of the wealth distribution experiences the greatest increase in wealth share of any decile from rising house prices, while the top ten per cent

experiences the greatest reduction in wealth share. The opposite is valid for a negative house price shock. The differing effects for each decile results from the heterogeneity of housing-related assets across the wealth distribution. However, the gain in wealth share the top ten per cent experiences from falling house prices is more prominent than their loss following increasing house prices in the short-run. This asymmetry is also present for 50 to 70 per cent of the wealth distribution. The asymmetry is driven by the ability of different deciles to adjust their portfolios in response to a house price shock.

The relationship between house prices and income inequality is more complicated than wealth inequality, similar to the wide-ranging results in the previous literature. A ten per cent increase in house prices, *ceteris paribus*, is expected to increase the income Gini coefficient by 1.2 per cent, decrease the Palma ratio by 2.1 per cent, and not affect the income share ratio between the top and bottom 20 per cent of the distribution. These differing results are partly driven by heterogeneity in the value of housing-related assets across the income distribution. Additionally, the rental market drives disproportionate housing costs for renters and an increase in income for rental owners, exacerbating income inequality. However, the relationship could be better behaved, and there appear to be additional mechanisms still to be found.

Controlling two inequalities concurrently initially makes the effect of house prices on wealth inequality smaller. However, once mitigating the simultaneity issue of the equation, there is minimal to no difference in the house price estimates. There is an accuracy gain from accounting for their common disturbances in the model. Lastly, LVRs are found to have no statistically significant impact on wealth inequality, but introducing LVRs increases the income Gini coefficient by 0.1 in the same period, all else equal.

1.4 Thesis Outline

Chapter 2 examines the literature on housing and economic inequality. Papers are broadly categorised according to the nations studied, the direction of causality analysed, and the paper findings. In addition to house prices, papers that consider LVRs, monetary policy, or other housing-related factors are considered to give a holistic overview of the housing and inequality literature. The gaps in the current literature and how this thesis contributes to the current knowledge are highlighted.

Chapter 3 then considers the best methodology to answer the research questions previously outlined. The primary issues faced for the analysis are the short period available relative to international studies and the annual frequency of the data points. To overcome this, an ARDL model, in combination with a principal component analysis and careful model selection, is used. Chapter 3 outlines the techniques utilised, why each approach was chosen, and some caveats associated with each analysis technique. Additionally, the variables used for the analysis are explicitly examined, including crucial measures such as the Gini coefficient (henceforth, Gini). Furthermore, the trends of house prices and inequality in NZ over time are discussed.

Chapter 4 breaks down the income inequality and house price findings. The relationship concerning rent prices and property value heterogeneity across the income distribution is considered to explore potential mechanisms. Finally, the impact of LVRs on income inequality is discussed. Chapter 5 considers the house price and wealth inequality results and shows that findings are highly robust to alternative specifications. The heterogeneity of the impact across the wealth distribution is estimated, followed by considering house price decreases instead of positive house price shocks.

Chapter 6 expands on the findings discussed throughout Chapter 4 and Chapter 5 in two unique ways. First, the joint disturbances of the error terms are accounted for to achieve an accuracy gain for the estimates. Second, a system of equations is used where income inequality is an explanatory variable in the wealth inequality model. A two-stage least-squares regression (2SLS) with a Bartik instrument mitigates the potential endogeneity issue of this equation. A robust sensitivity analysis ensures that concurrently considering two inequality measures via either approach is valid. Furthermore, the IVs are examined to determine how adequately they mitigate potential endogeneity. Finally, Chapter 7 summarises all of the findings across the whole analysis. Each research question is answered along with the implications of these findings. Finally, suggestions are given on where future research should focus in light of these results.

Chapter 2: Relevant Literature

2.1 Introduction

The trends, causes and consequences of inequality, both for individual countries and worldwide, have been the subject of many academic articles in recent years (Alfani, 2021; Blau et al., 2021; Clark et al., 2021; Ibrahim, 2022; Piketty, 2018; Valero, 2022). In NZ, inequality is a politicised topic that receives frequent attention from the media. Wilkinson and Jeram (2016) have highlighted that the number of articles from NZ media outlets discussing inequality has skyrocketed. This frequent attention may be why the public perceives income inequality as too high in NZ and continuing to worsen (Kolandai et al., 2022). That is despite the level of income inequality increasing very little, as although NZ's income inequality increased in the late 1980s and early 1990s, it has experienced relatively little change since (Creedy et al., 2018; Perry, 2016; Wilkinson & Jeram, 2016). However, it would be incorrect to imply that inequality is not an essential consideration for NZ. Several authors have demonstrated costs for more inequitable countries. For example, Frank (2007) showed that higher income inequality increases competition for positional goods, harming the middle class by increasing psychological and tangible costs. Furthermore, Cingano (2014) demonstrated a statistically significant negative relationship between income inequality and growth. Cingano estimated that rising inequality from 1985 to 2005 decreased NZ's growth rate by over ten per cent cumulatively from 1990 to 2010.

The NZ housing market has also been of rising focus in academia. This is primarily because of the significant house price increases seen over the previous decades, far above the long-run sustainable level (RBNZ, 2021a). These NZ academic articles

primarily focus on rising house prices, increasing housing expenditure, housing affordability, homeownership rates, the effect on well-being, and the difference between renters and homeowners (Barker, 2019; Bentley, 2021; Irwin & Irwin, 2018; Law & Meehan, 2013; Perry, 2021; Thorns, 2009). Only a few studies have directly explored the relationship between housing and inequality using NZ data (Rashbrooke et al., 2017; Symes, 2022), despite the importance of both topics. Even with little academic analysis of the relationship, there are regular claims from NZ political parties and media outlets that rising house prices are worsening inequality (*Affordable housing and rent*, 2022; Gaynor, 2016; McClure, 2021; Rashbrooke, 2014; Sabour, 2021), but what research there is to date does not support that claim.

This chapter analyses what the current literature has found when conducting empirical investigations of the housing and economic inequality relationship. First, the relationship between house prices and wealth inequality is explored in section 2.2. This is for studies utilising NZ and international data in sections 2.2.1 and 2.2.2, respectively. Next, section 2.3 considers papers that examine the house price and income inequality relationship. This is broken down by the papers finding that rising house prices worsen income inequality, followed by papers demonstrating the opposite direction of causality in section 2.3.1.

Section 2.4 outlines research that explicitly considers the impact of monetary policy on income and wealth inequality through the asset price inflation channel. In section 2.5, papers related to the housing market and inequality, but not explicitly the house price and inequality relationship, are discussed—factors including credit-risk guarantees, housing affordability, intergenerational wealth transfers, welfare, and homeownership rates. Finally, the previous literature is briefly summarised; the primary contributions of

this thesis to the current literature are accentuated, and the outline of the remaining chapters is given in section 2.6.

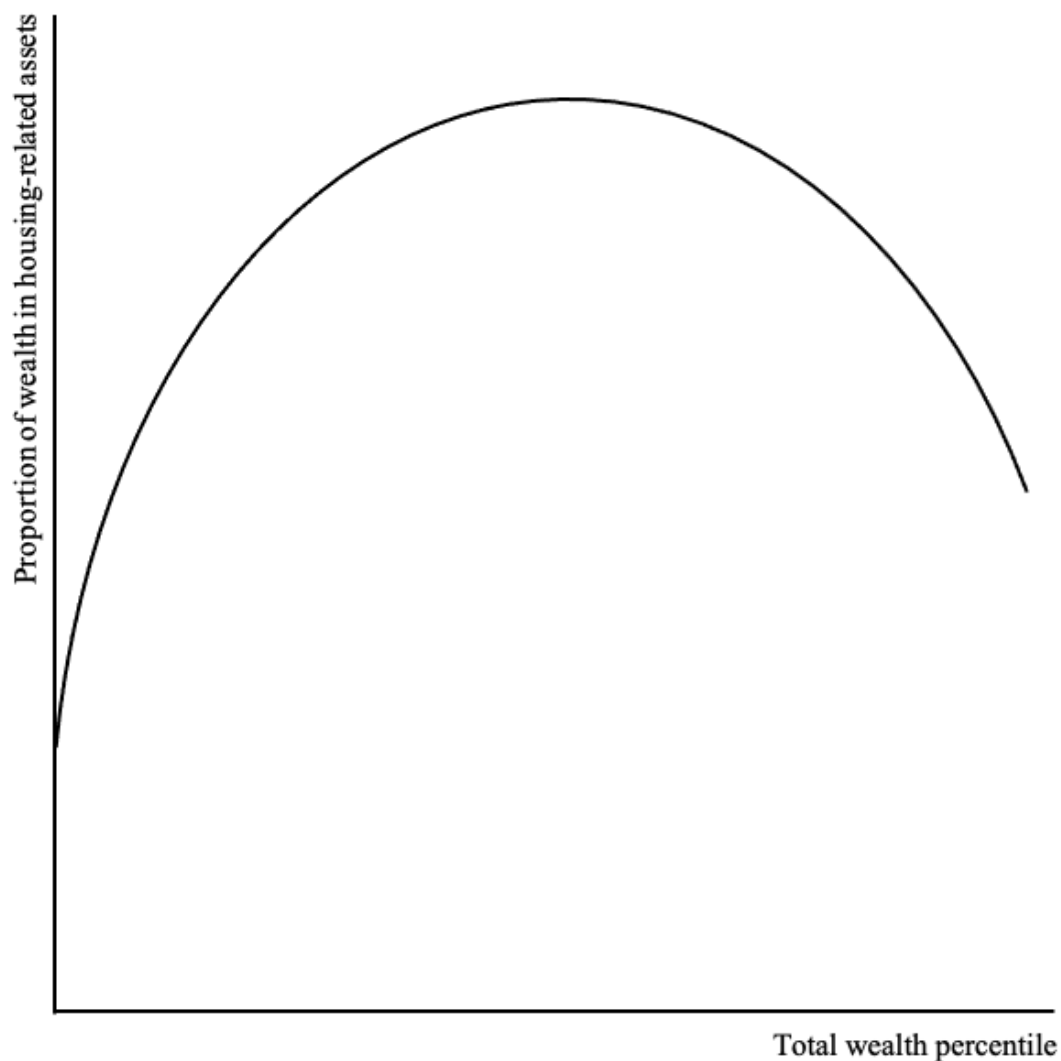
2.2 Wealth Inequality

Numerous studies have demonstrated an inverse association between house prices and wealth inequality. There are varying theoretical explanations for the association discussed throughout this section. Still, one of the most common explanations is the stark difference in portfolio allocation across wealth distributions. In advanced countries, those in the middle of the wealth distribution generally own the most significant proportion of net wealth in housing-related assets. In contrast, the wealthiest typically hold a more substantial percentage of net wealth in non-housing assets, such as equities and bonds. Furthermore, the least affluent generally have lower homeownership rates than those in the middle of the distribution. This creates a curved relationship of housing assets across the wealth distribution; the curve approximates the shape of an inverted U or J, depending on the specific characteristics of the distribution. For brevity, this will be referred to as the inverted U-curve relationship from now on. However, it is worth noting that the relationship between housing assets and wealth distributions is only sometimes presented as an inverted U-curve in the literature. This thesis incorporates the concept for a more straightforward discussion of portfolio allocations.

The approximate relationship of housing-related assets across the wealth distribution is represented in Figure 2.1. It is argued that house price increases primarily benefit the middle of the wealth distribution, with the highest proportion of wealth in housing-related assets. This decreases the gap between the middle of the wealth distribution and the top. It also increases the gap between homeowners and non-homeowners, but by a

comparatively smaller amount than the equalising impact in the middle of the distribution, leading to an overall decrease in wealth inequality. The empirical evidence from varying studies to support this theory is discussed throughout the rest of section 2.2.

Figure 2.1: The approximate relationship of wealth in housing-related relative to all assets across the net wealth distribution



Note: This diagram does not represent the actual values of any country. Instead, it is an approximated shape of housing-related assets across the wealth distribution. The curve is based on previous research papers for various developed countries.

It is important to note that those at the upper end of the wealth distribution, with a more significant proportion of wealth in non-housing related assets, have more liquidity in their household portfolio as bonds and equities are comparatively easier to convert to cash than housing¹ (Boar et al., 2022; Rashbrooke et al., 2017). This is because there are relatively higher transaction costs associated with selling housing assets, such as property taxes, real estate agent fees, lawyer fees, and closing costs. Furthermore, there is an associated time cost, as selling housing-related assets is relatively more time-consuming.

2.2.1 New Zealand Studies

A few studies have identified a negative association between house prices and wealth inequality using NZ data. Symes (2022) used a scenario-based approach to show that increasing house prices decreased overall national wealth inequality. Homeownership makes up a large proportion of NZ's wealth, with over 60 per cent of NZers owning their own home (Scobie et al., 2007; Stats NZ - Tataurangi Aotearoa, 2020; Symes, 2022). Still, Symes (2022) shows differences in the make-up of portfolios across the wealth distribution, demonstrating the inverted U-curve relationship. Symes theorises that increases in house prices close the gap between those in the middle and upper ends of the wealth distribution. While house prices also increase the gap between homeowners and non-homeowners, this is a comparatively smaller amount, ultimately

¹ Another consequence of the inverted U-curve relationship is that increases in other asset prices can worsen wealth inequality. For example, an increase in the value of equities will disproportionately benefit those at the higher end of the wealth distribution with a relatively larger proportion of equities in their portfolio. This results in a widening of the wealth gap between those at the bottom and the middle of the wealth distribution, and those at the top, ultimately increasing wealth inequality (Adam & Tzamourani, 2016; Bivens, 2015; Domanski et al., 2016; Kartashova & Zhou, 2021; Kuhn et al., 2020; O'Farrell & Rawdanowicz, 2017). While equity wealth is not a primary focus of this analysis, policymakers should be aware of this relationship.

decreasing national inequality overall. Symes estimated that a ten per cent increase in house prices results in a 0.7 per cent decrease in the wealth Gini on average. Symes also notes that he aims to explore this topic again in 2022, as the available data did not include the significant house price inflation from 2018 onwards. This thesis expands on Symes's sample period but not as far as 2020.

Rashbrooke et al. (2017) also demonstrated the inverted U-curve relationship with the wealthiest NZers owning a significant proportion of equities compared to housing-related assets. Rashbrooke et al. found that increasing house prices has a mildly equalising effect on the asset distribution in NZ. Wilkinson and Jeram (2016) primarily investigated house price increases' impact on income inequality and found a positive association. However, Wilkinson and Jeram also argue that worsening income inequality would “have probably exacerbated wealth inequality” (Wilkinson & Jeram, 2016, p. 3). Still, they did not conduct any empirical analysis to verify that claim, making inferences from their study difficult.

Scobie et al. (2007) found that because housing makes up a large share of household wealth in NZ, house price increases lead to wealth increases. The study did not specifically explore wealth inequality. Cheung (2011) also highlights that a large share of wealth in NZ comprises housing-related assets, arguing that tax incentives bias housing to be a more favourable form of savings/investment. The bias towards housing results in increased competition and therefore increases house prices; Cheung argues this substantiates wealth inequality by allowing those higher up on the distribution to own larger homes but worsens housing affordability for the rest of the wealth distribution.

2.2.2 International Studies

A considerable amount of literature on the housing and inequality relationship has been published using data from outside NZ, with numerous studies arguing that house price increases lead to improvements in wealth inequality. When considering the Euro area, Adam and Tzamourani (2016) found the same inverted U-shape for home ownership across the wealth distribution. Therefore, Adam and Tzamourani demonstrated that house price increases lead to decreases in overall wealth inequality. Similarly, Carpentier et al. (2018) considered twelve Euro-zone countries, finding that house price increases are negatively associated with wealth inequality.

Arrigoni (2022) found similar results when looking at the United States, United Kingdom, and France; gains in house prices primarily equalise wealth distributions. When also looking at the United Kingdom, Cribb et al. (2022) find that increasing house prices primarily benefits those in the middle of the wealth distribution. However, Cribb et al. (2022) note that because middle- and high-income families typically own the majority of housing, increased house prices increase the gap between the poorest and the rest. O'Farrell and Rawdanowicz (2017) examine North America and Europe and also show that house price increases are generally associated with decreases in wealth inequality. However, O'Farrell and Rawdanowicz (2017) emphasise that the impact depends on the net wealth distribution shape.

Many studies focus on only one country, limiting the generalisability of the results. Using data for Ireland, Horan et al. (2021) found that higher house prices are associated with improvements in wealth inequality. Meijers and Muysken (2022) investigated the Netherlands but only focussed on equality amongst the top 50 per cent of the wealth

distribution (i.e., primarily homeowners). However, they found that house price increases led to decreased inequality amongst this group. Therefore, Meijers and Muysken find similar equalising impacts of house prices when considering an alternative measure of wealth inequality.

Martínez-Toledano (2020) used Spanish data to demonstrate that house price increases are correlated with lowering wealth inequality. Martínez-Toledano expands on the literature by considering positive and negative shocks. Martínez-Toledano showed that despite the housing market's booms and busts from 1984 to 2013, wealth inequality in Spain remained relatively constant or increased slightly. Martínez-Toledano argues that wealthy individuals reshuffle their portfolios to contain more or less housing assets depending on the housing price movements. Preceding a bubble burst, housing concentration rose primarily due to wealthy individuals acquiring secondary dwellings. Housing concentration decreased following the burst as wealthy individuals converted housing-related assets to cash. Martínez-Toledano argues that this portfolio reshuffling offsets the positive effect of housing price increases on wealth inequality, leading to it remaining constant over time in a Spanish setting.

When using data from the United States of America (US), numerous studies found the inverted U-curve relationship, with the wealthiest Americans typically owning equities over housing-related assets. Thus, these studies showed that house price increases primarily help those in the middle of the distribution, resulting in improvements in wealth inequality (Bivens, 2015; Di, 2005; Kartashova & Zhou, 2021; Kuhn et al., 2020; Wolff, 2016). Wolff (2012) explicitly considered how shocks to the housing market impact wealth inequality. Wolff showed that house price decreases resulting from the Great Recession and GFC considerably impacted the American middle class,

worsening wealth inequality. Wolff later conducted research in 2017, which showed that mean wealth in America surpassed the previous peak before the GFC, but median wealth did not recover to the same point as previously (Wolff, 2017).

2.2.2.1 Worsening Wealth Inequality

Some studies have suggested that house price increases are associated with worsening wealth inequality. Looking at the United Kingdom and Sweden, Christophers (2019) argues that house price inflation worsens wealth inequality primarily because homeownership is decreasing. However, this study could be more extensive in its use of empirical analysis. Using data for London, Travers et al. (2016) argue that house price increases substantiate the difference in wealth between homeowners and non-homeowners, worsening wealth inequality. Liu and Bai (2022) found similar results when considering China. The authors argue that because the wealthiest members of a country typically own more housing than the poorest, house price increases lead to a more significant gap between the richest and poorest of a country, worsening wealth inequality overall. However, Q. Liu and Bai do not directly provide a robust analysis to support this hypothesis, limiting the validity of their argument.

The studies above are limited in the data used to support their arguments. However, other studies provide more robust evidence that higher house prices may worsen wealth inequality. These studies primarily examine the US, such as Di (2007b), who demonstrates that house price increases primarily exacerbate the wealth gap in the US. Di finds that house price increases result in wealth gains that disproportionately benefit the wealthiest Americans, ultimately widening the wealth gap. The difference in Di's findings from the previous section likely stems from a difference in the target groups of

the analysis. Therefore, considering alternative properties of wealth distributions may yield contrasting results. Furthermore, Di notes that housing wealth is more evenly distributed than other asset types. Wolff (2022) found that the rate of return, such as capital gains from housing assets, varies across the wealth distribution in the US. The wealthy benefit disproportionately from housing returns compared to middle-class or lower-income households. Wolff's study provides evidence that wealth distributions become more inequitable over the long term due to housing.

Wan and Knight (2023) examined China's housing wealth and, similarly to US studies, argued that rising house prices worsen wealth inequality. In contrast to other studies, the authors considered a decrease in house prices, explicitly finding that slowing house price inflation leads to wealth inequality growing slower than the counterfactual scenario. Therefore, the authors argue that faster house price growth would lead to wealth inequality worsening at a quicker rate, as seen in the periods before the paper's analysis.

2.3 Income Inequality

Many studies have explored the relationship between house prices and income inequality, with several studies suggesting that rising house prices worsen income inequality (Albouy et al., 2016; Dustmann et al., 2022; Grossmann et al., 2021; Travers et al., 2016; Vale & Camões, 2022). These authors typically identified that rising house prices lead to increased housing costs. Rental prices primarily drive this as they are highly correlated to house prices. Rising rental costs disproportionately impact lower-income individuals, who comprise a comparatively larger proportion of renters. Additionally, individuals higher up the income distribution generally own a larger share

of rental properties, meaning they benefit disproportionately from the additional rental income. Consequently, due to rising house prices, lower-income households devote more of their income to housing while higher-income households devote less (Grossmann et al., 2021), thus worsening real-income inequality overall.

Housing costs are an essential consideration in NZ, where 60 per cent of renters spend more than 40 per cent of their income on housing, the highest in the OECD (Perry, 2021). However, Perry (2016) is the only study to provide empirical evidence that house prices impact income inequality using NZ data. Perry found that house price increases result in disproportionately rising housing costs, worsening income inequality. The author calculated a Gini and Palma ratio before and after housing costs were considered to prove this.

More studies have examined income inequality and house prices using international data. Vale and Camões (2022) examine 57 countries over twenty years, finding that real and nominal house price increases lead to rising income inequality. The authors note that the impact depends on the portfolio allocation across the distribution and the wealth effect of higher house prices. Therefore, different effects are seen depending on the specific countries' factors. Potentially related to portfolio allocations, Abeysinghe and Hao (2014) found that rising house prices have a small but statistically significant impact on only some properties of the income distribution when considering Singapore. Specifically, the ratio of income shares for the top and bottom ten per cent of the income distribution decreased following rising house prices. In contrast, the authors found house prices to have no significant impact on the ratio of income shares for the top ten and bottom 20 per cent of the income distribution.

Albouy et al. (2016) expanded on the literature when examining the US by showing that rising house prices hit low-income earners twice—increasing rent expenditure and worsening housing affordability simultaneously. This can make it difficult for low-income earners to save for a large enough deposit to become homeowners and decrease their housing expenditures. Zheng et al. (2022) also examined the US but utilised a fixed effects model instead. Similarly to Albouy et al., Zheng et al. (2022) argued that increasing house prices lead to more inequitable income distributions. However, Zheng et al. omit that house prices are not a significant predictor of the income Gini variable in their regression. Instead, they find that house price increases lead to an increase in the income share of the top five and ten per cent of the income distribution. Because Zheng et al. (2022) do not consider the income share of any other decile in the distribution, it is hard to reliably conclude from their study that higher house prices lead to worsening income inequality. Instead, Zheng et al. contribute to the literature by demonstrating that top-income earners benefit from higher house prices. Furthermore, the authors' approach of predicting income shares of different quantiles across the distribution is a vital regression technique for the literature and should be used in this thesis. Vale and Camões (2022) also use this technique to address limitations associated with the Gini.

Focussing on Iran, Gholipour et al. (2016) found that increased housing costs lead to increased income inequality. The authors argue that because housing costs are highly associated with property prices, an increase in house prices leads to a worsening income distribution. Gholipour et al. expand on the literature by noting three other primary factors when property prices increase—first, intergenerational impacts. The wealthiest and poorest households become more separated over the long term as renters cannot afford rising house prices. Second, reducing migration across regions leads to disproportionate skill and productivity levels throughout a nation. Finally, a

concentration of wealth, as those with housing (particularly those who own rentals) receive a greater return from their assets than non-homeowners, eventually impacting wealth inequality. Gholipour et al. demonstrate that the impacts of residential property prices can be significant in a country over time. Ahmadzadeh et al. (2023) also focussed on Iran and found that rising house prices worsen income inequality.

Dustmann et al. (2022) studied Germany and expanded on the literature by showing that younger cohorts are spending more on housing costs than older generations at the same age. Dustmann et al. theorises that this will affect future generations' wealth accumulation and particularly impact low-income earners. Additionally, Dustmann et al. calculate income inequality measures before and after housing costs are accounted for, which needs to be done more in the inequality literature. When first beginning the research in 2018, the authors noted that the housing and income inequality relationship had received little attention in the academic literature, and there needs to be more evidence of the relationship (Dustmann et al., 2018).

2.3.1 Reverse Causality

The nature of the income inequality and house price association is contentious in the literature. Other studies have considered the opposite direction of causality by examining income inequality's effect on house prices. Many of these studies focussed on a group of countries, such as Hailemariam et al. (2021), who conducted a detailed examination of 17 OECD countries over 145 years. They demonstrate that increased income inequality significantly decreases real-house prices, all else being equal. Hailemariam et al. theorises that income inequality leads to higher theft, which is the mechanism to devalue property due to inherently greater risk. Goda et al. (2019) found

contrasting results when exploring 18 OECD countries over 35 years. They find a statistically significant cointegration relationship between absolute inequality and house prices. The authors argue that rising absolute inequality raises the total demand for houses in a market with limited supply, driving up house prices. They also demonstrate that relative inequality is not cointegrated with house prices, which the authors argue is expected. Similarly to Goda et al., Awaworyi Churchill et al. (2023) find that rising income inequality positively impacts house prices when considering a group of G7 countries over 246 years.

Other studies focused solely on one nation, like Zhang (2015), who found that higher income inequality is associated with higher house prices using Chinese data across 186 cities. When conducting a similar study on the same dataset a year later, the authors demonstrated that higher income inequality is correlated to increases in the house value-to-income (price-to-income) ratio (Zhang et al., 2016). However, Özmen et al. (2019) used four years of data from Turkey and found a negative association. Moreover, the authors find that the effect differs across the income distribution; income shares in the bottom three quintiles are positively related to housing prices, and income shares in the top quintile are negatively associated. Määttänen and Terviö (2014) also concluded that the effect of income inequality on house prices is dependent on distributions. Määttänen and Terviö utilised a unique assignment model approach where each household owns one house and wants to live in one house. Thus, every household is a potential buyer and seller. The authors did demonstrate that income inequality across six metropolitan areas in the US from 1998 to 2007 was negatively associated with house prices.

Kim and Rhee (2022) found an ambiguous relationship between house prices and income inequality, showing that the effect depends on the country's redistribution

policies. House price increases will worsen income inequality for countries with weak redistribution policies; in contrast, increasing house prices will have no effect if the country has strong redistribution policies². Finally, Hassani et al. (2019) examined the United Kingdom over 46 years and found no evidence of causality between income inequality and house prices. This further contributes to a wide range of results found when examining the relationship.

2.4 Monetary Policy

A few studies have explored monetary policy's role on house prices and subsequent inequality with varying results. O'Farrell and Rawdanowicz (2017) examined advanced countries. The authors demonstrated that lowering interest rates (expansionary monetary policy) generally makes mortgages more accessible to service, thus, increasing house prices and reducing wealth inequality. However, other asset channels worsen wealth inequality, such as increases in the price of bonds and equities. This means that monetary policy has an ambiguous impact on inequality and depends on the relative size and shapes of the distributions. Based on the findings of O'Farrell and Rawdanowicz, the shape of the inverted U-curve for each nation would change the housing and economic inequality relationship.

² Interestingly, the NZ public is an outlier compared to other OECD countries, being considerably less in favour of redistribution policies than expected, given the country's income and wealth inequality levels (Nel, 2022). Ansell and Cansunar (2021) found that as housing affordability worsens in a country, the general public becomes less supportive of redistributive policies and the government intervening in the housing market. Therefore, worsening housing affordability could be a factor in the surprisingly low support for redistributive policies in NZ; there is potential for future research on this topic, which unfortunately could not be explored during this thesis.

Similarly, Domanski et al. (2016) considered advanced countries and found that the low-interest rates since the GFC have raised house prices, improving wealth inequality. However, this only slightly offsets the effects of higher equity prices, which is one of the primary factors in worsening wealth inequality. Therefore, the overall impact of expansionary monetary policy on wealth inequality is negligible or at least increasing. Bivens (2015) had previously found a very similar result; the large-scale asset purchases by the Federal Reserve in the US worsened wealth inequality through equities increasing but improved wealth inequality when house prices rose. Lenza and Slacalek (2018) also found monetary policy to have minimal effect on wealth inequality, while De Luigi et al. (2023) found it depends on the measure of wealth inequality. August et al. (2022) found that homeowners and investors, typically more affluent in Canada, primarily benefit from expansionary monetary policy. In contrast to the more nuanced findings of other studies, August et al. (2022) primarily argue that expansionary monetary policy leads to more inequitable wealth distributions.

Other studies looked solely at how monetary policy affects income inequality. Leroy and El Herradi (2019) concluded that expansionary monetary policy strongly worsens income inequality when controlling for factors over 100 years. Leroy and El Herradi demonstrated quantitative easing and low-interest rates to have a moderately worsening effect on income inequality, despite some positive impacts on employment and mortgage refinancing. Mendes (2022) and de Sousa Vale (2022) support the findings of Leroy and El Herradi. In contrast, some papers have found that quantitative easing and expansionary monetary policy improve income inequality (Lennartz, 2022; Lenza & Slacalek, 2018; Samarina & Nguyen, 2019).

2.5 Housing Factors

Several studies looked at other aspects related to the housing market and inequality. Carpentier et al. (2018) added to the literature by considering macroprudential policy in twelve Euro-zone countries. Carpentier et al. demonstrate that high LVRs when acquiring a mortgage are associated with significantly positive gains in wealth inequality. Park and Kim (2022) support this finding using an RDD with South Korean data—a higher LVR is associated with narrowing the wealth distribution. In contrast, Zhai et al. (2023) find asymmetries in the LVR and wealth inequality relationship. When the return on housing-related assets is higher than equities, LVRs generally reduce wealth inequality. When the opposite is true, LVRs generally positively affect wealth inequality. These are among the few studies to consider the role of LVRs on wealth inequality.

Furthermore, only some studies have considered the relationship between LVRs and income inequality. Frost and van Stralen (2018) found that LVRs increase income inequality when examining a large panel of countries. Malovana et al. (2023) support this finding when using a different panel of countries, demonstrating that increasing LVRs by five percentage points from the baseline increased income inequality within five years. The increase in income inequality becomes further accentuated after seven years after the initial tightening of the policy. Ndou and Mokoena (2019) support the other studies' findings but consider the opposite direction of policy intervention in their analysis of South Africa. Ndou and Mokoena show that loosening LVR restrictions slows the growth of income inequality.

Many studies have demonstrated that higher homeownership rates are associated with decreasing wealth inequality (Horan et al., 2021; Kaas et al., 2019; Kuhn & Grabka, 2018). This is driven by the inverted U-curve relationship and the fact that homeowners accumulate relatively more wealth over time than non-homeowners (Di et al., 2007; Mathä et al., 2017). Foster and Kleit (2014) show that increasing homeownership rates in the US equalise wealth inequality, but housing affordability problems undermine this. Therefore, the equalising effects of homeownership seen throughout the 1980s and 1990s are no longer prevalent today when housing affordability is a more significant problem. Ultimately, the authors could not conclude the causal impact because of too many societal factors that could not be controlled for.

Many papers have considered the effect of house prices on net wealth instead of wealth inequality. This includes Fuller et al. (2020), who used data from 13 OECD countries to show that house price increases lead to increases in the wealth-to-income ratio in both the short and long term. This closely matches Baselgia and Martínez (2022), who use a panel of twelve OECD countries to show the same effect of house prices on the wealth-to-income ratio.

Di (2007a) found that homeowners will have higher future incomes than non-homeowners. They looked at the US and found this effect while also finding that the longer the period of homeownership, the greater the magnitude of this effect. Di (2007a) did not specifically explore income inequality, and the impact of homeownership on income inequality would likely depend on the proportion of housing assets in portfolios across the income distribution. Related to the work of Di (2007a), Causa et al. (2019) explored all of the OECD countries to uncover a potential relationship between housing and wealth accumulation. Causa et al. made two critical findings. First, countries with

high homeownership rates typically have high ownership among low-income earners, which other studies have found beneficial for distributions. Second, countries with large amounts of mortgage debt generally have high levels of wealth inequality, particularly affecting the lowest-income earners.

2.6 Summary

Many international studies have examined the relationship between house prices and economic inequality. For wealth inequality, the results generally support the theory that rising house prices have an equalising effect on wealth distributions. In contrast, the empirical results for income inequality are less concordant but slightly favour the theory that house prices worsen income inequality. When considering NZ, only some studies have empirically examined the house price and economic inequality relationship. Table 2.1 summarises the papers providing clear empirical evidence of the relationship between house prices and economic inequality using NZ data.

Table 2.1: A summary of NZ papers to empirically explore the housing and economic inequality relationship

Author	Measure	Approach	Data	Findings
Symes (2022)	Wealth Gini.	Scenario based.	2018 wealth distribution.	A 10% increase in house prices leads to a 0.7% decrease in the wealth Gini.
Rashbrooke et al. (2017)	The asset distribution.	Analysed wealth holdings across quantiles.	2002 to 2010 longitudinal data.	Rising house prices has a mildly equalising effect to the asset distribution.
Perry (2016)	Income Gini and Palma ratio.	Considered inequality before and after housing costs.	1982 to 2015 aggregated data.	The Gini and Palma ratio are higher when housing costs are taken into account.

This thesis contributes to the relatively small number of NZ papers examining the house price and economic inequality relationship. Additionally, many approaches and theoretical channels examined in the international literature are applied to the NZ relationship. Data analysis techniques are carefully selected to effectively capture the complex relationship between variables, with new approaches applied where value is added to the current literature. An overview of the methodology can be found in the following chapter, including the positives and negatives of the analysis approaches. In Chapter 4, the results of the income inequality analysis are presented and discussed, while the wealth inequality analysis is covered in Chapter 5. Additionally, the two dependent variables were considered concurrently in Chapter 6, followed by a summary of all the thesis findings in Chapter 7.

Chapter 3: Data and Methodology

3.1 Introduction

Hoover (1995) argues that methodology is a crucial component of all economic research and something that no economist is exempt from. Lousy research comes from economists who underestimate the importance of methodology. Thus, considering the best methodological approach before undertaking research is essential to robust and valid economic results. In the case of this thesis, a theoretical link between house prices and LVRs with economic inequality has already been established in the previous literature, as discussed in the previous chapter. Therefore, an appropriate methodological approach is required to test the empirical validity of this theoretical relationship in an NZ environment and make new developments on the earlier works. This means treating the data effectively and building correctly specified models with the most suitable techniques for the research goal. That can be easier said than done, but highly critical, as the data analysis methods used by researchers have become of growing importance when considering research results (Fidler & Gordon, 2013; Head et al., 2015; Nasrullah et al., 2021).

The primary issues for the analysis were the short data period available and the low frequency of some data. In particular, reliable inequality data in NZ is only available annually, limiting the number of observations that can be included in the analysis. This chapter focuses on the specific analysis techniques used to overcome these challenges as best as possible. Section 3.2.3 analyses the possible methods used to deal with the different frequencies of variables. Careful model specification was used to avoid overfitting for a short time—specifically, the selection of control variables is based on

their explanatory power from previous research. This is discussed more in-depth throughout section 3.2.2. Similarly, a principal components analysis is used to reduce the dataset's dimensionality and mitigate the multicollinearity of the variables; this is considered in section 3.2.3.1.

All the modelling techniques are outlined, including the critical assumptions of these techniques, and the models' robustness/sensitivity testing techniques are considered. All decisions are explained as to why each approach is suitable for the specific circumstances of this thesis and analysing the available data in a way that will yield reliable results. Specifically, the ARDL modelling technique tests cointegration relationships between variables and has performed well with small sample sizes. ARDL models are discussed throughout section 3.3.1. NARDL models allow for highlighting potential asymmetries in a relationship and separating these behaviours for the short- and long-run; NARDL models are considered in section 3.3.1.1. Models in the previous literature are expanded upon by considering wealth and income inequality concurrently. Two approaches are utilised to handle this specification, the SUR and the 2SLS, which are considered in sections 3.3.3 and 3.3.4, respectively.

3.2 Data

The data used in the analysis has been compiled from The World Inequality Database (WID), CoreLogic NZ, The World Bank, The Reserve Bank of NZ - Te Pūtea Matua (RBNZ), The OECD, The United Nations (UN), The International Monetary Fund (IMF), and the Statistics NZ (Stats NZ) Integrated Data Infrastructure (IDI). Some of the critical data is available back to 1950. However, many key control variables do not date this far, and wealth inequality data is only available from 1995 onwards. As such,

the income inequality relationship is examined from 1990 to 2020, while the wealth inequality relationship is analysed from 1995 to 2020.

3.2.1 Primary Variables Specifications

The primary measure of inequality utilised is the Gini, which is based on the work of Lorenz (1905) and Gini (1912). The Gini measures the extent a distribution deviates from perfect equality. The Gini's takes on a value between zero and 100 per cent, where zero is perfect equality, and 100 is perfect inequality. The Gini is a famous and widely accepted measure of inequality globally in economics and other fields. Its popularity is regularly attributed to its many desirable properties, such as interpretive simplicity and flexibility in different applications (Giorgi & Gigliarano, 2017; Mukhopadhyay & Sengupta, 2021; Witlox, 2016). However, the Gini is often criticised as well, primarily for: the inability to directly compare Gini's that measure different distributions (Ceriani & Verme, 2012); that starkly different looking distribution can have the same Gini (Liu & Gastwirth, 2020); and that the Gini is overly sensitive to changes in the middle of the distribution and less sensitive to changes in the tails of a distribution³ (Sitthiyot & Holasut, 2020).

Because of the criticism associated with the Gini, Liu and Gastwirth (2020) recommend utilising other inequality measures in research alongside the Gini. For this thesis, the alternative measures used were the Palma ratio, which considers the income/wealth share of the top ten per cent compared to the bottom 40 per cent of the distribution.

³ It should be noted that the Gini coefficient being less sensitive to changes in the middle of the distribution is widely reported in the literature. However, this claim has become more contested following the research of Gastwirth (2017).

Additionally, the S80S20 ratio, which measures the ratio of income/wealth shared between the top 20 and the bottom 20 per cent of a distribution. Utilising these measures alongside the Gini analysis will give a wide range of sensitivities to different income and wealth distribution properties. Furthermore, the alternative measures serve as a helpful robustness check of the Gini results and can be compared to other studies that have utilised these measures.

The additional inequality measures as a robustness check are crucial in this research. This is because the theoretical relationship established in the previous literature arises due to heterogeneity in housing wealth across the income and wealth distribution. Therefore, because of this heterogeneity, predicting different inequality measures could have starkly different magnitudes and contrasting signs for the house price variable. It is important to get a clear picture of where the heterogeneity is present and which deciles are impacted most by house price changes. Therefore, to estimate this, each decile's income/wealth share in the distribution is also used as a dependent variable alongside the three inequality measures. This is similar to Zheng et al. (2022), except all ten deciles are predicted, not only the top few. Because inequality changes result from distribution changes, this model predicting income/wealth share still makes theoretical sense and works with the same assumptions as predicting the other inequality measures. Therefore, all of the same control variables can be utilised.

The house price variable is based on a sales-price to appraisal ratio (SPAR). The SPAR utilises the idea that property-specific information will be accounted for in the appraisal price of a property; therefore, while an influx of high- or low-quality houses being sold may unfairly bias the median price in a particular month, this would be accounted for by dividing all sales values by the appraisal price (Armstrong et al., 2017). Thus, sales

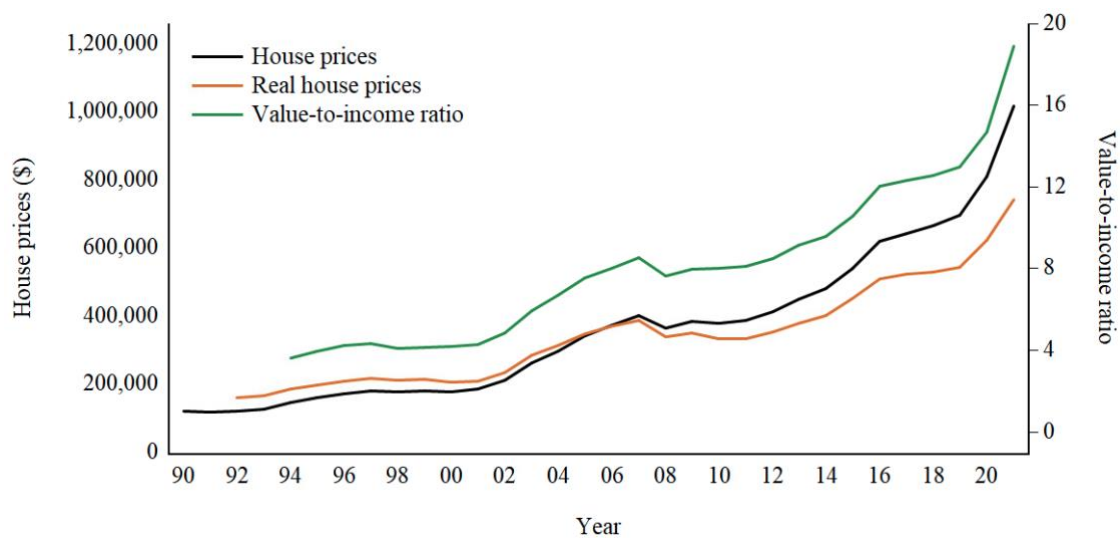
quality changes will not bias the house price statistics when using a SPAR. The SPAR has become a common alternative to the typical house price indexes (HPI) such as hedonic regression or repeat sales. It is used explicitly in NZ but has become commonplace in some Scandinavian countries as well (Shi, 2008). Because of its limited use globally, only a few papers have studied the SPAR. However, it is spoken favourably about in research by Armstrong et al. (2017) and Haan et al. (2009). Because of this positive research and the commonplace of the SPAR in NZ works, the SPAR was utilised as the house price variable for this thesis.

For additional sensitivity and robustness checks, the SPAR was also adjusted for inflation to create a house price measured in real terms variable. This is an essential consideration given the record high inflation rates NZ has recently seen (Stats NZ - Tātauranga Aotearoa, 2022a). Additionally, the SPAR values were divided by income to generate a primary housing affordability measure, the value-to-income ratio. As the Ministry of Housing and Urban Development - Te Tūāpapa Kura Kāinga (henceforth, MHUD) (2022) outlines, this is the most simple but easily interpretable measure of housing affordability. It would be more desirable to use MHUD's more comprehensive indicators that take into account mortgage deposit affordability, mortgage serviceability, and rent prices. However, this data is only available up to 2012, making it too short of a timespan for this thesis. It would be helpful for future researchers to consider these indicators when more data is available.

The two alternative house price measures were also chosen because they regularly appear in the literature (Hailemariam et al., 2021; Vale & Camões, 2022; Zhang et al., 2016), giving the analysis results comparability to previous works. The three different house price measures in NZ over time are presented in Figure 3.1. As expected, house

prices in real terms are flatter than the nominal HPI. It can also be seen that all three measures are very similar and follow essentially the same yearly changes over time. Therefore, it is likely that the sensitivity analyses using these alternative measures will yield very similar results due to the high correlation of these three variables.

Figure 3.1. House prices, real house prices, and the value-to-income ratio in NZ over time



Note: Data is sourced from CoreLogic NZ and RBNZ.

3.2.2 Control Variables

While income and wealth inequality are certainly related, each measure has some distinct determinants. The determinants of inequality can be broadly categorised into five groups, with some variables intersecting more than one group, including (i) demographic factors, (ii) economic development and technological change, (iii) globalisation, (iv) policy decisions, and (v) macroeconomic factors. Controlling for as many inequality determinants as possible is critical when exploring the housing and economic inequality relationship, as failure to include relevant variables can bias model

results. As Creedy et al. (2018) eloquently put, studying inequality is made considerably more difficult by the fact that the income and wealth "distribution is affected by so many complex interacting factors, many of which are central to the functioning of the economy" (p. 20). Kaasa (2005) makes a similar point and argues that as many factors of inequality as possible need to be included to have credible results where inferences can be made. However, in the case of NZ, only a limited number of years have available data, constraining how many variables can be included in a model. Furthermore, many of the variables are in an annual frequency, lowering the number of observations and further limiting the number of control variables that can be included in the model.

ARDL models are beneficial for dealing with short periods and have been demonstrated to outperform other modelling techniques (Choi & Chudik, 2019). Nevertheless, this benefit can be significantly reduced if too many variables are included on the right-hand side of the equation. This is known as overfitting, which has become a significant issue in all research that utilises quantitative techniques to explore the relationship between variables (Hawkins, 2004). The primary problem with overfitting is that the predicted model will be very closely matched to the data within that sample. Still, future instances may look starkly different, having different quirks and random variations than the current sample. Therefore, the specified model may perform poorly with different random variations, making it a poor predictor of future economic relationships. This calls into question the merit of the overfitted models' research findings (Babyak, 2004).

How many variables can be included in a model is directly related to the number of observations in the sample. If there are more observations, more predictor variables can be utilised. In contrast, when there are only a few observations, the model must contain all of the necessary information to be accurate, but nothing more. This is often referred

to as Occam's razor or the law of parsimony – “plurality should not be posited without necessity”; the simplest explanation is often the preferred one (Duignan, 2022, para. 1). Choi and Chudik (2019) empirically demonstrate this, showing that parsimonious model specifications are preferable when dealing with smaller sample sizes. Choi and Chudik argue that including all relevant variables may not always be desirable when dealing with a relatively short time dimension.

For this thesis, care is taken when identifying the most important determinants of each inequality so as not to overfit the model. Which control variables are used in models predicting income and wealth inequality is discussed in sections 3.2.2.1 and 3.2.2.2, respectively. Throughout the analysis, sometimes different variables that measure the same factor may be used as a robustness check; however, this was found to have a minimal difference in the model results. Additionally, the Schwarz information criterion (SIC), developed by Schwarz (1978), has been used for selecting all lag structures of the variables to be modelled. SIC is a parsimonious criterion, further decreasing the overfitting likelihood. It is also widely regarded as a consistent model selector, having desirable properties with asymptotic and exact consistency (Chaurasia, 2022).

3.2.2.1 Income Inequality

The current literature argues that numerous variables have a statistically significant relationship with income inequality. The unemployment rate, a measure of the proportion of the working-age population earning an income, is widely considered a significant predictor of income inequality. This is because a larger number of people making an income generally has an equalising effect on the income distribution. Therefore, numerous studies have demonstrated a positive association between the

unemployment rate and income inequality (Cloninger, 2016; Deyshappriya, 2017; González & Menendez, 2000; Mocan, 1999; Sheng, 2011), or found that higher unemployment disproportionately impacts low income earners (Jäntti, 1994).

For similar reasons to unemployment, the population's median age is a significant determinant of income inequality, as it will influence how much of the population is of working age to earn an income (Cloninger, 2016; Francis et al., 2018). Younger residents typically do not make an income, while older residents have decreased motivation to increase their income and are more likely to retire. This forms a quadratic age-earnings curve which is relatively well-known in economics (Gohmann et al., 1998; Murphy & Welch, 1990). The median age is considered the preferred statistic in demographic research studies (Fogarty et al., 2000; Jarman et al., 2018; Payne, 2012) as it is more robust than the mean age and more resistant to errors from very old residents of the population. However, Kaasa (2005) suggests that the percentage of children and elderly relative to the total working population could more accurately represent the age influence on income inequality than the median age. This is known as the age dependency ratio, and it more accurately considers the direct effect of age on income distribution. Hence, it was chosen ahead of the median age for this study. Similarly, Francis et al. (2018) argue that life expectancy and fertility rates are determinants of income inequality as they influence the number of working-age individuals, so both were included.

The Kuznets curve is a well-established economic concept that suggests a quadratic relationship between gross domestic product (GDP) per capita and income inequality. As nations initially grow and increase GDP per capita, income inequality rises but then decreases at higher levels of GDP per capita. Deyshappriya (2017) and Nielsen and

Alderson (1997) provide empirical evidence to support the Kuznets curve, so real GDP per capita was controlled for in the model. Real GDP per capita was chosen ahead of median income, as it considers a broader range of earning factors than just wages, and controls for population size, thus, providing a more comprehensive overview.

Deyshappriya (2017) and Sarel (1997) find the terms of trade to have a significant influence on income inequality. Similarly, Kaasa (2005) finds that exports and imports substantially affect income inequality, and Leroy and El Herradi (2019) controlled for trade openness in their inequality model. Both the trade volume ratio and the terms of trade were trialled as control variables and found to be significant predictors. There was a negligible difference in the significance or magnitude of other variables by using one variable ahead of the other. Hence, the trade volume variable was primarily used, but terms of trade could be easily included instead. Kaasa (2005) also found that foreign investment affects income inequality, which was also included. Additionally, inflation is consistently found to impact real wages and the income distribution (Berisha et al., 2022; Monnin, 2014), so it is included. In the end, the included control variables for income inequality were real GDP per capita, trade volume, the unemployment rate, the inflation rate, foreign investment, age dependency, fertility rates, and life expectancy.

3.2.2.2 Wealth Inequality

For wealth inequality, multiple control variables regularly appear in the previous literature. Some of these are the same as income inequality, such as the age dependency ratio, fertility rate, and life expectancy; in some part, these variables act similarly on wealth inequality as they do income inequality because these variables change the number of working-age residents in a country. This alters how many individuals can

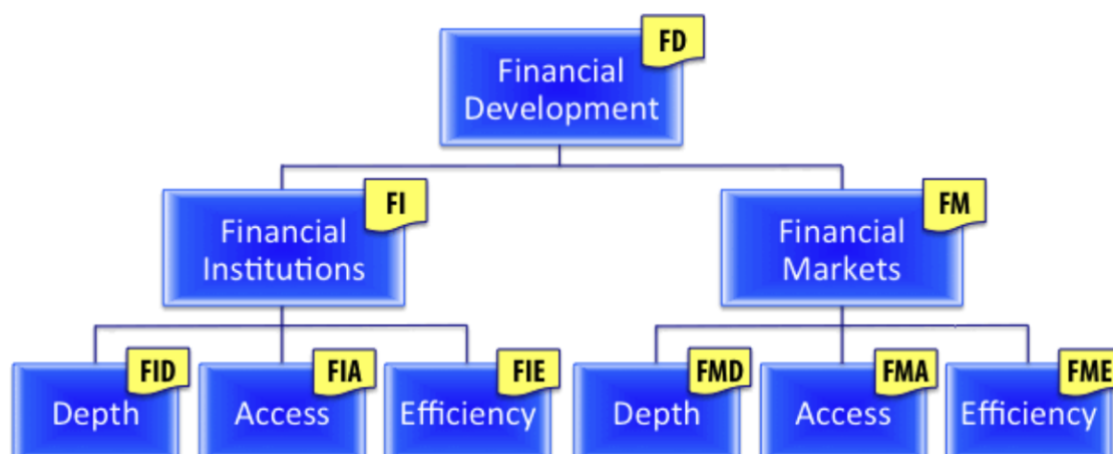
earn and increase their net wealth through wages. This is known as Modigliani's life-cycle hypothesis (LCH) and is a widely recognised and highly researched economic theory (Ando & Modigliani, 1963; Jappelli & Modigliani, 1998; Modigliani & Brumberg, 1954; Shefrin & Thaler, 1988). The LCH theorises that people can build up their savings (and net wealth) while working and then run down their savings once they have retired. Therefore, a change in the relative ratio of residents below working or above retirement age will impact a nation's wealth inequality. However, that is not the complete picture of wealth inequality and age. There are other factors such as intergenerational wealth transfers, the heterogeneity of asset types across age groups, the within and between inequality of cohorts, and different consumption behaviours of age groups that will all impact the extent of the age effect on wealth inequality (Almås & Mogstad, 2012; Chen et al., 2018; Vandenbroucke & Zhu, 2017). Nevertheless, these three variables were all controlled for in the wealth inequality model to account for any channels through which age impacts wealth inequality.

The other variable controlled for in the wealth inequality model but also used in the income inequality model is a country's real GDP per capita. This is supported by Arrigoni (2022) and Bagchi et al. (2019), who both control for real GDP per capita in their regression models predicting wealth Gini. Arrigoni (2022) also controls interest rates to capture the effect of monetary policy on wealth inequality. Instead of interest rates, a more direct approach is taken in this thesis by controlling for share and house prices. Multiple studies, such as O'Farrell and Rawdanowicz (2017), Domanski et al. (2016), and Bivens (2015), have argued that monetary policy's impact on wealth inequality happens through changing house and equities prices. This is because of the heterogeneity in ownership of these assets across the wealth distribution. Because house and share prices are included in the model already, there is no need to include interest

rates because the impact of monetary policy is already considered. Other research also supports the relationship between share prices and wealth inequality without directly considering monetary policy (Bryant & Süßmuth, 2019; Gomez, 2017).

The final control variable included in the wealth inequality model was the financial development of NZ. Financial development and integration are widely known as an impacting factor on the wealth inequality of a country (Frost et al., 2020; Hasan et al., 2020; Zhang, 2017). The IMF indexes for financial development were utilised to capture this effect. These indexes build on the works of Čihák et al. (2012) and Čihák et al. (2013). The full methodology used to create the indexes can be explored in Svirydzhenka (2016). Still, to briefly recapitulate, nine indexes capture the depth, access, and efficiency of financial institutions and markets in a country. The indexes vary in their granularity and can therefore be chosen explicitly for different research methods. This thesis initially utilised all nine indexes, but some with a heavier weighting, as discussed more extensively in section 3.2.3.1. The connection between the nine indexes is visually represented in Figure 3.2. In summary, the control variables included in the wealth inequality model were real GDP per capita, age dependency, fertility rates, life expectancy, share prices, and the financial development indexes.

Figure 3.2: An overview of the IMF financial development indexes



Note: This figure has been created by Svirydzenka (2016) based on the works of Čihák et al. (2012) and Čihák et al. (2013).

The complete list of the variables used throughout the analysis and modelling in alphabetical order can be found in Table 3.1. This table also includes the variable descriptions, how they were calculated, and where the data is obtained from.

Table 3.1: A list of variables used in the analysis, their description, and their data source

Variable	Description	Source
Age dependency	The number of individuals younger than 15 or older than 64 divided by the working-age population	The World Bank
CPI	Measures the price of a fixed basket of goods and services purchased by NZ households (June 2006 = 1000)	RBNZ
Fertility rate	Number of live births to women divided by the number of women	The UN
Financial development	Multiple IMF indexes for financial development in markets and institutions where a higher value indicates greater financial depth, access and efficiency	The IMF
Gini coefficient	An inequality index for income and wealth inequality based on the work of Lorenz (1905) and Gini (1912). The Gini coefficient is a value between 0% and 100%, where 100% is perfect inequality and 0% is perfect equality.	WID
Foreign investment	Net foreign inflows (for more than ten percent of voting stock) as a percentage of GDP	The World Bank
House prices	The CoreLogic NZ house price index (HPI) using a sales-price to appraisal ratio (SPAR)	CoreLogic NZ
Inflation rate	The year difference of log consumer price index (CPI)	Calculated from RBNZ data
Life expectancy	Average life expectancy at birth for both genders, measured in years	The UN
LVR	A dummy variable for whether a loan-to-value ratio restriction is in place for residential properties or not	Created from RBNZ information
Palma ratio	The income/wealth share of the top 10% of the distribution divided by the share of the bottom 40% of the distribution	WID

Variable	Description	Source
Real GDP per capita	Inflation adjusted GDP (calculated using the expenditure based approach) divided by the population	RBNZ
Real house prices	The CoreLogic HPI inflation adjusted	Calculated from CoreLogic NZ and RBNZ data
Real wage	Inflation adjusted average weekly earnings divided by the number of hours worked in a week	RBNZ
Rent prices	NZ annual rent price index (2015 = 100)	OECD
S80S20	The income/wealth share of the top 20% of the distribution divided by the share of the bottom 20% of the distribution	WID
Share prices	Share price index calculated as an average of the daily closing price (2015 = 100)	OECD
Share (D/P)	The income/wealth share for a given decile (where D = 0% to 10%, ..., 90% to 100%) or percentile (where P = 0% to 1%, ..., 99% to 100%) of the income/wealth distribution	WID
Terms of trade	Export price index divided by the import price index multiplied by 100	RBNZ
Trade Volume	RBNZ export volume index divided by the import volume index	Calculated from RBNZ data
Unemployment rate	The number of unemployed people expressed as a percentage of the labour force.	RBNZ
Value-to-income	House prices divided by real average yearly earnings	Calculated from RBNZ and CoreLogic NZ data

3.2.3 Treatment

One of the critical issues encountered during the analysis was the different frequencies of variables to be included, a common issue in time series analysis (Foroni & Marcellino, 2013). Table 3.2 shows the highest frequency available for each variable and the years the data is available. It can be seen that, while many variables do have quarterly or even daily data available, some key variables are only reported annually. The variable that causes the most problem in this analysis is the income and wealth inequality measures which are only released annually. This is a problem as it is more desirable to maintain the highest frequency data possible so that important information is maximised in the analysis. Therefore, because inequality is such a critical variable, the question becomes, what is the best strategy for combining low-frequency and higher-frequency data?

Table 3.2: The frequency of the variables used in the analysis and the years the data is available for in raw form

Variable	Years available	Highest frequency available
Age dependency	1960 – 2021	Annual
CPI	1988 – 2022	Quarterly
Fertility rate	1950 – 2022	Annually
Financial development	1980 – 2020	Annually
Income inequality	1950 – 2021	Annually
Foreign investment	1970 – 2020	Annually
House prices	1989 – 2022	Quarterly
Inflation rate	1988 – 2022	Quarterly
Life expectancy	1950 – 2022	Annually
Real GDP per capita	1987 – 2022	Monthly
Real wage	1994 – 2022	Quarterly
Rent prices	1970 – 2022	Quarterly
Share prices	1967 – 2022	Daily/Monthly
Share (D/P)	1995 – 2022	Annually
Terms of trade	1990 – 2022	Quarterly
Trade Volume	1990 – 2022	Quarterly
Unemployment rate	1989 – 2022	Quarterly
Value-to-income	1994 – 2022	Quarterly
Wealth inequality	1995 – 2021	Annually

There are three primary options for combining mixed-frequency data. First, interpolate the missing data points for the low-frequency variable using the known data points until the variable is the same frequency as the highest. This is known as temporal disaggregation, which has become very common in the data analysis literature (Di Fonzo, 2003; Sax & Steiner, 2013). A higher frequency indicator variable that is highly correlated to the disaggregated variable can also be used to yield more accurate results. Temporal disaggregation has great applicability but performs better for some data analysis methods than others. For running regressions, it allows the higher frequency variables to be included in the model without a considerable loss of information. The caveat is that the economic validity of an analysis based heavily on interpolated variables is questionable; that is particularly important in this thesis, where the dependent variables of the regression would be disaggregated. Because of this caveat, we used temporal disaggregation as a subsidiary sensitivity analysis to the primary modelling techniques. Specifically, the package from Sax and Steiner (2013) is used with the interpolation framework outlined by Chow and Lin (1971). The modelling results using the interpolated data are presented in Appendix B.

Another option for combining mixed frequency data is to use the mixed data sampling (MIDAS) regression model proposed by Ghysels et al. (2004) and expanded on by Ghysels et al. (2005), Ghysels et al. (2006), and Ghysels et al. (2007). MIDAS regression models can have broad applicability in economics and finance. No loss of information and no data interpolation are necessary when using a MIDAS model. The disadvantage of MIDAS is parameter proliferation with the number of lag polynomials needed to achieve the most efficient model form (Foroni et al., 2015; Sueppel, 2020); this can lead to “over parameterised models, in-sample overfitting, and poor predictive performance” (Mogliani & Simoni, 2021, p. 833). Additionally, the MIDAS model

provides less flexibility to use other, more advanced approaches alongside the primary modelling method. However, many would argue that the MIDAS technique has greater efficiency than the third and final critical method for combining mixed-frequency data, aggregating the high-frequency data to the lowest frequency. This is a widespread method in time series analysis, especially before other techniques were developed.

Two approaches can be taken for aggregation: quarters/months in a year are averaged to yield one annual data point; alternatively, the same quarter/month is used every year as the annual data point. Because of the limited flexibility of other techniques when using a MIDAS model and the over-fitting risk when only having such a short period available for this analysis, the aggregation technique was chosen as the primary method. However, the MIDAS results are used as a sensitivity analysis; they are presented in Appendix C. Quarter four (Q4)/December was used as the yearly data point for every high-frequency variable. This aggregation approach was chosen due to a lower autocorrelation of a variable throughout time than the averaging method. However, the averaging technique was also used as a sensitivity analysis due to maintaining additional information in the model and is provided in Appendix D. Some variables were missing the Q4/December data point in sporadic cases. The Q3/November data point was used as a proxy in those situations.

There may be some concern about the relatively small number of observations available for modelling due to using the annualised data. However, as Giles (2014) argues, when testing for a cointegration relationship between variables, it is not the number of observations that matters but the time span of the dataset that matters most. There are nearly 30 years of data available for both measures of inequality. While the low number of observations limits the number of lags that can be utilised in a model, it still allows

the relationship to be robustly tested and inferences to be drawn on the house price and economic inequality relationship. The key is careful selection in all analysis techniques to ensure that the low number of observations is sufficient for meaningful conclusions.

Once the data is annualised, most variables are transformed into their natural logarithmic form to allow more straightforward interpretations and comparisons of the resulting regression coefficients. However, some variables are left in levels, as they contain either zero or negative values. Furthermore, most variables already in a percentage form, such as the unemployment and inflation rate, are also left in levels. The control variables are primarily left in levels, which is less significant of an issue as they are still controlled for in the model and do not necessarily need to be interpreted. However, some wealth inequality measures contain negative values and cannot be transformed, creating a more prominent issue for interpreting these results. How this issue is addressed is discussed throughout section 5.2.1 and more thoroughly in section 5.2.2. Additionally, none of the equations in section 3.3 or throughout the rest of the thesis are written with natural logs included; all regression result tables show what form the variable takes for clarity on how the coefficients should be interpreted.

3.2.3.1 Principal Components

As shown in section 3.2.2, many variables impacting income and wealth inequality must be controlled for in the model. Therefore, excluding relevant variables could remove important predictive information from the model, lower the accuracy, or even bias the results. Additionally, a significant correlation between income and wealth inequality determinants, respectively, creates a potential multicollinearity issue in each model. Multicollinearity or collinearity leads to inflated standard errors for highly correlated

variables, which biases statistical testing and, in extreme cases, can bias the regressors' (Allen, 1997). There is a significantly reduced chance of a variable being statistically significant when it is highly correlated to other predictor variables in the model. Therefore, an ideal approach for this thesis would mitigate the overfitting and multicollinearity issues. It would consequently maintain as much determinant information as possible while still being a parsimonious model design and limiting the high correlation between the predictor variables. Hence, a principal components analysis (PCA) was undertaken with the other modelling techniques.

PCA is a dimensionality reduction technique that reduces the number of variables in a time series analysis. This is done by transforming multiple variables into a new principal component (PC) variable. PCs are mathematically orthogonal vectors and a linear combination of the original features that maximise variation. Two separate PCs are generated for this study, combining twelve possible control variables into two PCs. First, the age dependency ratio, life expectancy, and fertility rates are combined into a Population PC variable. These three variables impact inequality via a similar channel; therefore, their combined impact can be represented through one variable instead. Second, the nine IMF financial development indexes are combined into a single Development PC variable. Like the other PC, these nine variables all impact wealth inequality similarly. Therefore, their combined impact can be adequately represented as one variable to maintain the maximum information and reduce dimensionality. However, in the end, only five indexes were used for the final PC due to the low variation across time for four of the indexes. The process used to create a PC and the breakdown for each PC used in this thesis is provided in Appendix E.

PCA offers many advantages in the context of this study. However, there are two main caveats for using them in a regression; first, PCs lose their theoretical explanations compared to the original features, so it can be challenging to interpret the resulting coefficient; second, the PCA transformation favours variables with higher variation, but there is no guarantee that the variables with more variation have greater predictive power for a particular dependent variable in a model (Leung, 2022). The lower variance variables could have greater predictive power over a particular inequality measure. However, they will receive a lower weight in the PC resulting in poorer model performance and biased estimates.

The first issue is less prominent because the PCA transformation is only undertaken on control variables. Because there is less need to interpret the PCs in the context of this study, this problem is of lesser importance as they will still be controlled for in the model. The second issue is a more significant problem as there is no guarantee that the high-weighted variables are the best predictors. A careful and robust sensitivity analysis somewhat overcomes this issue to ensure that any findings are robust to the PC variables. Ideally, the PC variables will only control for multiple determinants at once, making the magnitude of other predictors more representative of the actual value. Altering PC specifications should keep the sign and significance of other variables the same, but this is carefully considered. The critical thing to note for the two PCs used in this study is that the theoretically biggest predictors of inequality, age dependency and the leading financial development index both give the most significant share of variation in their respective PCs. This is shown in Appendix E. This means that the highest weighted variables should theoretically have the most predictive power in their respective models. Still, careful sensitivity analysis is later conducted to support the use of PCs.

3.2.4 Variable Testing

Variable testing is broken down into sequential stages based on the results of each step. The first testing stage involved considering the descriptive statistics of variables used throughout the analysis, provided in Table 3.3. There are a few interesting findings from this rudimentary table, such as the stark difference between wealth and income inequality in NZ. The average Gini is noticeably larger for wealth inequality at 72.5 per cent compared to the income Gini of 45.7 per cent⁴; it is also important to note that the wealth S80S20 variable has a negative mean and median since the bottom ten per cent of the wealth distribution has more outstanding liabilities than assets in their designation.

⁴ Caution should be taken when comparing Gini coefficients of entirely different distributions (Ceriani & Verme, 2012); they have only been briefly compared here to help highlight the stark difference between income and wealth inequality in NZ, amongst other statistics comparisons. Because there is a difference in the income and wealth Gini's of nearly 30, it is reasonable to conclude that wealth inequality is more inequitable. However, comparing Gini coefficients representing different distributions within a few points of each other should be executed cautiously.

The difference between income and wealth shares across the distribution in 2020 is provided in Table 3.4 and represented graphically in

Decile of distribution	Income share (%)	Wealth share (%)
0 to 10	2.88	-1.37
10 to 20	4.45	0.29
20 to 30	5.44	0.9
30 to 40	6.36	1.95
40 to 50	7.47	3.27
50 to 60	8.68	4.86
60 to 70	10.11	7.01
70 to 80	11.98	10.26
80 to 90	15.13	16.19
90 to 100	27.5	56.65

Note: Data is sourced from the WID.

Figure 3.3. These values are used to create the 2020 income and wealth Lorenz curves shown in Figure 3.4. This further highlights that the NZ wealth distribution is relatively more inequitable than the income distribution. Additionally, it is essential to point out that wealth inequality has experienced very little change from 1995 to 2020, especially relative to income inequality. This can be seen by the small standard deviations and ranges for all of the measures of wealth inequality compared to the relatively larger values for the measures of income inequality. It can also be seen in Figure 3.5 that the wealth Gini fluctuates in a similar pattern to the income Gini throughout this period, but the fluctuations are considerably smaller. The income Gini experiences greater variance

and has been primarily trending downwards, even before 1995. Unfortunately, the wealth inequality data is only available after 1995, limiting the ability to see the greater trend of wealth inequality in NZ.

The significant change in house prices must also be noted. The HPI has increased from \$159,000 to \$809,000 over 26 years, as shown in Figure 3.6 below. This enormous change has contributed to the very high standard deviation of \$187,000. The standard deviation is almost half the mean, demonstrating the significant variation in NZ house prices over this period. When considering the year-on-year changes in house prices in Figure 3.7, it can be seen that only six periods from 1990 to 2022 experienced a decrease in house prices from the previous December.

The wealth share to experience the most change was the distribution's top decile; the same is true for the income shares. This is presented visually in Figure 3.8, where both trend upwards throughout the analysis period, but the top income share increases by a greater amount. The lowest variation share was the 20 to 30 per cent for the wealth and income distribution, as each had the lowest standard deviations. In addition to considering the basic descriptive statistics, the Jarque and Bera (1987) test for normality is utilised where the null hypothesis is a normal distribution. The only variable of concern from this test is share prices, suggesting a non-normal distribution. Throughout the analysis, this issue was addressed by using the logarithmic form of share prices.

Table 3.3: Descriptive statistics of the key variables used in the analysis

Variable	Mean	Median	Minimum	Maximum	Standard Deviation	Jarque-Bera
Income Gini	45.688	45.832	37.562	52.449	3.386	1.140
Wealth Gini	72.462	72.484	72.076	72.774	0.184	0.718
Income Palma	1.375	1.363	1.293	1.493	0.054	1.814
Wealth Palma	31.667	31.697	30.840	32.324	0.410	0.545
Income S80S20	4.806	4.777	4.611	5.088	0.148	2.209
Wealth S80S20	-66.558	-66.665	-67.602	-65.045	0.666	0.475
House prices (\$)	382,516	374,986	159,080	808,667	187,215	1.964
Real house prices (\$)	348,976	344,547	198,485	623,109	122,257	1.637
Value-to-income	7.879	7.990	3.939	14.685	3.196	1.502
Wealth share (0% to 10%)	-1.382	-1.38	-1.4	-1.37	0.008	0.380
Wealth share (10% to 20%)	0.290	0.29	0.29	0.29	0	-
Wealth share (20% to 30%)	0.910	0.91	0.9	0.92	0.007	1.083
Wealth share (30% to 40%)	1.963	1.96	1.94	1.99	0.014	0.509

Variable	Mean	Median	Minimum	Maximum	Standard Deviation	Jarque-Bera
Wealth share (40% to 50%)	3.290	3.29	3.25	3.34	0.024	0.446
Wealth share (50% to 60%)	4.898	4.89	4.83	4.98	0.039	0.774
Wealth share (60% to 70%)	7.062	7.06	6.96	7.19	0.062	0.774
Wealth share (70% to 80%)	10.324	10.315	10.2	10.48	0.076	0.817
Wealth share (80% to 90%)	16.259	16.245	16.09	16.44	0.084	0.383
Wealth share (90% to 100%)	56.387	56.42	55.76	56.89	0.298	0.687
Income share (0% to 10%)	2.931	2.94	2.78	3.1	0.090	0.581
Income share (10% to 20%)	4.628	4.63	4.44	4.89	0.135	0.841
Income share (20% to 30%)	5.491	5.485	5.36	5.65	0.080	0.721
Income share (30% to 40%)	6.391	6.36	6.29	6.64	0.091	5.019
Income share (40% to 50%)	7.422	7.39	7.25	7.6	0.086	1.187
Income share (50% to 60%)	8.697	8.675	8.52	8.94	0.110	0.941
Income share (60% to 70%)	10.207	10.24	9.88	10.52	0.154	0.170
Income share (70% to 80%)	12.245	12.345	11.87	12.56	0.201	2.113
Income share (80% to 90%)	15.264	15.315	14.91	15.48	0.170	2.079

Variable	Mean	Median	Minimum	Maximum	Standard Deviation	Jarque-Bera
Income share (90% to 100%)	26.721	26.545	25.65	28.36	0.734	1.525
Age dependency ratio	52.290	52.356	50.270	55.761	1.534	1.170
Fertility rate	1.998	1.985	1.879	2.142	0.073	1.183
Foreign investment	1.495	1.609	-3.812	5.587	2.016	2.680
$\Delta \ln$ (CPI), Inflation	0.020	0.019	0.001	0.039	0.010	0.694
Life expectancy	79.93	80.19	76.84	82.36	1.74	1.936
Real GDP per capita	0.044	0.045	0.035	0.055	0.006	0.766
Real wage	22.586	22.602	19.414	26.476	1.981	1.218
Rent prices	89.126	86.846	72.479	114.489	12.319	2.120
Share prices	88.889	74.499	59.329	184.988	32.999	13.218 ***
Terms of trade	117.543	113.688	95.793	150.000	18.032	2.215
Trade volume	0.689	0.672	0.540	0.892	0.102	1.487
Unemployment rate	5.335	5.400	3.400	7.900	1.146	0.550

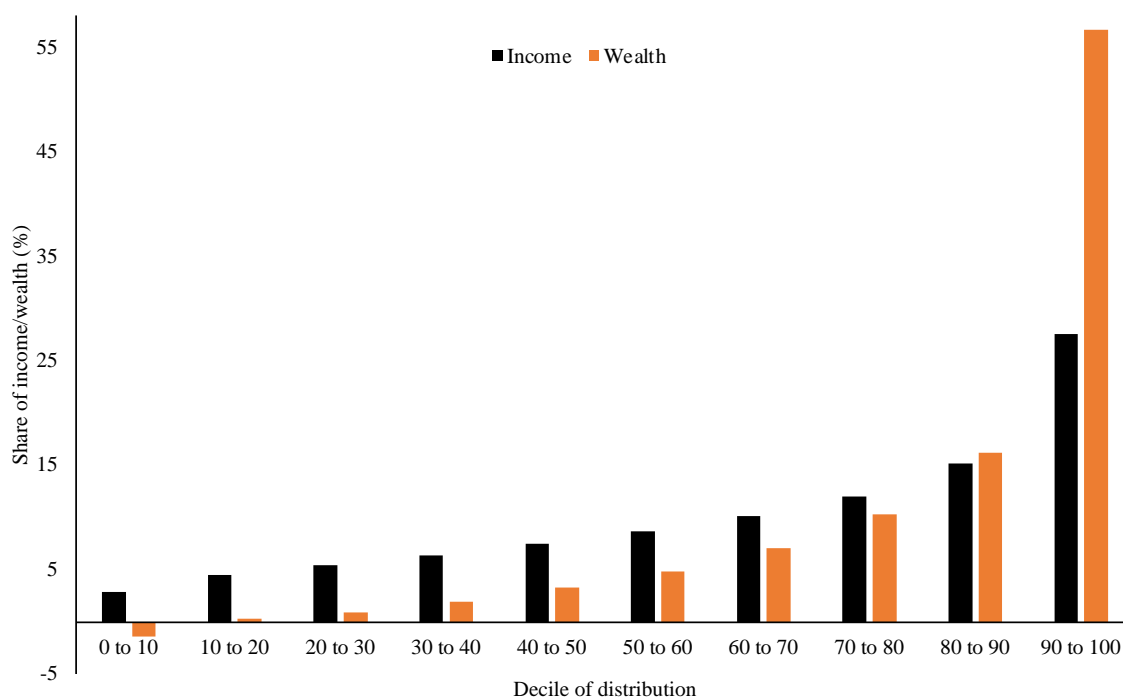
*Notes: Data is included from 1995 to 2020 only ($n = 26$), the null hypothesis of the Jarque-Bera test is a normal distribution, and (***) is significant at the 1% significance level.*

Table 3.4: Share of income and wealth across the 2020 distribution

Decile of distribution	Income share (%)	Wealth share (%)
0 to 10	2.88	-1.37
10 to 20	4.45	0.29
20 to 30	5.44	0.9
30 to 40	6.36	1.95
40 to 50	7.47	3.27
50 to 60	8.68	4.86
60 to 70	10.11	7.01
70 to 80	11.98	10.26
80 to 90	15.13	16.19
90 to 100	27.5	56.65

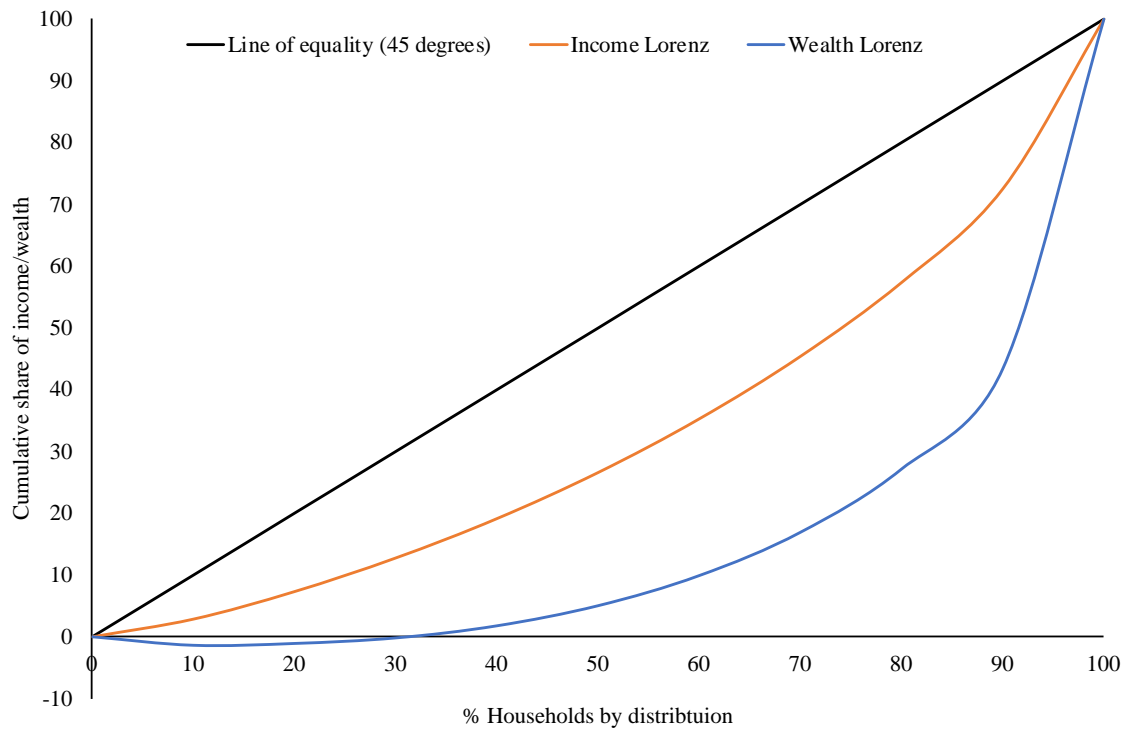
Note: Data is sourced from the WID.

Figure 3.3: Share of income and wealth across the 2020 distribution



Note: The data plotted is from Table 3.4.

Figure 3.4: Income and wealth Lorenz curves in 2020



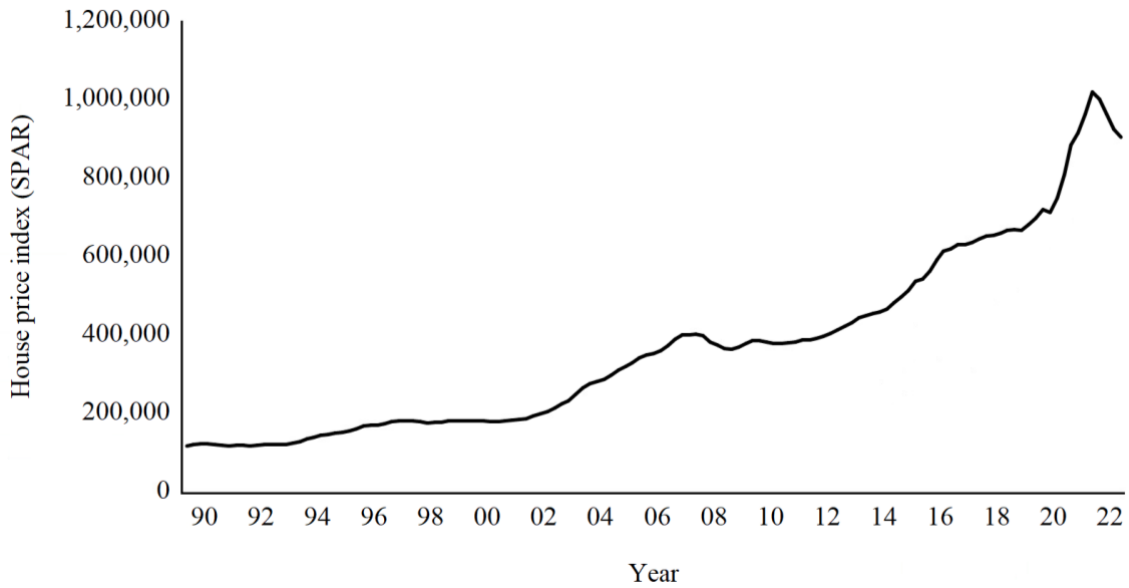
Note: The data plotted is from Table 3.4.

Figure 3.5: NZ wealth and income Gini from 1955 onwards



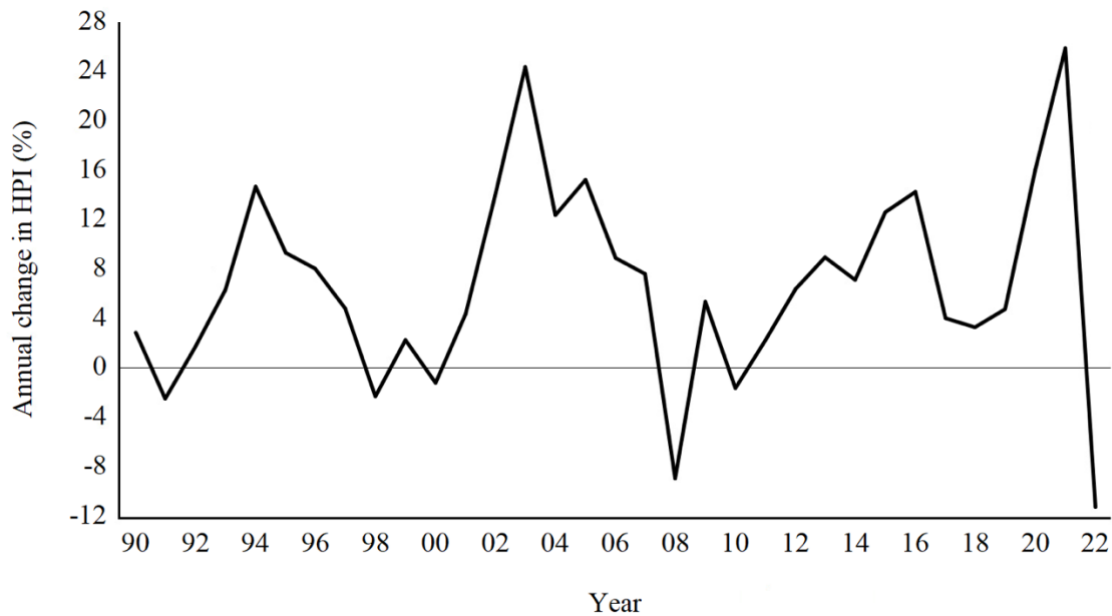
Note: The two series have been plotted on separate axis given the low variability of the wealth Gini over time relative to the income Gini. The data is sourced from the WID.

Figure 3.6: NZ house price index from 1990 to 2022



Note: Data is sourced from CoreLogic NZ.

Figure 3.7: Annual percentage change in NZ house prices from 1990 to 2022



Note: Annual change is for December prices in the present period against December prices in the previous period and data is sourced from CoreLogic NZ.

Figure 3.8: Wealth and income share of the top ten per cent of the distribution



Note: Data is sourced from the WID.

3.2.4.1 Order of Integration Testing

To determine the order of integration for all variables used in modelling, variables were tested for a unit root at levels and first difference, both with a constant and with a constant & trend. Unit root testing procedures are known to have low test power (Lucas, 1996), especially at smaller sample sizes, meaning a decreased probability of concluding a variable does not have a unit root. Because of this, two separate unit root tests and a stationarity test were utilised for greater certainty on the actual order of integration. These tests are based on the work of Phillips and Perron (1988), Cheung and Lai (1995), and Kwiatkowski et al. (1992); commonly referred to as the Phillips-Perron (PP), Augmented Dickey-Fuller (ADF), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests shown in Table 3.5, Table 3.6, and Table 3.7, respectively. Variables were considered from 1992 or 1995 onwards based on whether they would be included in the income or wealth inequality model. However, it made a negligible difference to the

significance results. Therefore, all values reported in the tables below used a sample from 1995 to 2020 for testing.

Table 3.5: Phillips–Perron unit root test on all variables and the principal components to be used in modelling

Variable	<i>At levels:</i>		<i>At first difference:</i>	
	With constant	With constant & trend	With constant	With constant & trend
ln(House prices)	1.277	-1.542	-3.269 **	-2.867
ln(Real house prices)	0.449	-1.729	-3.008 **	-2.984
ln(Value-to-income)	0.483	-1.826	-2.864 **	-2.445
ln(Rent price)	-0.543	-2.114	-3.807 ***	-3.740 **
ln(Income Gini)	-2.229	-3.058	-10.057 ***	-10.010 ***
ln(Income Palma)	-1.456	-2.574	-8.428 ***	-8.391 ***
ln(Income S80S20)	-0.754	-2.712	-8.500 ***	-8.462 ***
ln(Wealth Gini)	-2.426	-2.501	-5.110 ***	-4.848 ***
ln(Wealth Palma)	-2.408	-2.576	-5.412 ***	-5.267 ***
Wealth S80S20	-2.875 *	-2.943	-6.514 ***	-6.221 ***
Wealth share (0% to 10%)	-3.15 **	-3.218	-7.4719 ***	-7.1047 ***
Wealth share (20% to 30%)	-2.0177	-2.3051	-5.2252 ***	-5.0535 ***
Wealth share (30% to 40%)	-2.5781	-2.7199	-5.8477 ***	-5.4939 ***

Variable	<i>At levels:</i>		<i>At first difference:</i>	
	With constant	With constant & trend	With constant	With constant & trend
Wealth share (40% to 50%)	-2.4651	-2.599	-5.7945 ***	-5.4248 ***
Wealth share (50% to 60%)	-2.3729	-2.4207	-4.9632 ***	-4.8159 ***
Wealth share (60% to 70%)	-2.3976	-2.4502	-5.1715 ***	-4.9836 ***
Wealth share (70% to 80%)	-2.418	-2.4888	-4.945 ***	-4.7836 ***
Wealth share (80% to 90%)	-2.5777	-2.6782	-5.1543 ***	-4.9903 ***
Wealth share (90% to 100%)	-2.4212	-2.4936	-5.1151 ***	-4.8584 ***
Income share (0% to 10%)	-1.3389	-3.3769 *	-9.524 ***	-9.4781 ***
Income share (10% to 20%)	-0.0087	-2.76	-9.0182 ***	-9.1334 ***
Income share (20% to 30%)	-1.1342	-2.7792	-7.2139 ***	-7.1645 ***
Income share (30% to 40%)	-0.9487	-2.5149	-8.0703 ***	-8.0105 ***
Income share (40% to 50%)	-1.3852	-2.6746	-7.7919 ***	-7.7305 ***
Income share (50% to 60%)	-2.6245 *	-2.7017	-6.7307 ***	-6.6716 ***
Income share (60% to 70%)	-1.8094	-2.2834	-5.579 ***	-5.5297 ***
Income share (70% to 80%)	-1.3386	-1.2797	-6.4156 ***	-6.3921 ***

Variable	<i>At levels:</i>		<i>At first difference:</i>	
	With constant	With constant & trend	With constant	With constant & trend
Income share (80% to 90%)	-2.5917 *	-3.3025 *	-12.8159 ***	-12.7966 ***
Income share (90% to 100%)	-2.2691	-2.3974	-8.2117 ***	-8.1792 ***
ln(Inflation rate)	-3.462 **	-3.580 **	-8.554 ***	-8.475 ***
ln(Real wage)	-0.467	-3.279 *	-4.912 ***	-4.613 ***
ln(Real GDP per capita)	0.111	-2.303	-5.045 ***	-4.969 ***
ln(Share prices)	-0.268	-2.589	-7.031 ***	-6.830 ***
ln(ToT)	0.288	-3.541 *	-10.849 ***	-13.280 ***
ln(Unemployment rate)	-1.604	-1.957	-4.451 ***	-4.260 **
ln(Foreign investment)	-4.120 ***	-4.722 ***	-9.720 ***	-8.984 ***
Development PC	-2.218	-2.093	-4.913 ***	-4.942 ***
Population PC	-3.823 ***	0.140	-1.152	-3.728 **

Notes: Null hypothesis is the variable contains a unit root. Values represent the t-stat of the test and () is significant at 10%; (**) significant at 5%; and (***) significant at 1%. The lag length of the test is chosen according to the Schwarz information criterion.*

Table 3.6: Augmented Dickey–Fuller unit root test on all variables and the principal components to be used in modelling

Variable	<i>At levels:</i>		<i>At first difference:</i>	
	With constant	With constant & trend	With constant	With constant & trend
ln(House prices)	0.670	-2.963	-2.655 *	-2.806
ln(Real house prices)	0.150	-2.526	-2.962 *	-2.969
ln(Value-to-income)	0.748	-2.476	-2.310	-2.418
ln(Rent price)	-0.438	-1.642	-3.791 ***	-3.723 **
ln(Income Gini)	-2.265	-3.131	-10.120 ***	-10.067 ***
ln(Income Palma)	-1.451	-2.455	-8.427 ***	-8.392 ***
ln(Income S80S20)	-0.836	-2.675	-8.460 ***	-8.424 ***
ln(Wealth Gini)	-2.364	-2.429	-4.872 ***	-4.750 ***
ln(Wealth Palma)	-2.317	-2.473	-5.321 ***	-5.192 ***
Wealth S80S20	-2.833 *	-2.894	-5.888 ***	-5.713 ***
Wealth share (0% to 10%)	-3.15 **	-3.218	-6.5153 ***	-6.3177 ***
Wealth share (20% to 30%)	-1.98	-2.2412	-5.173 ***	-5.0189 ***
Wealth share (30% to 40%)	-2.555	-2.6778	-5.4088 ***	-5.2638 ***

Variable	<i>At levels:</i>		<i>At first difference:</i>	
	With constant	With constant & trend	With constant	With constant & trend
Wealth share (40% to 50%)	-2.5056	-2.5726	-5.0543 ***	-4.9322 ***
Wealth share (50% to 60%)	-2.2574	-2.3014	-4.9223 ***	-4.7956 ***
Wealth share (60% to 70%)	-2.3492	-2.3946	-4.8653 ***	-4.7472 ***
Wealth share (70% to 80%)	-2.2887	-2.3539	-4.8276 ***	-4.7071 ***
Wealth share (80% to 90%)	-2.47	-2.56	-4.9886 ***	-4.8694 ***
Wealth share (90% to 100%)	-2.3596	-2.4228	-4.8793 ***	-4.7576 ***
Income share (0% to 10%)	-0.8953	-3.418 *	-8.9021 ***	-8.8468 ***
Income share (10% to 20%)	-0.2111	-2.7848	-9.0097 ***	-9.0168 ***
Income share (20% to 30%)	-1.0403	-3.3056 *	-7.1063 ***	-7.0581 ***
Income share (30% to 40%)	-0.9382	-2.344	-8.0703 ***	-8.0104 ***
Income share (40% to 50%)	-1.3382	-2.5568	-7.8066 ***	-7.748 ***
Income share (50% to 60%)	-3.377 **	-3.4667 *	-6.8113 ***	-6.768 ***
Income share (60% to 70%)	-1.4327	-1.5337	-5.4897 ***	-5.4945 ***
Income share (70% to 80%)	-1.2596	-1.8194	-6.4783 ***	-6.4637 ***

Variable	<i>At levels:</i>		<i>At first difference:</i>	
	With constant	With constant & trend	With constant	With constant & trend
Income share (80% to 90%)	-2.4068	-2.8906	-5.1102 ***	-5.7567 ***
Income share (90% to 100%)	-2.1489	-2.2851	-8.2117 ***	-8.18 ***
ln(Inflation rate)	-3.462 **	-3.580 **	-6.585 ***	-6.490 ***
ln(Real wage)	-0.514	-3.199	-4.942 ***	-4.735 ***
ln(Real GDP per capita)	0.183	-2.000	-5.000 ***	-4.912 ***
ln(Share prices)	-0.356	-2.362	-7.263 ***	-7.029 ***
ln(ToT)	1.591	-1.680	-8.695 ***	-9.657 ***
ln(Unemployment rate)	-1.604	-1.882	-4.451 ***	-4.267 **
ln(Foreign investment)	-4.127 ***	-4.652 ***	-7.143 ***	-7.024 ***
Development PC	-2.060	-2.105	-5.005 ***	-5.078 ***
Population PC	-4.177 ***	-1.605	-1.130	-3.713 **

Note: See notes for Table 3.5.

Table 3.7: Kwiatkowski–Phillips–Schmidt–Shin stationarity test on all variables and the principal components to be used in modelling

Variable	<i>At levels:</i>		<i>At first difference:</i>	
	With constant	With constant & trend	With constant	With constant & trend
ln(House prices)	0.664 **	0.061	0.262	0.098
ln(Real house prices)	0.704 **	0.059	0.161	0.114
ln(Value-to-income)	0.663 **	0.064	0.129	0.075
ln(Rent price)	0.710 **	0.106	0.092	0.092
ln(Income Gini)	0.854 ***	0.057	0.079	0.047
ln(Income Palma)	0.698 **	0.143 *	0.065	0.038
ln(Income S80S20)	0.972 ***	0.143 *	0.080	0.047
ln(Wealth Gini)	0.189	0.127 *	0.135	0.123*
ln(Wealth Palma)	0.220	0.137 *	0.164	0.1209*
Wealth S80S20	0.197	0.142 *	0.292	0.302 ***
Wealth share (0% to 10%)	0.2017	0.1435 *	0.3269	0.332 ***
Wealth share (20% to 30%)	0.2486	0.1473 **	0.1998	0.1663 **
Wealth share (30% to 40%)	0.1978	0.1309 *	0.3126	0.3375 ***

Variable	<i>At levels:</i>		<i>At first difference:</i>	
	With constant	With constant & trend	With constant	With constant & trend
Wealth share (40% to 50%)	0.1952	0.1392 *	0.3156	0.3499 ***
Wealth share (50% to 60%)	0.1624	0.1248 *	0.122	0.1044
Wealth share (60% to 70%)	0.1864	0.1374 *	0.1705	0.1622 **
Wealth share (70% to 80%)	0.1893	0.1323 *	0.1244	0.1083
Wealth share (80% to 90%)	0.2047	0.1082	0.1305	0.1252 *
Wealth share (90% to 100%)	0.1887	0.128 *	0.1355	0.1228 *
Income share (0% to 10%)	0.9454 ***	0.1055	0.1015	0.0854
Income share (10% to 20%)	1.0472 ***	0.1928 **	0.1352	0.0571
Income share (20% to 30%)	0.9644 ***	0.094	0.0523	0.0458
Income share (30% to 40%)	0.9829 ***	0.095	0.0621	0.0612
Income share (40% to 50%)	0.9148 ***	0.1087	0.0512	0.0508
Income share (50% to 60%)	0.1981	0.1455 *	0.0437	0.034
Income share (60% to 70%)	0.7443 ***	0.1453 *	0.0651	0.0509
Income share (70% to 80%)	0.8516 ***	0.1645 **	0.1263	0.0889

Variable	<i>At levels:</i>		<i>At first difference:</i>	
	With constant	With constant & trend	With constant	With constant & trend
Income share (80% to 90%)	0.6958 **	0.1962 **	0.1589	0.1098
Income share (90% to 100%)	0.2055	0.1572 **	0.0686	0.0387
ln(Inflation rate)	0.142	0.076	0.288	0.158 **
ln(Real wage)	0.674 **	0.076	0.120	0.115
ln(Real GDP per capita)	0.735 **	0.106	0.083	0.096
ln(Share prices)	0.644 **	0.116	0.155	0.057
ln(ToT)	0.707 **	0.165 **	0.291	0.130 *
ln(Unemployment rate)	0.256	0.088	0.101	0.101
ln(Foreign investment)	0.313	0.108	0.084	0.061
Development PC	0.676 **	0.184 **	0.177	0.087
Population PC	0.894 ***	0.248 ***	0.709 *	0.094

Notes: Null hypothesis is the variable is stationary. Values represent the t-stat of the test and () is significant at 10%; (**) significant at 5%; and (***) significant at 1%. The lag length of the test is chosen according to the Schwarz information criterion.*

Table 3.8: Summary of the three stationarity tests and the implied order of integration for each variable

Variable	PP	ADF	KPSS	Order of Integration at levels
ln(House prices)	Stationary at first difference	Non-stationary	Stationary at first difference	-
ln(Real house prices)	Stationary at first difference	Non-stationary	Stationary at first difference	-
ln(Value-to-income)	Stationary at first difference	Non-stationary	Stationary at first difference	-
ln(Rent prices)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
ln(Income Gini)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
ln(Income Palma)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
ln(Income S80S20)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
ln(Wealth Gini)	Stationary at first difference	Stationary at first difference	Stationary at levels	-
ln(Wealth Palma)	Stationary at first difference	Stationary at first difference	Stationary at levels	-
Wealth S80S20	Stationary at first difference	Stationary at first difference	Stationary at levels	-
Wealth share (0% to 10%)	Stationary at first difference	Stationary at first difference	Stationary at levels	-
Wealth share (20% to 30%)	Stationary at first difference	Stationary at first difference	Stationary at levels	-
Wealth share (30% to 40%)	Stationary at first difference	Stationary at first difference	Stationary at levels	-

Variable	PP	ADF	KPSS	Order of Integration at levels
Wealth share (40% to 50%)	Stationary at first difference	Stationary at first difference	Stationary at levels	-
Wealth share (50% to 60%)	Stationary at first difference	Stationary at first difference	Stationary at levels	-
Wealth share (60% to 70%)	Stationary at first difference	Stationary at first difference	Stationary at levels	-
Wealth share (70% to 80%)	Stationary at first difference	Stationary at first difference	Stationary at levels	-
Wealth share (80% to 90%)	Stationary at first difference	Stationary at first difference	Stationary at levels	-
Wealth share (90% to 100%)	Stationary at first difference	Stationary at first difference	Stationary at levels	-
Income share (0% to 10%)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
Income share (10% to 20%)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
Income share (20% to 30%)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
Income share (30% to 40%)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
Income share (40% to 50%)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
Income share (50% to 60%)	Stationary at first difference	Stationary at levels	Stationary at levels	-
Income share (60% to 70%)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
Income share (70% to 80%)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)

Variable	PP	ADF	KPSS	Order of Integration at levels
Income share (80% to 90%)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
Income share (90% to 100%)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
ln(Inflation rate)	Stationary at levels	Stationary at levels	Stationary at levels	I(0)
ln(Real wage)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
ln(Real GDP per capita)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
ln(Share prices)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
ln(ToT)	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
ln(Unemployment rate)	Stationary at first difference	Stationary at first difference	Stationary at levels	-
ln(Foreign investment)	Stationary at levels	Stationary at levels	Stationary at levels	I(0)
Development PC	Stationary at first difference	Stationary at first difference	Stationary at first difference	I(1)
Population PC	Stationary at levels	Stationary at levels	Stationary at first difference	-

Notes: Summary is based on a significance level of 5% and below; a non-stationary test result suggests the variable may be I(2) or greater; (-) means the order of integration is inconclusive as there are contradicting results across the three tests.

The results from the unit root and stationarity tests are summarised in Table 3.8 above. The table shows that the three tests draw comparable results for 21 out of the 39 variables, meaning there is considerably more certainty around the order of integration at levels for these variables. However, for the other 18 variables, there is a greater level of uncertainty around the order of integration, with at most two of the tests being in unison with each other. These 18 variables were investigated visually following the tests. The time series graphs at both levels and the first difference for the majority of them are included in Appendix F; there remains uncertainty around the order of integration for many variables, which leads to a greater level of caution when selecting the appropriate modelling framework; this shall be discussed in greater detail in section 3.3.

In addition to the typical unit root testing, the dependent variables used in modelling were also tested for structural breaks. Identifying structural breaks, also called change points, is a critical component of economic research that acts as a form of quality control and helps ensure robust results when modelling economic phenomena (Aue & Horváth, 2013; Perron, 2006). The breakpoint unit root test utilised for this thesis is the Augmented Dickey-Fuller test through innovational outlier, which is built around the framework of Perron (1989), Perron and Vogelsang (1992), Vogelsang and Perron (1998), and Banerjee et al. (1992), as outlined by EViews (2018). The results from the breakpoint unit root tests are presented for the dependent variables in levels and the first difference in Table 3.9 and Table 3.10, respectively.

Table 3.10 shows that all dependent variables are stationary at the first difference; however, that was the case from the previous unit root testing (see Table 3.8), suggesting a structural break is unnecessary for modelling the first differenced forms of

the primary dependent variables. Table 3.9 indicates that there is no structural break present for any wealth inequality measures as all of the test specifications fail to reject the null hypothesis that a unit root is present, which as Glynn et al. (2007) highlight, also assumes that no structural break is present. Contrastingly, the income inequality measures reject the null hypothesis, specifically the Palma ratio and the S80S20, which reject the null for almost every specification. This contrasts the previous unit root testing and suggests that these variables are $I(0)$ at levels when a structural break is accounted for. These structural breaks and associated break dates will be considered/controlled for in modelling using dummy and/or multiplicative dummy variables. Additionally, the cumulative sum (CUSUM) of residuals and CUSUM-of-squares for the residuals test will be utilised on all modelling techniques to ensure stability and highlight any potentially missed structural breaks from this testing.

Table 3.9: Breakpoint unit root testing on the dependent variables at levels

	<i>Intercept only</i>		<i>Trend and Intercept</i>		
	Intercept only	Intercept only	Trend and Intercept	Trend only	
Variable					Break Date
ln(Income Gini)	-3.208	-3.357	-7.024 ***	-4.375 *	2005
ln(Income Palma)	-4.970 *	-6.062 ***	-5.930 ***	-4.754 **	2004
ln(Income S80S20)	-4.346 *	-5.901 ***	-5.710 ***	-4.655 **	2010
ln(Wealth Gini)	-3.257	-4.531	-5.072 *	-4.472 *	2009
ln(Wealth Palma)	-2.861	-3.658	-4.378	-3.677	2008
Wealth S80S20	-3.408	-4.215	-4.581	-3.756	2010

Note: See notes for Table 3.5.

Table 3.10: Breakpoint unit root testing on the dependent variables at first difference

	<i>Intercept only</i>		<i>Trend and Intercept</i>		
Trend Specification:					
Break Specification:	Intercept only	Intercept only	Trend and Intercept	Trend only	
Variable					Break Date
ln(Income Gini)	-6.878 ***	-7.942 ***	-7.654 ***	-6.537 ***	2008
ln(Income Palma)	-10.207 ***	-10.266 ***	-10.098 ***	-9.758 ***	2014
ln(Income S80S20)	-8.840 ***	-8.255 ***	-8.009 ***	-7.145 ***	2014
ln(Wealth Gini)	-5.974 ***	-5.670 ***	-5.338 **	-5.137 **	2001
ln(Wealth Palma)	-6.299 ***	-6.196 ***	-5.762 ***	-5.625 ***	2008
Wealth S80S20	-7.398 ***	-7.005 ***	-6.413 ***	-6.178 ***	2000

Note: See notes for Table 3.5.

3.3 Modelling

Five unique modelling approaches are utilised throughout this thesis. Section 3.3 outlines the structure of each modelling technique, why each method was employed, and some of the advantages and disadvantages of each approach.

3.3.1 Autoregressive Distributed Lag

The general form of a linear time series model representing the relationship between inequality and house prices is shown in equation 3.1, where y_t represents a measure of inequality at a given period, t (where $t = 1, \dots, n$), α_0 represents a constant term, and α_1 illustrates a time trend. γ is the linear coefficient for house prices, H_t , and β_j are the linear coefficients for all of the control variables, x_j , specific to each inequality measure (where $j = 1, \dots, k$). ε_t is a capture all error term that needs to be uncorrelated with the explanatory variables in all time periods.

$$y_t = \alpha_0 + \alpha_1 t + \gamma H_t + \sum_{j=1}^k \beta_j x_{j,t} + \varepsilon_t \quad (3.1)$$

This general model is typically ameliorated in one of two ways: by controlling for the fact that inequality in the current period is a function of past values of inequality or by considering that the effect of house prices/control variables on inequality may not be immediate but instead spread over several periods. The first refers to an autoregressive model (AR), shown in equation 3.2, where ψ_i are the linear coefficient for each lagged inequality variable, y_{t-i} (where $i = 1, \dots, p$); while the latter refers to a distributed lag model (DL), represented in equation 3.3, where γ_l are the linear coefficients for each

lagged house price variable, H_{t-l} (where $l = 0, \dots, q$). The control variables are not lagged, so they only represent the contemporaneous effect on the inequality measure.

$$y_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^p \psi_i y_{t-i} + \gamma H_t + \sum_{j=1}^k \beta_j x_{j,t} + \varepsilon_t \quad (3.2)$$

$$y_t = \alpha_0 + \alpha_1 t + \sum_{l=0}^q \gamma_l H_{t-l} + \sum_{j=1}^k \beta_j x_{j,t} + \varepsilon_t \quad (3.3)$$

It is a requirement for both AR and DL models that the dynamic effects between variables do not change over the sample period. This requires all the model's variables to be stationary so that the mean, variance, and autocorrelation patterns remain the same over time. Generally speaking, all-time series models require all included variables to have identical orders of integration [e.g., all I(0) or all I(1)] to generate unbiased regressors. For instance, all variables need to be non-stationary for ordinary least squares (OLS) and vector auto regression (VAR) estimation (Shrestha & Bhatta, 2018), or they all need to be I(1) for cointegration testing such as Engle and Granger (1987), Johansen (1995), or Phillips and Ouliaris (1988). This has led some researchers to difference every variable in a model out of an abundance of caution to ensure they are all stationary for OLS or VAR. This yields equation 3.4 and equation 3.5 for the AR and DL model, respectively, where Δ represents the change in the variable since the previous period. But, differencing all variables can lead to a potential over-differencing problem which presents new issues for researchers (De Prado, 2018), such as fitted models that are significantly different from the proper model (Hossain et al., 2019).

$$\Delta y_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^p \psi_i \Delta y_{t-i} + \gamma \Delta H_t + \sum_{j=1}^k \beta_j \Delta x_{j,t} + \varepsilon_t \quad (3.4)$$

$$\Delta y_t = \alpha_0 + \alpha_1 t + \sum_{l=0}^q \gamma_l \Delta H_{t-l} + \sum_{j=1}^k \beta_j \Delta x_{j,t} + \varepsilon_t \quad (3.5)$$

The ARDL model is an alternative approach to differencing that allows variables with alternative orders of integration to be included in the same model. That is an essential benefit for this thesis because the order of integration is uncertain for many variables, as shown in Table 3.8. However, while the ARDL is good at utilising a mixture of I(0) and I(1) variables, the ARDL model cannot include any variable that are I(2) at levels, e.g., variables that are only stationary after being differenced twice. The only variables that present any potential issue from the integration testing are house prices, real house prices, and the value-to-income ratio. Each of these three variables has one test result that suggests they are I(2) or greater at levels. However, each of them has two test results suggesting I(1) or less, so it is more likely that low test power has resulted in the null not being rejected in the ADF for these variables. ARDL models also perform best when the dependent variables are I(1) instead of I(0). All income inequality measures appear to be conclusively I(1), while there is greater uncertainty around the wealth inequality measures. However, once again, most test results suggest I(1) for the wealth inequality measures.

The ARDL has been an option for economic researchers for many decades but has grown significantly in use following the contributions of Pesaran and Shin (1995) and Pesaran et al. (2001). The ARDL model can analyse the cointegration between variables while remaining robust to the misspecification of integration orders. Additionally, the

ARDL approach allows researchers to explore the short-run dynamics and potentially long-run behaviours between variables using relatively small sample sizes and following a method similar to OLS (Duasa, 2007).

$$y_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^p \psi_i y_{t-i} + \sum_{j=1}^k \sum_{l_j=0}^{q_j} \phi_{j,l_j} x_{j,t-l_j} + \varepsilon_t \quad (3.6)$$

The ARDL is a combination of the AR and DL models, where the control variables and house prices can be lagged. The general ARDL form is shown in equation 3.6. In the context of this study, α_0 is an unrestricted constant term or drift component, and α_1 is an unrestricted time trend for years, t (where $\alpha_0, \alpha_1 \neq 0$). ϕ_{j,l_j} are the linear coefficients of the x variables (where $j = 1, \dots, k$) and their lags, l_j (where $l_j = 0, \dots, q_j$), where the x variables include house prices and a series of controls specific for each measure of inequality. It is required that all of the x regressors are not cointegrated among themselves. Not every x regressor needs to be lagged in the model.; hence, l_j can be zero, indicating no lags or any number greater than zero. ε_t is a capture all white noise error term that must be serially uncorrelated, have a zero mean, and constant variance-covariances over time (Pesaran & Shin, 1995). Out of a further abundance of caution, all models throughout the thesis are estimated utilising heteroskedasticity- and autocorrelation-consistent (HAC) standard errors so that statistical testing remains accurate if a model ε_t does not meet these requirements. HAC standard errors are derived from the work of Newey and West (1987).

From equation 3.6, the conditional error correction model (CECM) model can be derived, which is represented in equation 3.7. The $\mu_{y,i}$, μ_{j,l_j} , and ω_j regressor terms represent the short-run adjustment to equilibrium from a change in the regressor, while

the π_y and π_j regressor terms are considered the long-run adjustment between a variable with the measure of inequality.

$$\Delta y_t = \alpha_0 + \alpha_1 t + \pi_y y_{t-1} + \sum_{j=1}^k \pi_j x_{j,t-1} + \sum_{i=1}^{p-1} \mu_{y,i} \Delta y_{t-i} + \sum_{j=1}^k \sum_{l_j=0}^{q_j-1} \mu_{j,l_j} \Delta x_{j,t-l_j} + \sum_{j=1}^k \omega_j \Delta x_{j,t} + \varepsilon_t \quad (3.7)$$

Using equation 3.6 and the Beveridge-Nelson decomposition, the potential long-run relationship between the measure of inequality and each k regressor can be found. This requires weighing the cumulative impact of each k regressor over time, which is done by using the long-run multiplier, θ_j , specified in equation 3.8.

$$\theta_j = \frac{\sum_{l_j=0}^{q_j} \phi_{j,l_j}}{\sum_{i=1}^p \psi_i} \quad (3.8)$$

Pesaran et al. (2001) state that before calculating the long-run multiplier, it is first necessary to test the existence of a long-term levels relationship using a bounds test, which is an application of a standard F- or Wald test. The bounds test attempts to identify if a cointegrating relationship is present between the dependent variable and the regressors in the equation. It compares the CECM from equation 3.7 with the traditional error correction model (ECM), where all π (long-term) regressors are excluded. The ECM is shown in equation 3.9 where ECT_{t-1} is the error correction term (ECT) or the speed of adjustment of the dependent variable from a shock to the dependent variable in

the previous period. The null hypothesis of the bounds test is that the variables are not cointegrated and is defined by:

$$H_0 = \pi_y \cap \{\pi_j\}_{j=1}^k = 0 \quad \forall j$$

The alternative hypothesis of the bounds test is that the variables are cointegrated and is defined by:

$$H_1 = \pi_y \cup \{\pi_j\}_{j=1}^k \neq 0$$

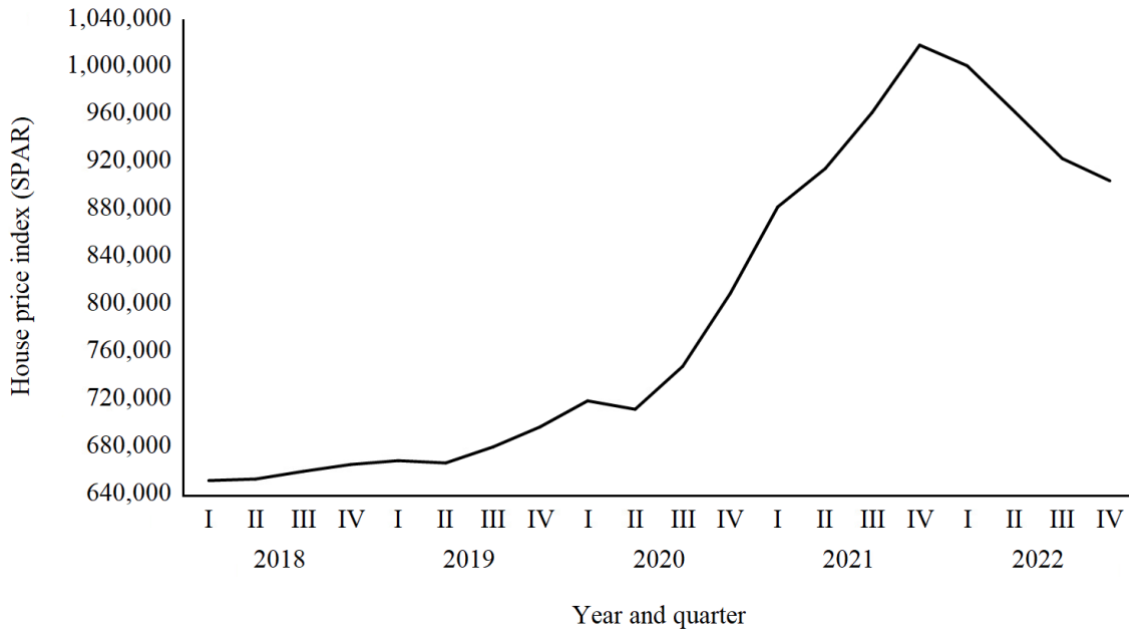
Although, Pesaran et al. (2001) note that the true alternative hypothesis can take a variety of different forms specific to each phenomenon. The original proposed critical values used for the bounds test in these models can be found in Pesaran et al. (2001, p. 301). However, Narayan (2005) argues that these critical values are unrealistic for most experimental settings as they are estimated based on a sample size of 1000. Narayan (2005, p. 1990) offers alternative and potentially more realistic critical values for smaller sample sizes. Both sets of critical values will be considered in this study. If the null hypothesis is rejected, the long-run values can be interpreted from equation 3.7, and the ECM model can be used for short-run dynamics. If the null hypothesis is not rejected, then only the initial ARDL model shown in equation 3.6 can be used for interpretations, and no short- or long-run dynamics can be considered.

$$\Delta y_t = \alpha_0 + \alpha_1 t + ECT_{t-1} + \sum_{i=1}^{p-1} \mu_{y,i} \Delta y_{t-i} + \sum_{j=1}^k \sum_{l_j=1}^{q_j-1} \mu_{j,l_j} \Delta x_{j,t-l_j} + \sum_{j=1}^k \omega_j \Delta x_{j,t} + \varepsilon_t \quad (3.9)$$

3.3.1.1 Non-linear Autoregressive Distributed Lag

Non-linear relationships between variables can take a variety of different forms and can be modelled in a range of ways. One method is to use two different specifications of the same variable in the model; for example, including house prices and house prices squared as explanatory variables to estimate a parabolic relationship with inequality. This was done throughout the analysis but yielded insignificant or unconvincing results. Another option is to use a NARDL model from Shin et al. (2014), which allows testing for asymmetries in the relationship between two variables—for example, comparing the impact on inequality from a positive change in house prices to a negative change. This is an especially important consideration because since February 2022, NZ house prices have been trending downwards (QV, 2023) and there are many predictions that this will continue throughout the rest of 2023 (Ninness, 2023). This is big news considering the general upwards trend of house prices from 2018 to 2021 as seen in Figure 3.9. Because of these decreases and the fact they are expected to continue longer, it leads to a question of whether there is a difference in the house price and wealth inequality relationship for positive and negative changes of house prices. That theoretical question of asymmetries is tested using a NARDL approach.

Figure 3.9: NZ house price index from 2018Q1 to 2022Q4



Note: Data is sourced from CoreLogic NZ.

The NARDL model has several benefits over other models that test for asymmetries. First, it allows for variables of mixed order to be included in the same model, which is a primary benefit for this analysis. Second, it can incorporate asymmetries in the long run, short run, or combined. Therefore, the NARDL model offers flexibility and can estimate more complex economic phenomena (Shin et al., 2014).

$$\Delta y_t = \alpha_0 + \alpha_1 t + \pi_y y_{t-1} + \theta^+ H_{t-1}^+ + \theta^- H_{t-1}^- + \sum_{j=1}^k \pi_j x_{j,t-1} + \sum_{i=1}^{p-1} \mu_{y,i} \Delta y_{t-i} + (3.10)$$

$$\sum_{r=0}^u \delta_r^+ \Delta H_{t-r}^+ + \sum_{z=0}^h \delta_z^- \Delta H_{t-z}^- + \sum_{j=1}^k \sum_{l_j=0}^{q_j-1} \mu_{j,l_j} \Delta x_{j,t-l_j} + \sum_{j=1}^k \omega_j \Delta x_{j,t} + \varepsilon_t$$

The NARDL model is presented in equation 3.10. It is the same as the CECM shown in equation 3.7 with a few additions. The first lag of the partial sum for a positive change in house prices, H_{t-1}^+ , and a negative change, H_{t-1}^- , are included. The x variables now

only include equation-specific control variables, and house prices are not included as an x variable. The lags for the first difference of a positive change, ΔH_{t-r}^+ (where $r = 0, \dots, u$), and the first difference of a negative change, ΔH_{t-z}^- (where $z = 1, \dots, h$), have also been included. The δ_r^+ coefficients represent the short-run dynamics from a positive change in house prices, while δ_z^- are the dynamics from a negative change. The long run coefficient for a positive and negative change in house prices are calculated using $\frac{\theta^+}{\pi_y}$ and $\frac{\theta^-}{\pi_y}$, respectively. If the long-run coefficients are equal to each other, there is no asymmetry, and hence there is an equivalent impact on inequality from a positive or negative change in house prices. Thus, a Wald test can be used where the null hypothesis is:

$$\text{Long run asymmetry } H_0: \frac{\theta^+}{\pi_y} = \frac{\theta^-}{\pi_y}.$$

Similarly, the short-run asymmetry can be tested where the null hypothesis is:

$$\text{Short run asymmetry } H_0: \sum_{r=0}^u \delta_r^+ = \sum_{z=0}^h \delta_z^-$$

The income inequality model was found to have no asymmetries in the short- or long-run. Because of this, the NARDL model results are included solely in Appendix G and are excluded from the primary discussion in Chapter 4. In contrast, the wealth inequality model was found to have some asymmetries present in the house price relationship and this is analysed throughout section 5.2.3.

3.3.1.2 Loan-to-Value Ratio

NZ presents a unique opportunity to consider the effect of LVRs on economic inequality in a way that has yet to be regularly done in the previous literature. This is because there are multiple explicit “cut-off” points of LVRs for residential mortgages in NZ. LVR restrictions began in October 2013 but were removed in 2020 due to the Covid-19 lockdown restrictions (RBNZ, 2022). The LVR restrictions were later reinstated in March 2021 by RBNZ due to unsustainable house price increases at the time (RBNZ, 2021b). LVR restrictions have been reviewed and tightened multiple times since March 2021 but have never been removed again. Other researchers have noticed this opportunity from NZ, such as Gatt (2023), who specifically chose NZ for LVR research due to the specific start of the LVR framework in response to the financial crises. This allowed the author to track the response of NZ house prices from LVR restrictions over time, yielding valid and more credible results than studying other countries with a more fuzzy introduction of LVRs. While other research has considered the effect of LVRs on economic inequality previously (Carpantier et al., 2018; Frost & van Stralen, 2018), not many papers have been able to directly see the impact of starting or stopping LVR restrictions on income and wealth inequality. Because of the multiple changes to LVRs in NZ, there is a greater potential that the true causal impact of introducing and removing LVRs on economic inequality can be found.

Park and Kim (2022) is one paper that had a similar situation to NZ when analysing the effects of LVRs on wealth inequality in South Korea, as LVRs were introduced at a specific date. This allowed the authors to utilise a RDD, where the effect of a treatment is analysed by comparing observations directly on either side of a cut-off point where there is a discrete jump in treatment likelihood. Park and Kim compare the effect of

LVRs between a control group (those with mortgages before the LVR was introduced) and the treatment group (those who obtained mortgages after the LVR was introduced). Park and Kim (2022) note that a RDD will come closer to finding the causal impact of introducing an LVR than other methods. Building on their previous work, something similar to a RDD is used in this thesis to see if the relationship holds in a different developed nation; additionally, the impact of LVRs on income inequality is considered using this approach, and the effect of both introducing and removing an LVR can be analysed due to the changes throughout the Covid-19 lockdown period. A regression discontinuity in time (RDiT) is used where inequality measures are compared directly before and after the LVR is introduced. An essential requirement for the RDiT model to hold is that “time-varying confounders [must] change smoothly across the cut-off date” (Nguyen, 2023, Regression Discontinuity chapter, section. 24.9, para. 1).

After experimenting with various lag structures, it was discovered that LVRs have no statistically significant impact on wealth inequality across all specifications. As a result, the outcomes of the LVR model are presented solely in Appendix H, and they are not discussed through the primary wealth inequality discourse of Chapter 5. This goes against the results of Carpentier et al. (2018) and Park and Kim (2022). However, it could be that the extent of an LVR policy makes a significant difference to wealth inequality in NZ context. The switching on/off of an LVR restriction does not impact on the wealth distribution, but how tight the LVR restrictions are might. Alternatively, it could be that the asset returns from housing-related assets are too close to more illiquid asset types, meaning LVRs have no impact on wealth inequality. This theory would only be true if the research of Zhai et al. (2023) is correct. Future research should further explore both of these potential explanations using NZ data. Conversely to wealth

inequality, introducing LVRs are found to have a statistically significant impact on the income inequality model, which is discussed in-depth throughout section 4.3.

3.3.2 Quantile Regression

The relationship between house prices and inequality results from heterogeneity for housing-related assets across the income/wealth distribution. Therefore, there could also be potential heterogeneity in the house price relationship across different quantiles of the Gini; this is what the quantile regression, introduced by Koenker and Bassett Jr (1978), is designed to consider. Instead of OLS/ARDL, which considers the relationship between house prices and the conditional mean of inequality, a quantile regression considers the relationship between house prices and the conditional quantile of inequality. Quantiles can take on any range specified by the user, such as percentiles, deciles, quintiles, etcetera. Alongside the benefits in heterogeneity interpretation, the quantile regression would also help deal with the heavy tails present in the inequality data, especially the income inequality variable that has been continuously trending downward over the study period. While the quantile regression was attempted, it was largely unsuccessful in delivering valuable results. A Wald test on the different quantile slopes being equivalent to each other was used. This test failed to reject the null hypothesis that the house prices slope was different across different quantiles of the income or wealth Gini, as shown in Table 3.11. Overall, there was no suggestion of asymmetry for any test, so the results were excluded from the main discussion. However, the full results of the quantile regression can be found in Appendix I.

Table 3.11: Wald test on the quantile regression results

Inequality measure	Chi-square test statistic	Chi-square degrees of freedom	p-value
<i>Quantile slope equality test</i>			
Income	0.5335	4	0.9702
Wealth	1.3648	4	0.8503
<i>Symmetric quantiles test</i>			
Income	0.1797	2	0.914
Wealth	0.3730	2	0.8299

Notes: Estimated equation $\tau = 0.5$ and number of test quantiles = 5. Null hypothesis is symmetry/equality across all of the test quantiles

3.3.3 Seemingly Unrelated Regression

Income and wealth inequality are analysed through separate models with a unique set of explanatory variables. However, a strong case can be made that there is also a relationship between income and wealth inequality. Many studies have demonstrated an association between income and wealth inequality (Benhabib et al., 2017; Berman et al., 2016; Dustmann et al., 2022; Gholipour et al., 2016; Simpson, 2009). Regularly attributing earnings inequality to impact wealth accumulation and, therefore, wealth inequality, but the relationship also goes in reverse. As individuals increase their wealth, they can generally devote more time (and money) to education than less wealthy individuals (Braga et al., 2017). This allows more opportunities to increase human capital, which has been demonstrated to lead to higher incomes (Lee & Lee, 2018). Additionally, wealthier individuals typically earn a more significant income on the

assets they own (asset returns) than less wealthy individuals, which also impacts income inequality (Fagereng et al., 2016).

There are two primary approaches to account for this relationship between the two dependent variables of each equation. First, the dependent variable of one equation can be included as an explanatory variable of the other equation, creating a system of equations; i.e., the income (wealth) inequality variable can be included in one model as the dependent variable and as an explanatory variable in the wealth (income) inequality model. This is shown in equations 3.11 and 3.12, derived from equation 3.6 previously; where W_t is wealth inequality, I_t is income inequality, and the additional explanatory variables and lags are uniquely selected for each model, denoted by subscript W and I for wealth and income inequality, respectively. W_t or I_t can have a contemporaneous relationship with the dependent variable or include short-run dynamics (where $e = 0, \dots, z$). The downside to this approach is it creates a potential endogeneity issue due to the simultaneity between the two dependent variables. An approach to overcome the endogeneity issue is considered in section 3.3.4.

$$W_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^p \psi_{W,i} W_{t-i} + \sum_{j=1}^k \sum_{l_j=0}^{q_j} \phi_{W,j,l_j} x_{W,j,t-l_j} + \sum_{e=0}^z \beta_{I,e} I_{t-e} + \varepsilon_{W,t} \quad (3.11)$$

$$I_t = \beta_0 + \beta_1 t + \sum_{i=1}^p \psi_{I,i} I_{t-i} + \sum_{j=1}^k \sum_{l_j=0}^{q_j} \phi_{I,j,l_j} x_{I,j,t-l_j} + \sum_{e=0}^z \beta_{W,e} W_{t-e} + \varepsilon_t \quad (3.12)$$

The second method is that each model can be estimated separately without including the dependent variables as explanatory variables. However, it can be assumed that the error terms of the two equations are contemporaneously related. This is known as a

seemingly unrelated regression (SUR) and has the benefit of no endogeneity issue but an efficiency gain due to the added information from the common disturbances. In the case of this thesis, it is reasonable to assume in a NZ context that the income and wealth inequality error terms are related to each other. Each regression equation for wealth and income inequality is presented in equations 3.13 and 3.14. The classical regression assumptions for each equation are maintained, with the additional SUR assumptions that the contemporaneous covariance between $\varepsilon_{W,t}$ and $\varepsilon_{I,t}$ is constant for all t and that the intertemporal covariance between $\varepsilon_{W,t}$ and $\varepsilon_{I,t}$ is zero for all explanatory variables in all periods (Srivastava & Giles, 1987). SUR uses a generalised least square approach over OLS, leading to an efficiency gain only if the errors are contemporaneously related, so this must be tested.

$$W_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^p \psi_{W,i} W_{t-i} + \sum_{j=1}^k \sum_{l_j=0}^{q_j} \phi_{W,j,l_j} x_{W,j,t-l_j} + \varepsilon_{W,t} \quad (3.13)$$

$$I_t = \beta_0 + \beta_1 t + \sum_{i=1}^p \psi_{I,i} I_{t-i} + \sum_{j=1}^k \sum_{l_j=0}^{q_j} \phi_{I,j,l_j} x_{I,j,t-l_j} + \varepsilon_{I,t} \quad (3.14)$$

3.3.4 Two-Stage Least-Squares

As outlined in section 3.3.3, wealth and income inequality both impact each other creating a simultaneous relationship. The problem with this simultaneity is that there will be an endogenous regressor when trying to estimate equations 3.11 and 3.12. Endogeneity leads to biased estimators and models that no inference can be drawn from (Wooldridge et al., 2017). A standard method to overcome endogeneity is a 2SLS model with an instrumental variable (IV). 2SLS involves an initial equation where the

endogenous regressors are each estimated with all the exogenous variables and IVs. Any regressor included in both equations is assumed to be exogenous. The first stage is shown in equations 3.15 and 3.17, generating values for the predicted income inequality variable, $\widehat{I}_{e,t}$, and predicted wealth inequality variables, $\widehat{W}_{e,t}$. IVs can be lagged or have only a contemporaneous relationship with the endogenous regressor (where $v = 0, \dots, d$). The predicted values from the first stage are then used in place of the endogenous regressor in the second equation; the second stage equations are shown in equation 3.16 for predicting wealth inequality and equation 3.18 for predicting income inequality. The predicted values will be exogenous when using the correct IV for the first equation, mitigating the endogeneity issue.

$$\widehat{I}_{e,t} = \alpha_0 + \alpha_1 t + \sum_{i=1}^p \psi_{W,i} W_{t-i} + \sum_{j=1}^k \sum_{l_j=0}^{q_j} \phi_{W,j,l_j} x_{W,j,t-l_j} + \sum_{v=0}^d \beta_{I,IV} IV_{I,t-v} + \varepsilon_{I,t} \quad (3.15)$$

$$W_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^p \psi_{W,i} W_{t-i} + \sum_{j=1}^k \sum_{l_j=0}^{q_j} \phi_{W,j,l_j} x_{W,j,t-l_j} + \sum_{e=0}^z \beta_{e,I} \widehat{I}_{t-e} + \varepsilon_{W,t} \quad (3.16)$$

$$\widehat{W}_{e,t} = \beta_0 + \beta_1 t + \sum_{i=1}^p \psi_{I,i} I_{t-i} + \sum_{j=1}^k \sum_{l_j=0}^{q_j} \phi_{I,j,l_j} x_{I,j,t-l_j} + \sum_{v=0}^d \beta_{W,IV} IV_{W,t-v} + \varepsilon_{\widehat{W},t} \quad (3.17)$$

$$I_t = \beta_0 + \beta_1 t + \sum_{i=1}^p \psi_{I,i} I_{t-i} + \sum_{j=1}^k \sum_{l_j=0}^{q_j} \phi_{I,j,l_j} x_{I,j,t-l_j} + \sum_{e=0}^z \beta_{e,W} \widehat{W}_{t-e} + \varepsilon_{I,t} \quad (3.18)$$

Equations 3.15 and 3.17 each have a unique set of IVs that must meet two requirements for valid results. First, the IV must be associated with the endogenous variable being predicted. Second, the IV must only affect the dependent variable of the second

equation through the endogenous variable (Wooldridge et al., 2017). In other words, the IV cannot directly impact the dependent variable of the second equation or through any other variable besides the endogenous variables; this second requirement is known as the exclusion restriction and is typically more challenging to attain than the first. Furthermore, there must be at least as many IVs included in the first stage as there are endogenous regressors.

The first IV trialled is the lagged values of the endogenous variable, which is a common IV to use in time series analysis (Bellemare et al., 2017; Fair, 1970; Murray, 2006). However, this approach has received scrutiny on whether the lagged IV mitigates endogeneity or meets the exclusion restriction (Reed, 2015; Wang & Bellemare, 2020). It only meets the exclusion restriction if the lagged IVs do not belong in the second equation. In other words, if the relationship between income and wealth inequality is contemporaneous only, then the lagged IV meets the exclusion restriction. A reasonable argument can be formed that the relationship is more than contemporaneous; the inequality dynamics may have intergenerational links and long-time spans (De Nardi, 2004; Erikson & Goldthorpe, 2002). Therefore, a Bartik instrument was used to supplement the lagged IV, which may be preferable in satisfying the exclusion restriction. A Bartik instrument is an example of a shift-share instrument (Bartik, 1991), which averages a set of shocks for a variable using an exposure-share weights (Borusyak et al., 2021). In this case, the exposure is to global inequality trends, and the weighting is the income/wealth share of each percentile of NZ in a starting year.

The Bartik instrument weighting began in 1980, so it is distant enough from the starting date of the analysis to not have any correlation with the inequality dynamics from 1990 onwards. Therefore, each percentile's income/wealth share in 1980 is the starting

weight. However, wealth inequality data is only available from 1995 onwards. Because there is not a long enough timespan available, a wealth inequality Bartik instrument could not be generated. Next, each percentile's income share can grow according to that specific percentile's global income share trend. How each predicted income share, $\widehat{\omega}_{t,p}$ (where $p = 0\%$ to 1% , ..., 99% to 100%), is calculated has been shown in equation 3.19, where $\Pi_{t,p}$ is the global income share of a percentile in a given period and $\overline{\omega}_{1980,p}$ is NZ's income share of a given percentile in 1980. Once each percentile predicted value is calculated, the predicted income Gini is calculated for each year. This predicted Gini serves as an alternative IV in equation 3.17. Because of the rising use of Bartik instruments and their value for econometric analysis, the NZ income inequality Bartik instruments have been provided for other researchers in Appendix J.

The predicted income Gini IV isolates the share of NZ income inequality driven by global trends. Global inequality growth is theoretically not driving the wealth and income inequality simultaneity. Suppositionally, the NZ-specific wealth and income inequality growth is associated with $\varepsilon_{I,t}$ and $\varepsilon_{W,t}$, respectively. This arises because the relationship's earnings inequality, human capital formation, and asset return channels are driven by NZ-specific forces and not overseas dynamics. Positive shocks to the NZ share of income (wealth) inequality lead to changes in wealth (income) inequality based on human behaviours, irrespective of changes to the international share of inequality. If this assumption is valid, the Bartik instrument will remove the NZ-specific growth of inequality and, therefore, would meet the exclusion restriction to solve for the endogeneity (Goldsmith-Pinkham et al., 2020).

Unfortunately, equations 3.15 and 3.16 could not be estimated as neither IV approach could yield robust results. A wealth inequality Bartik instrument cannot not be

generated as data is not available for a long enough period from the start of the analysis. Additionally, the lagged IV variable is unsatisfactory because the effect of wealth inequality on income inequality was found to be more than contemporaneous. This makes theoretical sense, as we would expect unequal wealth accumulation as a result of earnings inequality to occur over many periods. Lagged IVs only satisfy the exclusion restriction if the relationship of the endogenous regressor is contemporaneous, so using this approach would lead to biased estimated. Furthermore, when including enough lags of wealth inequality as an IV to build a valid model, the number of observations is dramatically reduced. For these reasons, equations 3.12 and 3.16 are excluded from the discussion in section 6.3. However, these models should be a focus for future research when more data is available.

$$\widehat{\omega}_{t,P} = \omega_{1980,P} * \left(1 + \left[\frac{\Pi_{t,P} - \Pi_{1980,P}}{\Pi_{1980,P}} \right] \right) \quad (3.19)$$

3.4 Summary

The relationship between house prices, wealth and income inequality, and all control variables is summarised in Figure 3.10. The critical addition to this model from previous studies is that the relationship between wealth and income inequality is being considered. Additionally, arrows in both directions represent a simultaneous relationship between the two inequalities. The modelling techniques have been carefully selected to robustly model the complex relationship between variables with only a small sample size available. A holistic summary of all the modelling techniques used in order of their execution from top to bottom is presented in Figure 3.11. In addition to the methods listed in this figure, a considerable amount of stability and sensitivity testing is

undertaken on each model. The results of the analysis are presented and discussed for income inequality in the following chapter, wealth inequality in Chapter 5, and the two dependent variables considered concurrently in Chapter 6.

Figure 3.10: A dependency graph showing the full relationships between all of the variables being modelled

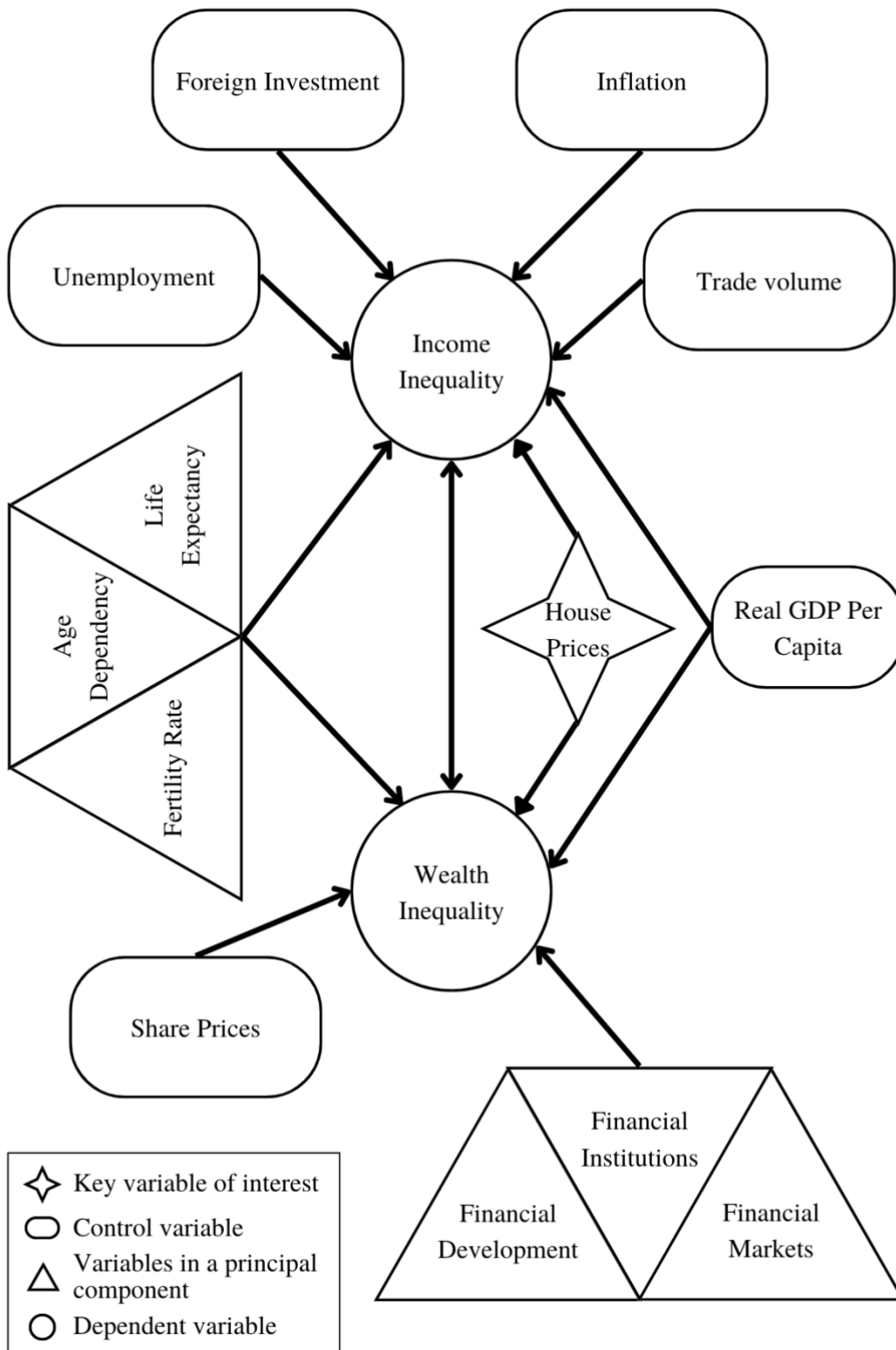
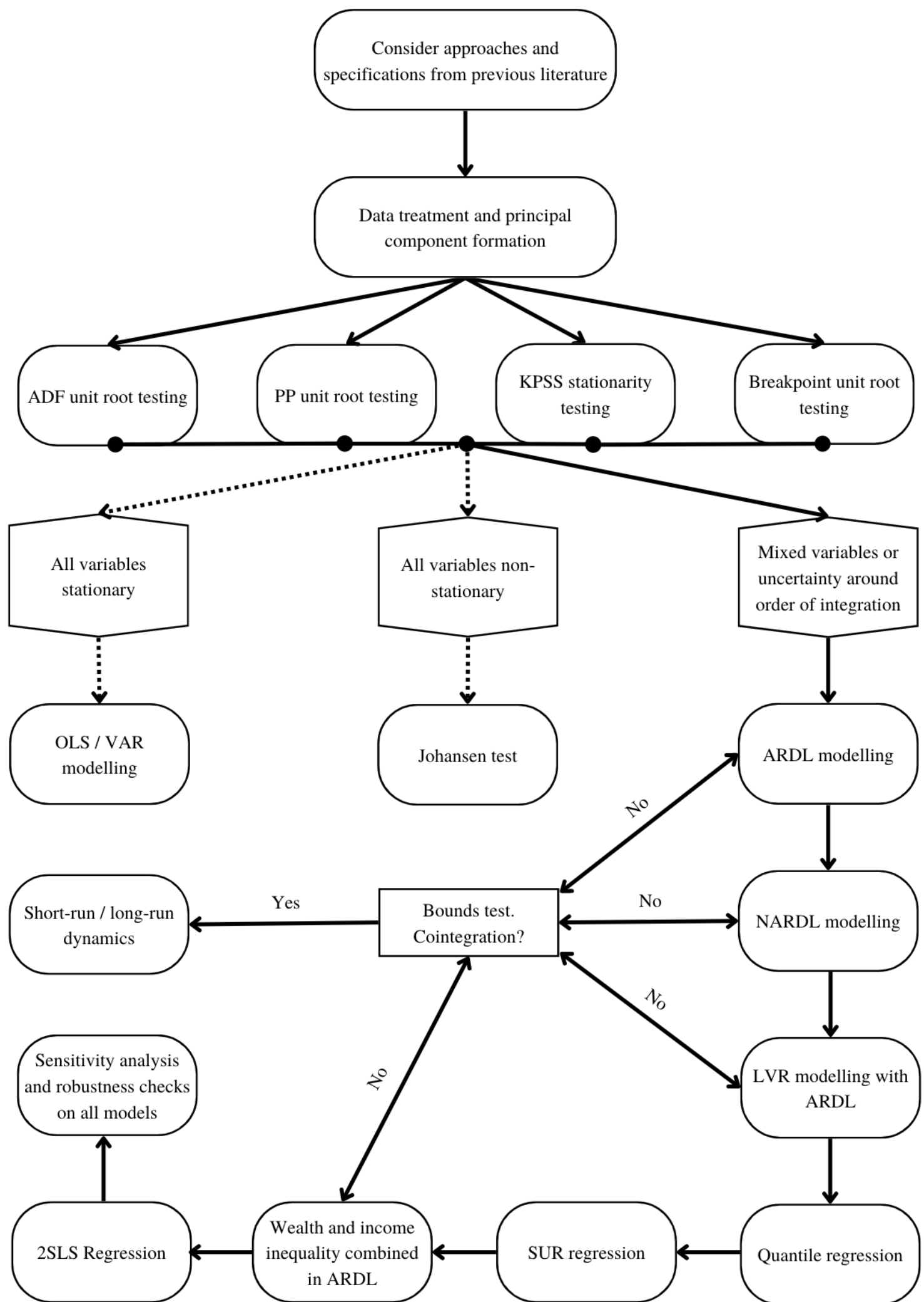


Figure 3.11: Full outline of the data analysis techniques and models used throughout the thesis in sequential order



Notes: Dotted lines present an approach/results that aren't applicable for these circumstances, but would be useful for other research. Lines with double arrows suggest either model could be used for interpretations depending on the results of the bounds cointegration test. This figure is based off the work of Shrestha and Bhatta (2018), Sarkodie and Owusu (2020), and Nasrullah et al. (2021).

Chapter 4: Income Inequality

4.1 Introduction

Throughout this thesis so far, the importance of the house price and economic inequality relationship has been considered, what the previous literature has done so far has been summarised, and the plan for examining the relationship in an NZ context has been outlined. This chapter examines the relationship between the NZ housing market and income inequality. The role house prices play in income inequality is discussed in section 4.2; additionally, some potential mechanisms of this relationship are considered. First, by considering the role of the NZ rental market in section 4.2.2, and second, by analysing the heterogeneity of house price impacts across the income distribution in section 4.2.3. A robust sensitivity analysis follows this in section 4.2.1 to consider the validity of the findings. Furthermore, the role of LVRs in income inequality is scrutinised in section 4.3, and a summary of all the findings is provided in section 4.4.

4.2 Price Changes

When specifying the income inequality ARDL model lag structure, the first approach trialled was setting the control variables' lag length according to the VAR lag order selection that minimised the SIC. The lags for the primary variables of interest – income inequality and house prices – were automatically selected based on the model that minimised the SIC overall. However, this resulted in unpredictable results, overfitted models with implausibly high R-squared values, and highly temperamental coefficients to changing the maximum lag. This is caused by relatively inconclusive VAR lag order selection results for some control variables. The second approach was to automatically

select most of the lag structures based on the model that minimised SIC overall. The downside of this approach is that to avoid overfitting the model, the maximum lag length can only be set to two. However, this made minimal difference to the lags. No VAR lag order selection suggested that any variables had a lag structure greater than two. Furthermore, trialling a mixture of automatic and fixed selection with a maximum lag greater than two did not substantially change the model results.

Figure 4.1 presents the SIC of the top 20 models trialled, where it can be seen the top three models all had a relatively similar SIC to each other. Upon further examination, they all had similar lag structures, with only a maximum of one lag difference in any variable. Additionally, all three models have analogous results for the sign and significance of variables. Hence, the primary model was chosen based on the most parsimonious lag structure of the top three models. As a result, model 35 represented in Figure 4.1, or the estimated model with the lowest overall SIC, was used to estimate the relationship. The final ARDL equation for this model is represented in equation 4.1.

Using equation 4.1, the CECM is derived for the Bounds cointegration testing, and the results of the tests are presented in Table 4.1. Using the F-Bounds test and the Narayan critical values, the null hypothesis of no cointegration is only rejected at a significance level of ten per cent and above with an $I(0)$ order of integration. Similarly, when using the Pesaran et al. critical values, the null is only rejected for the $I(0)$, but with a five per cent significance level and above. The null is never rejected for the $I(1)$ critical values. Pesaran et al. (2001) explains that the $I(0)$ critical values act as a lower bound when all of the explanatory variables are $I(0)$, while the $I(1)$ critical value is the upper bound when all of the x variables are $I(1)$. Because this analysis has a mixture of $I(0)$ and $I(1)$ explanatory variables, the true critical value is between the lower and upper bounds.

However, the actual critical value cannot be calculated, and thus, the Bounds test for income inequality cointegration is ultimately inconclusive.

This cointegration test result does not necessarily mean that the variables are unrelated, just that there is insufficient evidence from the F-Bounds test to suggest the variables are cointegrated. The same result is found when using the t-Bounds test. Because the presence of cointegration is uncertain, caution should be exercised when trying to separate the short- and long-run dynamics of the house price and income inequality relationship. The results of the short- and long-run estimates are provided in Appendix K. However, the ARDL model estimates shown in Table 4.2 are used for the subsequent discussion in this chapter as they do not require a rejection of the Bounds null hypothesis to be interpreted.

$$\begin{aligned} \ln(I_t) = & \alpha_0 + \alpha_1 t + \psi_1 \ln(I_{t-1}) + \phi_0 \ln(H_t) + \phi_1 \Delta \ln(CPI_t) + & (4.1) \\ & \phi_2 \ln(RGDP_t) + \phi_3 \text{Popl } PC_t + \phi_4 \ln(\text{Trade Vol}_t) + \phi_5 \text{For Invest}_t + \\ & \phi_6 \text{Unemp Rate}_t + \phi_7 \text{Unemp Rate}_{t-1} + \phi_8 \text{Break}_t + \phi_9 \text{Break}_t \cdot t + \varepsilon_{I,t} \end{aligned}$$

Figure 4.1: The Schwarz information criterion of the top 20 lowest models for the ARDL income inequality estimation

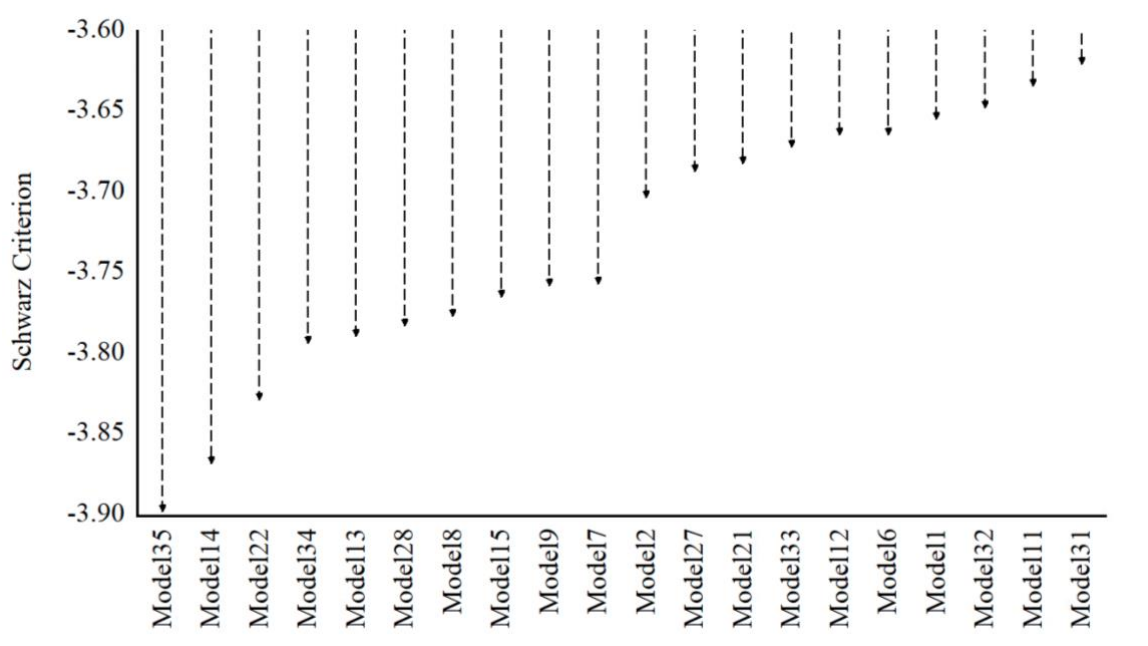


Table 4.1: Cointegration testing for the CECM from the ARDL model predicting ln(Income Gini)

	Significance level	I(0)	I(1)
<i>Pesaran et al. F-bounds critical values</i>		<i>Asymptotic: n=1000</i>	
	10%	2.53	3.59
	5%	2.87	4
	2.50%	3.19	4.38
	1%	3.6	4.9
<i>Narayan F-bounds critical values</i>		<i>Finite Sample: n=35</i>	
	10%	2.879	4.114
	5%	3.426	4.79
	1%	4.704	6.537
		<i>Finite Sample: n=30</i>	
	10%	2.977	4.26
	5%	3.576	5.065
	1%	5.046	6.93
<i>t-Bounds test critical values</i>		<i>Asymptotic: n=1000</i>	
	10%	-3.13	-4.37
	5%	-3.41	-4.69
	2.50%	-3.65	-4.96
	1%	-3.96	-5.31
<i>Test statistic values</i>			
Test type	Value	Decision	
F-statistic	3.123	Inconclusive	
t-statistic	-3.6026	Inconclusive	

Note: Null hypothesis for Bounds test is there is no cointegration relationship in levels ($H_0: \pi_y \cap \{\pi_j\}_{j=1}^k = 0$).

Table 4.2: Results of the ARDL model predicting ln(Income Gini)

Variable	Coefficient	t-statistic
ln(Income Gini (-1))	0.3741 ** (0.1699)	2.2013
ln(House prices)	0.1803 *** (0.0605)	2.9806
ln(Real GDP per capita)	0.8531 ** (0.3631)	2.2654
Population PC	-0.0645 (0.0847)	-0.7622
Unemployment rate	0.0308 ** (0.0142)	2.168
Unemployment rate (-1)	0.0224 (0.013)	1.7198
ln(Trade volume)	0.2721 ** (0.1102)	2.4693
Foreign investment	0.004 (0.0024)	1.6686
Inflation rate	0.0046 * (0.0023)	1.9755
Structural break	-16.4914 (20.6425)	-0.7989
Multiplicative structural break	0.0082 (0.0103)	0.7969
Constant	4.1247 (2.6484)	1.5574
Time trend	-0.0348 *** (0.011)	-3.1492
<i>Model diagnostics</i>		
R-squared	0.8900	
Adjusted R-squared	0.7500	
S.E. of regression	0.0378	
Schwarz criterion	-3.8972	

Notes: The standard error is reported in parenthesis underneath the coefficients. HAC standard errors & covariance have been used throughout. (*) is significant at 10%; (**) significant at 5%; and (***) significant at 1%.

There are many interesting results from the ARDL in Table 4.2. First, house prices have a statistically significant and positive contemporaneous relationship with the income Gini; this result matches the findings of many studies (Albouy et al., 2016; Dustmann et al., 2022; Grossmann et al., 2021; Travers et al., 2016). When house prices increase by ten per cent, the income Gini is expected to increase by 1.8 per cent in the same period, holding all else constant⁵. There are no NZ studies to compare these results with. Furthermore, comparability is limited due to the absence of log models with statistically significant Gini coefficients in international studies. However, Gholipour et al. (2016) found a 1.25 per cent increase in the income Gini following a ten per cent rise in housing costs, holding other factors constant. Assuming house prices and housing costs are closely related, this gives an approximate comparison, suggesting that 1.8 per cent is a large estimate.

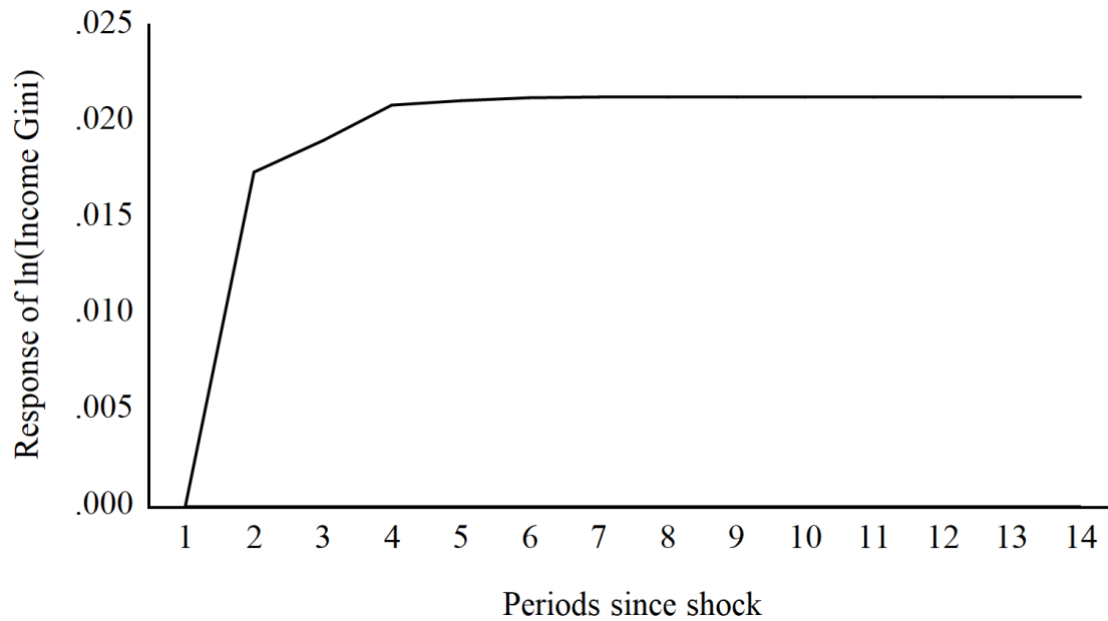
It is vital to note that some yearly increases in NZ house prices have been greater than ten per cent over the last three years. Year-on-year changes to the income Gini in NZ are known from 1951 to 2021. A 1.8 per cent increase would be the 14th largest increase in the income Gini recorded throughout this period. When considering negative changes, it would be the 32nd most considerable change to the income Gini over the 71 years of recorded change. Overall, it is not necessarily a large change in income inequality relative to NZ's historical trends. However, the relative importance of the increase depends on each individual's perspective and goals.

⁵ The income Gini variable is represented in logarithmic form in this model. Therefore, the coefficient represents a 1.8 per cent increase in the Gini coefficient, i.e., a percentage increase of a percentage variable (where the Gini is bounded between 0 and 100).

Second, the house price variable has no statistically significant lags in any specification of the ARDL model. This provides evidence of limited short-run dynamics between house prices and income inequality. A house price shock results in a relatively quick movement to the long-run equilibrium. This is presented visually through the accumulated impulse response function in Figure 4.2. Following a shock to house prices, the income Gini quickly increases in the first period. This is followed by smaller increases over the years two to four, followed by very little change in the income Gini after four periods from the initial shock.

However, the impulse response function shown in Figure 4.2 is generated from the ECM. Because the Bounds test was inconclusive, the ECM should be used cautiously. There is potential that the adjustment to long-run equilibrium is faster than four periods, but this cannot be confirmed. Either way, these results provide evidence of a dynamically stable model. Furthermore, the results suggest that the house price and income inequality mechanisms act quickly, and there is a quick adjustment period following a shock. For example, if the relationship is driven by disproportionate housing costs across the income distribution, this adjustment to long-run equilibrium occurs within a few years at most. House prices increase, housing costs relative to income across the distribution change, and income inequality is impacted all relatively quickly. Policymakers should be aware of the short adjustment period to income inequality from a house price shock.

Figure 4.2: The accumulated response of $\ln(\text{Income Gini})$ following a shock to $\ln(\text{House prices})$



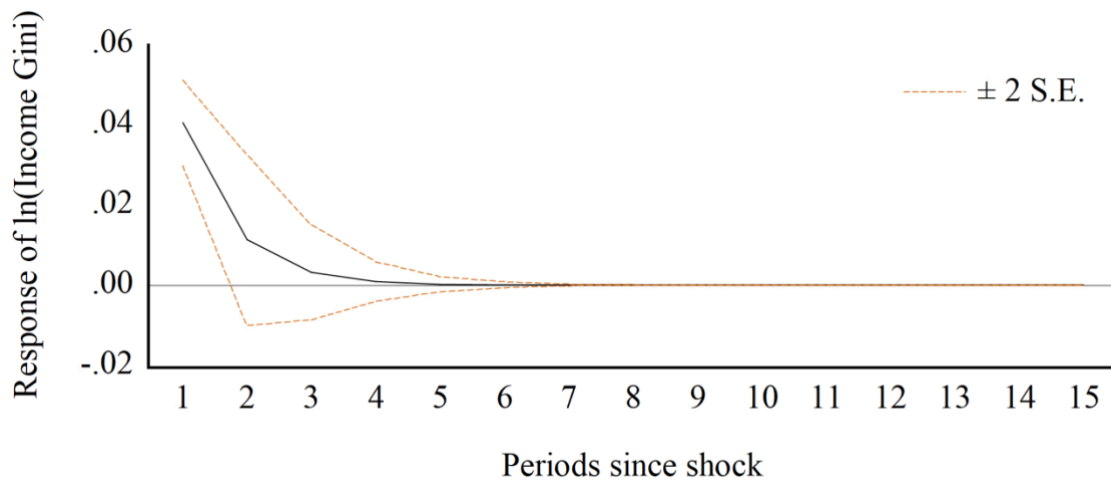
Note: Initial shock is a Cholesky one standard deviation innovation, adjusted for degrees of freedom.

Third, the lagged income Gini shown in Table 4.2 is a statistically significant and positive value. This provides evidence that a positive shock to the income Gini in the previous period increases the income Gini in the current period. Specifically, a one per cent increase in the income Gini leads to a 0.37 per cent increase in the income Gini in the following period, holding all else held constant⁶. A positive shock to the income Gini is persistent over time; however, the effect of past income Gini values on present values is diminishing over time because the value is less than one. This is presented visually through the impulse response function in Figure 4.3, where the marginal impact of the income Gini shock is essentially zero from period four after the shock onwards.

⁶ The income Gini variable is represented in logarithmic form in this model. Therefore, the coefficient represents a 0.37 per cent increase in the Gini coefficient, i.e., a percentage increase of a percentage variable (where the Gini is bounded between 0 and 100).

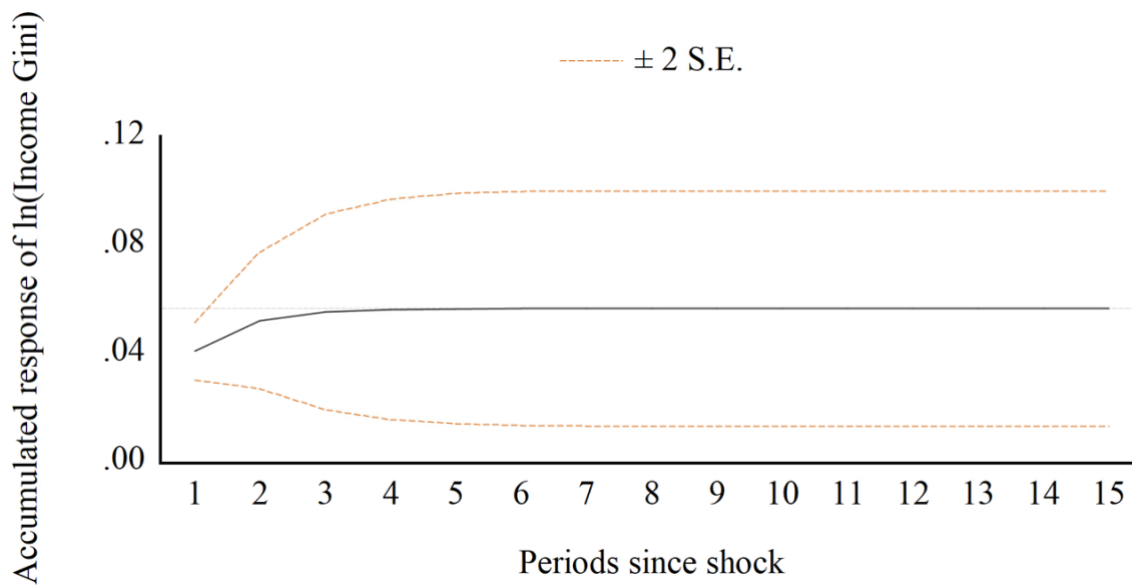
The persistence of the shock is presented in Figure 4.4, showing the accumulated response of the income Gini. A positive shock to income inequality results in a permanent increase to income inequality in later periods. Unlike the impulse response function in Figure 4.2 which is formed using the ECM, there is greater certainty on the validity of these two impulse response functions as they generated using the AR terms of the original ARDL model. However, Figure 4.3 and Figure 4.4 support the dynamics of Figure 4.2 that stability is achieved in around four periods after the initial shock. Therefore, this gives greater certainty that the impulse response function in Figure 4.2 is valid. Additionally, Figure 4.5 shows that inverse root of the AR polynomial [$\phi^{-1}(1)$] lies within the unit circle, supporting that the income inequality ARDL model is dynamically stable.

Figure 4.3: The marginal response of $\ln(\text{Income Gini})$ following a shock to $\ln(\text{Income Gini})$



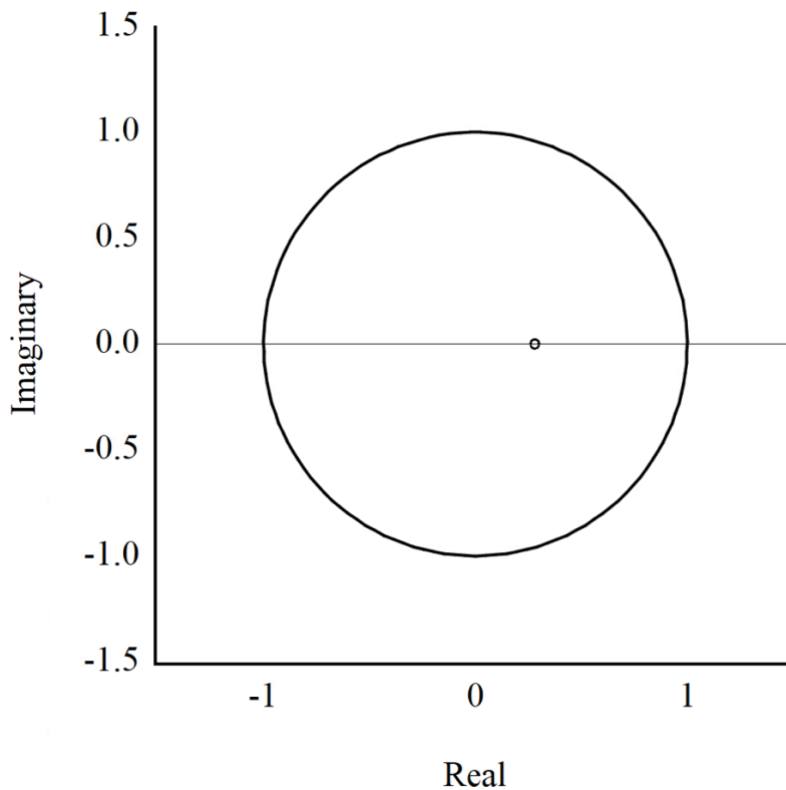
Note: Initial shock is a one standard deviation innovation.

Figure 4.4: The accumulated response of $\ln(\text{Income Gini})$ following a shock to $\ln(\text{Income Gini})$



Note: Initial shock is a one standard deviation innovation.

Figure 4.5: The inverse roots of the AR polynomials in the income inequality ARDL model



Note: The larger circle represents the unit circle, while the smaller circle represents the inverse root of the AR(1) polynomial in equation 4.1.

Fourth, only the contemporaneous real GDP per capita, unemployment, and trade volume variables in Table 4.2 statistically impact the income Gini at the five per cent significance level. Additionally, all three of these statistically significant variables have positive coefficients. It makes sense that as the unemployment rate increases, so does income inequality (Cysne, 2009). In other studies, trade is also reasonably common to increase income inequality (Adão et al., 2022; Furusawa et al., 2020). However, the positive coefficient for real GDP per capita is interesting.

The positive real GDP per capita coefficient is driven by the Kuznets curve, which argues that as nations initially grow and increase GDP per capita, income inequality

risers but decreases at higher GDP levels per capita. The positive coefficient may suggest that NZ still has a GDP per capita low enough to result in increasing income inequality. I.e., NZ's GDP per capita has not yet surpassed the Kuznets curve's global maximum. When altering the model to include real GDP per capita and real GDP per capita squared, both coefficients are positive but become statistically insignificant. Additionally, this model's house price variable coefficient decreases to 0.179 and remains statistically significant, representing a minimal change from the original model. Overall, the positive real GDP per capita coefficient is not an issue for interpreting the house price variable, but it is an exciting finding. It could be helpful for future researchers to explore the Kuznets curve in a NZ environment.

4.2.1 Sensitivity and Robustness

A diverse series of diagnostic checks are executed on the income inequality ARDL model. First, the potential multicollinearity of the explanatory variables was considered. Table 4.3 presents the correlation between the explanatory variables in the income inequality ARDL model, and it can be seen that there is a high correlation between many of these variables. The biggest variables of concern are house prices and real GDP per capita, which cannot be removed, given their importance in the previous literature. However, the problem with multicollinearity is that it causes implausibly large R-squared values and statistically insignificant regressors. Neither of these appears to be a problem when considering the results in Table 4.2. First, there are several statistically significant variables in the model. Second, the R-squared is 0.89, and the adjusted R-squared is similar at 0.75; It doesn't appear the model has an inflated R-squared solely because of the high correlation between explanatory variables. Thus, multicollinearity was considered a minor issue in this ARDL model.

Figure 4.6 displays the model's actual, fitted, and residual values, and the model does not seem overfitted to the sample. The residual disturbances appear reasonably well-behaved throughout the sample period, but the model underestimates income inequality in 2018 and 2019, although it corrected in 2020. There is no apparent reason why the model underestimates income inequality these years. The normality of the residuals is confirmed by the histogram of residuals in Figure 4.7, which shows a high p-value for the Jarque-Bera test, suggesting a normal distribution. The stability of the estimated model is examined using recursive, CUSUM, and CUSUM-of-squares for the residuals in Figure 4.8, Figure 4.9, and Figure 4.10, respectively. These figures provide evidence of model stability, with no crossings of the critical lines. This is especially good considering the small sample size used for the model. However, the recursive residuals appear higher than expected from 2017 to 2019, likely driven by when the model underpredicted the income Gini.

Table 4.4 and Table 4.5 examine the serial correlation and autocorrelation of the residuals, respectively. Autocorrelation is not an issue in the model, but the serial correlation is present for lags three and above. Adding additional lags of the dependent variable does not solve the problem; even adding ten lags of the income Gini variable (an AR(10) model) still resulted in a statistically significant LM test for lags three and above. While no serial correlation for two lags may be acceptable given the short data period and annual frequency of the data, readers should be aware of this caveat, especially if they intend to use the model for forecasting. HAC standard errors are used throughout the analysis to compensate for the serial correlation. The final diagnostic check is the Breusch-Pagan-Godfrey test for heteroskedasticity, which does not reject the null hypothesis of homoskedasticity at any level, indicating that the model variances are constant over time. It is worth noting that all diagnostic tests above are performed

on all subsequently predicted models in this chapter but are not discussed or presented in such detail again.

Table 4.3: Correlation matrix of the explanatory variables in the ARDL model predicting $\ln(\text{Income Gini})$

<i>Variable</i>	1.	2.	3.	4.	5.	6.
1. $\ln(\text{House prices})$	1					
2. $\ln(\text{Real GDP per capita})$	0.984	1				
3. $\ln(\text{Trade volume})$	-0.898	-0.899	1			
4. Population PC	-0.895	-0.912	0.800	1		
5. Foreign investment	-0.278	-0.349	0.246	0.454	1	
6. Unemployment rate	-0.519	-0.570	0.603	0.556	0.132	1
7. Inflation rate	0.080	0.113	-0.064	-0.147	0.008	-0.373

Figure 4.6: The actual, fitted, and residual values of the ARDL model predicting $\ln(\text{Income Gini})$

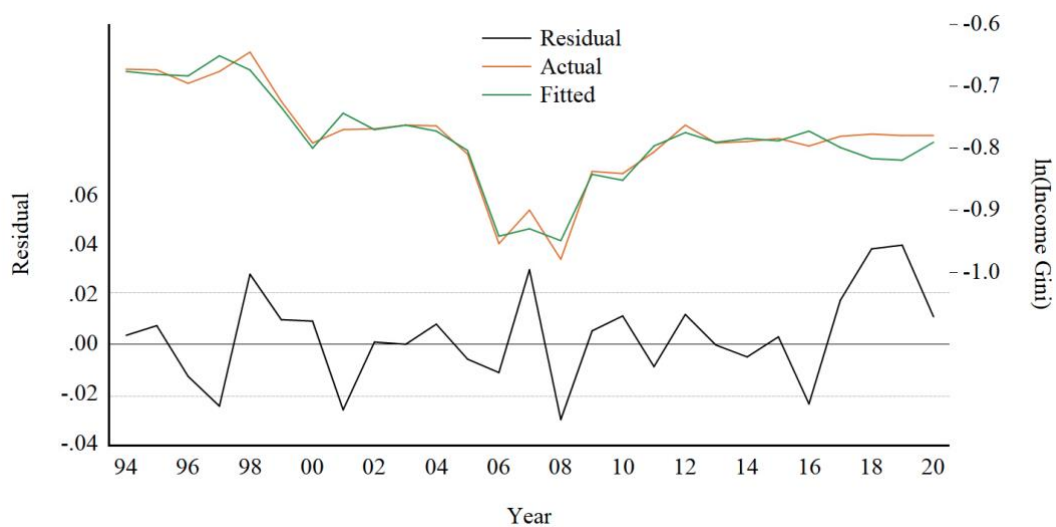
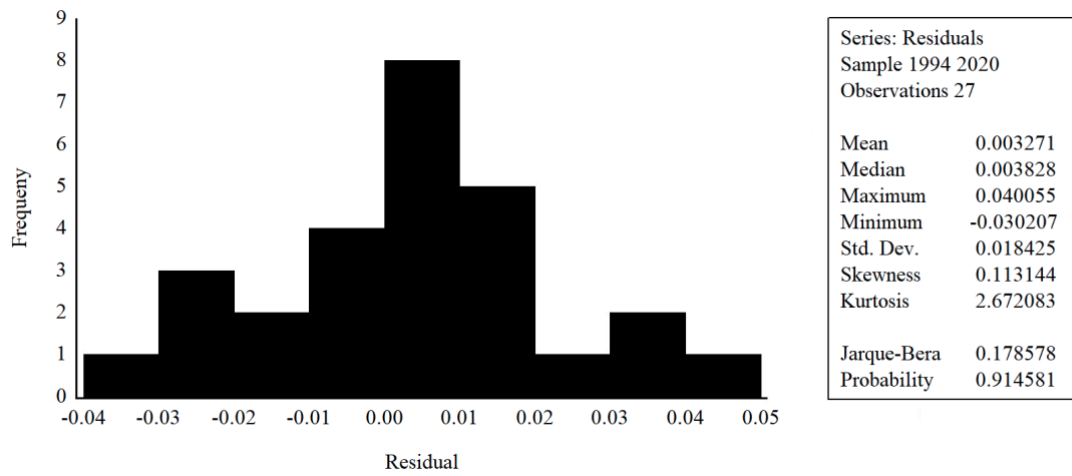


Figure 4.7: Histogram of the residuals from the ARDL model predicting ln(Income Gini)



Note: The null hypothesis of the Jarque-Bera test is a normal distribution.

Figure 4.8: The recursive residuals from the ARDL model predicting ln(Income Gini)

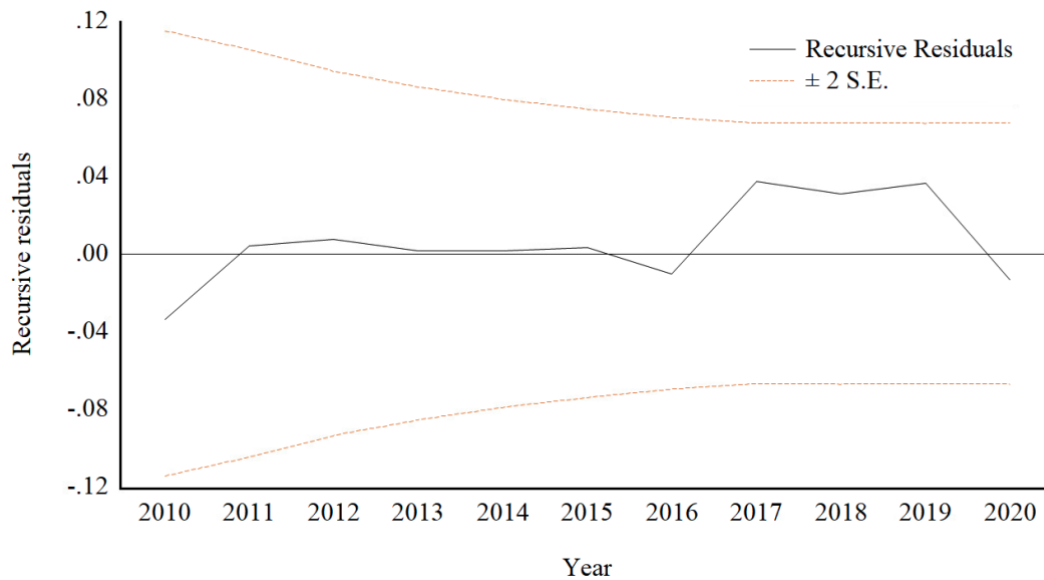


Figure 4.9: The cumulative sum of the residuals from the ARDL model predicting $\ln(\text{Income Gini})$

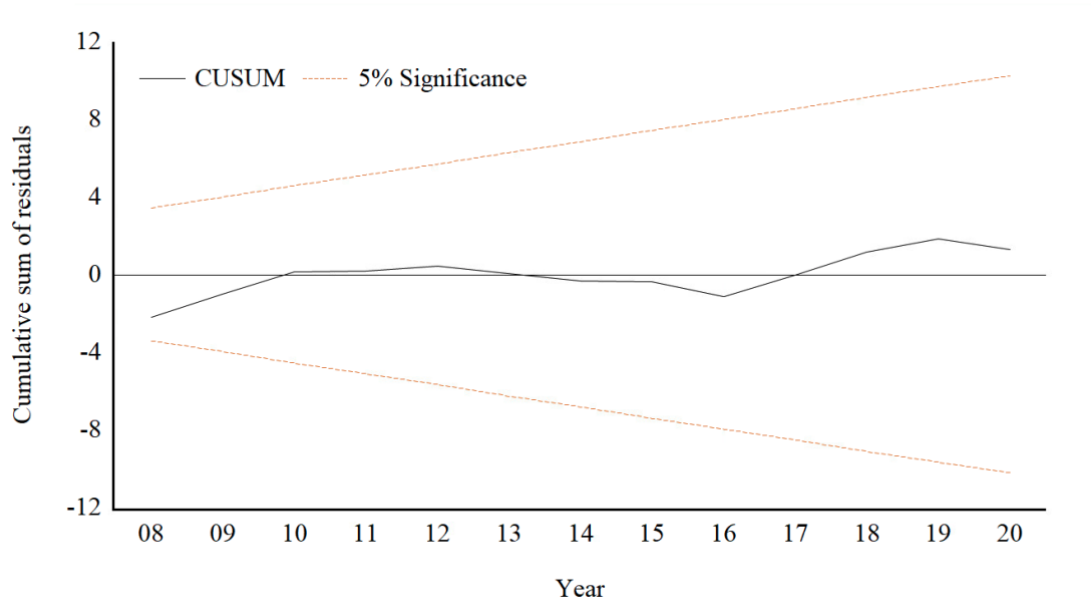


Figure 4.10: The cumulative sum of squared residuals from the ARDL model predicting $\ln(\text{Income Gini})$

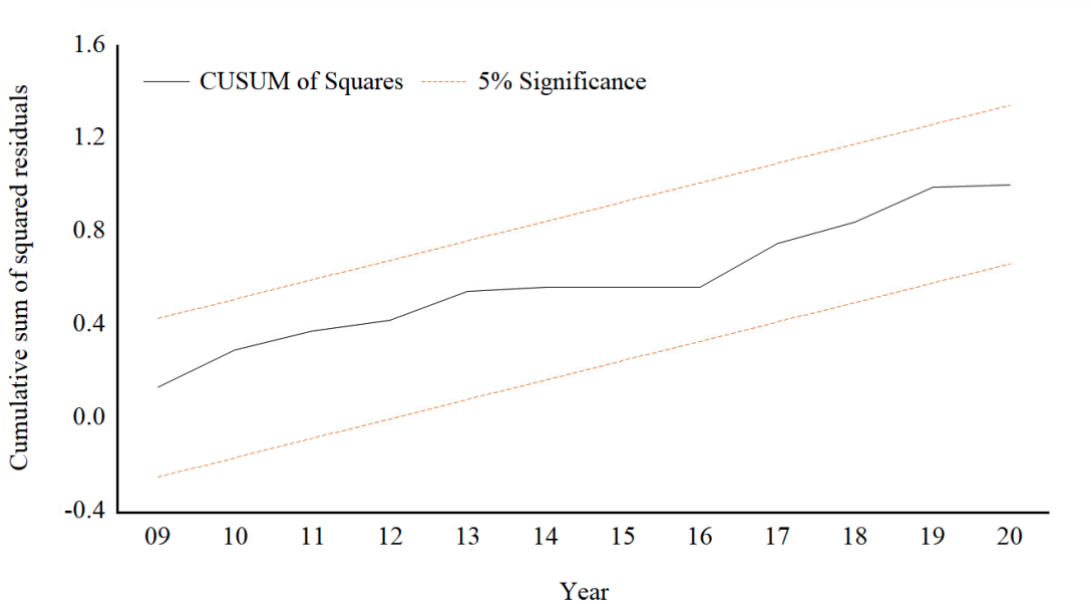


Table 4.4: Serial correlation LM test for the ARDL model predicting ln(Income Gini)

Lags	f-statistic	p-value
1	3.4695	0.0921
2	1.4933	0.2636
3	3.6214	0.0488
4	4.6593	0.0221
5	3.4317	0.0519
6	3.5059	0.0527

Note: Null hypothesis is no serial correlation up to the specified number of lags.

Table 4.5: Correlogram of residuals for the ARDL model predicting ln(Income Gini)

Lags	<i>Residuals</i>		<i>Residuals Squared</i>	
	Q-Stat	p-value	Q-Stat	p-value
1	2.2088	0.137	1.7466	0.186
2	2.2608	0.323	1.7741	0.412
3	7.683	0.053	1.8532	0.603
4	7.9643	0.093	2.8919	0.576
5	8.2272	0.144	3.2666	0.659
6	8.7007	0.191	4.5096	0.608
7	9.1269	0.244	4.644	0.703
8	12.388	0.135	5.2753	0.728
9	12.496	0.187	7.0069	0.636
10	13.373	0.204	7.4518	0.682
11	13.389	0.269	7.5879	0.75
12	16.136	0.185	7.9265	0.791

Notes: Null hypothesis is no autocorrelation up to specified lag level and () is significant at 10%; (**) significant at 5%; and (***) significant at 1%.*

The next diagnostic check is trialling multiple alternative model specifications to ensure income inequality and house price findings robustness. First, two alternative measures of income inequality and house prices were estimated. The model estimates from the four alternative specifications, along with the original, are presented in Table 4.6. When using the Palma ratio as the dependent variable instead of the Gini, the impact of house prices is statistically significant but negative. A ten per cent increase in house prices is associated with a two per cent decrease in the Palma ratio, holding all else constant. Because it is a negative coefficient, the wealth share of either the top ten per cent or bottom 40 per cent of the income distribution is decreasing due to rising house prices. Both deciles cannot experience a simultaneous loss in income share as this would result in a positive coefficient. Additionally, because the house price coefficient in model two is less than one in absolute terms, the change in the income share of the bottom 40 per cent must be greater than the change of income share to the top ten per cent. In contrast, house prices make no statistically significant difference in the ratio of income shares between the top and bottom 20 per cent of the income distribution. This matches the results of Abeyasinghe and Hao (2014).

The results of models two and three in Table 4.6 suggest three things: (i) the change in the Palma ratio is primarily driven by the change of income share in the 20 to 40 per cent of the income distribution; (ii) the results of an analysis exploring income inequality and house prices will vary based on the target group or measure of income inequality; (iii) there is heterogeneity in the impact of house prices across the income distribution. The heterogeneity is further explored in section 4.2.3. When considering models four and five, it can be seen that an increase in real house prices leads to a slightly larger increase in the income Gini than nominal house prices. In contrast, an increase in the housing affordability measure leads to a considerably greater impact on

the income Gini relative to nominal house prices. Housing affordability is expected to be more prominent in magnitude because higher house prices, a reduction in the real wage, or a combination of both can drive an increase in the housing affordability measure. Both mechanisms would be expected to worsen income inequality, hence the larger magnitude.

The real house price measure in model four is slightly more surprising, although the coefficient is within one standard error from the house price coefficient in model one. Additionally, Vale and Camões (2022) also found that increases in real house prices worsen income inequality. One explanation for the greater magnitude is that an increase in real house prices can be driven by either an increase in nominal house prices or a lower inflation rate. Low inflation rates are associated with a higher real wage (Minarik, 1978). If inflation's effect on real wages disproportionately benefits those higher on the income distribution, it could lead to a greater coefficient magnitude. Ultimately, this cannot be tested using this dataset, but could be the focus of future research. Nevertheless, the result highlights that worsening affordability and rising real house prices are associated with increases in the income Gini.

Only model two in Table 4.6 resulted in rejecting the null for the t- and F-Bounds tests. The other models all had inconclusive results with test values between the lower and upper critical values. This provides evidence of a cointegrating relationship between all the explanatory variables and the Palma ratio. Because of this cointegration, the short- and long-run dynamics can be estimated for model two, with the latter being presented

in Table 4.7⁷. Like in model two, the long-run house price coefficient is still statistically significant and negative. However, it is smaller in magnitude in the long-run, suggesting there is some correction from the initial change to the income Palma estimated in Table 4.6.

⁷ The short-run dynamics are not included because house prices only have a contemporaneous relationship with income inequality, or at the very least, a quick adjustment to the long-run equilibrium with little short-run dynamics. Therefore, house prices do not appear in the ECM, and including the ECM would be outside of the scope of this thesis. However, the ECM was checked and has the desirable property of a statistically significant and negative ECT. Additionally, the ECT is close to one in absolute terms supporting the evidence of dynamic stability and fast adjustments to long-run equilibrium following a shock to long-run equilibrium.

Table 4.6: Estimated ARDL coefficients for a range of income inequality and house price specifications

<i>Model</i>	<i>(1)</i>		<i>(2)</i>		<i>(3)</i>		<i>(4)</i>		<i>(5)</i>	
<i>Dependent variable</i>	<i>ln(Income Gini)</i>		<i>ln(Income Palma)</i>		<i>ln(Income S80S20)</i>		<i>ln(Income Gini)</i>		<i>ln(Income Gini)</i>	
Variable	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
ln(Income Gini (-1))	0.3741 ** (-0.1699)	2.2013					0.3721 ** (0.1688)	2.2046	0.289 (0.1934)	1.4944
ln(Income Palma (-1))			-0.1456 ** (0.0684)	-2.1276						
ln(Income S80S20 (-1))					-0.1589 (0.3064)	-0.5188				
ln(Income S80S20 (-2))					-0.2982 ** (0.1328)	-2.2448				
ln(House prices)	0.1803 *** (-0.0605)	2.9806	-0.207 *** (0.0615)	-3.3693	-0.0371 (0.0266)	-1.3935				
ln(Real house prices)							0.1819 ** (0.07)	2.5997		
ln(Value-to-income)									0.1989 *** (0.0664)	2.9928
ln(Real GDP per capita)	0.8531 ** (-0.3631)	2.2654	-0.3813 (0.4853)	-0.7859	-0.2037 (0.2427)	-0.839	1.5011 * (0.7499)	2.0018	1.7289 *** (0.544)	3.1782
Population PC	-0.0645 (-0.0847)	-0.7622	0.1298 ** (0.0541)	2.4004	0.0373 (0.0342)	1.0899	-0.0749 (0.0873)	-0.8586	-0.0347 (0.0982)	-0.3529
Unemployment rate	0.0308 ** (-0.0142)	2.168	-0.0197 ** (0.009)	-2.1836	-0.0246 *** (0.0073)	-3.3546	0.0296 * (0.0143)	2.0691	0.0332 ** (0.0139)	2.3965
Unemployment rate (-1)	0.0224 (-0.013)	1.7198	-0.0092 (0.0054)	-1.7128	0.0047 (0.0068)	0.696	0.0217 (0.0136)	1.5876	0.0291 ** (0.0107)	2.7193
ln(Trade volume)	0.2721 ** (-0.1102)	2.4693	-0.0486 (0.0802)	-0.6066	-0.0226 (0.0712)	-0.317	0.2833 * (0.1585)	1.7873	0.3049 ** (0.1091)	2.7957
Foreign investment	0.004 (-0.0024)	1.6686	-0.0031 (0.0023)	-1.38	-0.0017 (0.0013)	-1.3097	0.0043 (0.0026)	1.6463	0.0037 (0.0025)	1.4568
Inflation rate	0.0046 * (-0.0023)	1.9755	-1.4045 *** (0.335)	-4.193	-1.0169 ** (0.3625)	-2.8051	-1.1563 (0.7215)	-1.6028	-1.501 * (0.7301)	-2.0558

<i>Model</i>	<i>(1)</i>		<i>(2)</i>		<i>(3)</i>		<i>(4)</i>		<i>(5)</i>	
<i>Dependent variable</i>	<i>ln(Income Gini)</i>		<i>ln(Income Palma)</i>		<i>ln(Income S80S20)</i>		<i>ln(Income Gini)</i>		<i>ln(Income Gini)</i>	
Variable	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Structural break	-16.4914 (-20.6425)	-0.7989					-18.2813 (20.7496)	-0.881	-6.7519 (17.1488)	-0.3937
Multiplicative structural break	0.0082 (-0.0103)	0.7969					0.0091 (0.0103)	0.8793	0.0033 (0.0085)	0.391
Constant	4.1247 (-2.6484)	1.5574	0.7569 (2.3029)	0.3287	1.7648 (1.1055)	1.5964	3.3221 (2.84)	1.1698	6.1728 *** (2.0522)	3.008
Time trend	-0.0348 *** (-0.011)	-3.1492	0.0242 *** (0.0056)	4.3537	0.0091 * (0.0044)	2.0649	-0.0291 ** (0.0106)	-2.7457	-0.0339 *** (0.0087)	-3.8777
<i>Cointegration relationship testing</i>										
F-Bounds test	3.123		6.1462 ***		3.8565		3.0620		3.1475	
t-Bounds test	-3.6026		-5.0745 ***		-3.4600		-3.5947		-3.7488	

Note: See notes for Table 4.2 and Table 4.1.

Table 4.7: Estimated long-run coefficients using the ARDL approach (dependent variable = $\ln(\text{Income Palma})$)

Variable	Coefficient	t-statistic
$\ln(\text{House prices})$	-0.1411 *** (0.0443)	-3.1859
$\ln(\text{Real GDP per capita})$	-0.4664 (0.4553)	-1.0245
Population PC	0.0691 (0.0405)	1.7086
Unemployment rate	-0.027 ** (0.0125)	-2.157
Foreign investment	-0.0022 (0.0019)	-1.1521
$\ln(\text{Trade volume})$	-0.0894 (0.0617)	-1.4498

Note: See notes for Table 4.2.

To ensure model robustness, it is essential to consider the role of control variables. The original model included six control variables, resulting in 64 possible combinations of control variables that could be modelled⁸. Therefore, 64 distinct models were estimated, each with various control variables removed to assess each control variable's impact. The unique combinations and the ARDL results for all 64 models can be found in Appendix L. Table 4.8 provides a statistical summary of all the house price coefficients from the 64 models.

⁸ There are 64 unique combinations if the control variable can only take on the same lag structure as the original ARDL model. If the control variables can take on different lag lengths, there would be more than 64 possible combinations.

It can be seen from Table 4.8 that the mean and median house price coefficient from the 64 models is slightly lower than the Table 4.2 estimate of 0.18. Therefore, when fewer control variables are included in the model, house prices will, on average, have a more minor impact on income inequality than when all control variables are included. However, the highest coefficient is 0.267, and 23 of the 64 models have a higher coefficient than 0.18. The minimum is also a positive value, suggesting that positive house price shocks always lead to an increase in the income Gini, never a decrease. However, ten out of the 64 coefficients are not statistically different from zero at the ten per cent significance level or below.

When examining the models with statistically insignificant house price variables, three control variables consistently made a difference to the statistical significance of the house price coefficient: real GDP per capita, unemployment, and inflation. Excluding some combination of these three variables will generally result in a model where house prices do not impact the income Gini. Given that these three control variables are commonplace in the income inequality literature (Berisha et al., 2022; Cloninger, 2016; Deyshappriya, 2017; Monnin, 2014; Nielsen & Alderson, 1997; Sheng, 2011), it seems reasonable to conclude that excluding these variables would result in omitted variable bias, leading to incorrect estimates (Wooldridge et al., 2017). The other three control variables are less influential on the significance of the house price variable. Most importantly, the Population PC variable never changes the sign or significance of the house price coefficients. Overall, the relationship between house prices and income inequality remains reasonably robust when considering different model specifications, although some explanatory variables play a pivotal role.

Table 4.8: A summary of the house price coefficients for all 64 of the income inequality control variable combinations

Measure	Value
Mean	0.1686
Median	0.1686
Minimum	0.0717
Maximum	0.2667
Significant at the 10% level	54
Significant at the 5% level	32
Significant at the 1% level	8
Significant only above the 10% level	10
Total models	64

Note: The specification of the 64 models and the full results are given in Appendix L.

4.2.2 Rent Prices

One common explanation of the mechanism behind the income inequality and house price relationship is that as house prices increase, so do rent prices. This is likely true, as NZ's house and rent prices have a correlation of 0.95, and rent prices are argued to be closely bounded to house prices in the long-run (Gallin, 2008; Zhai et al., 2018). Higher rent prices lead to rising housing-related costs for those lower on the income distribution, making up a greater proportion of renters. This is demonstrated in Table 4.9 where housing costs are the greatest for renters compared to any other tenure status. Simultaneously, those who own rental properties experience an increase in income, and rental owners tend to be those higher up the income distribution. Therefore, the

disproportionate change in housing costs across the income distribution worsens real income inequality. To test this theory, two alternative model specifications are used. First, rent prices are included as a control variable in the ARDL. Second, rent prices are used instead of house prices because if this is the theoretical mechanism, rent prices would adequately capture the entire relationship. The results of both these models have been presented in Table 4.10.

Table 4.9: A breakdown of housing costs by tenure status from 2015 to 2021

Tenure	Income	Income after housing costs	Housing costs	Housing costs as a proportion of income
Renters	\$ 82,023	\$ 62,156	\$ 19,867	24%
Owners	\$ 107,537	\$ 90,677	\$ 16,860	16%
Family-trust	\$ 141,030	\$ 127,672	\$ 13,358	9%

Notes: Data is sourced from the Stats NZ IDI. The family-trust tenure status is when the housing wealth of a household is predominantly held within a family-trust. For a more granular breakdown of the information in this table, see the link in Appendix A.

Table 4.10: The income inequality ARDL model capturing rent prices with two alternative specifications

<i>Model</i>	<i>(1)</i>		<i>(2)</i>	
Variable	Coefficient	t-statistic	Coefficient	t-statistic
ln(Income Gini (-1))	0.3654 *	1.818	0.3485 *	1.9675
	(0.201)		(0.1771)	
ln(House prices)	-0.137	-0.6755		
	(0.2028)			
ln(Rent)	0.0311	0.1478	-0.0891	-0.9175
	(0.2101)		(0.0971)	
ln(Rent (-1))	0.7688 **	2.3722	0.721 **	2.5158
	(0.3241)		(0.2866)	
ln(Rent (-2))	-1.0021 **	-2.3382	-0.7889 ***	-3.547
	(0.4286)		(0.2224)	
ln(Real GDP per capita)	2.8542 **	2.8885	2.5776 ***	4.4253
	(0.9881)		(0.5825)	
Population PC	-0.1524	-1.5871	-0.1485	-1.7104
	(0.096)		(0.0868)	
Unemployment rate	0.0446 ***	3.2696	0.0423 ***	3.5087
	(0.0137)		(0.0121)	
Unemployment rate (-1)	0.033 *	2.117	0.0322 **	2.7437
	(0.0156)		(0.0117)	
ln(Trade volume)	0.0097 ***	3.5205	0.0084 ***	3.7331
	(0.0028)		(0.0023)	
Foreign investment	0.4117 **	2.3056	0.3905 **	2.7935
	(0.1785)		(0.1398)	
Inflation rate	-1.7232 **	-2.843	-1.4758 **	-2.4807
	(0.6061)		(0.5949)	
Structural break	13.6904	0.4293	3.1411	0.1655

<i>Model</i>	<i>(1)</i>		<i>(2)</i>	
Variable	Coefficient	t-statistic	Coefficient	t-statistic
	(31.8898)		(18.9796)	
Multiplicative structural break	-0.0068 (0.0159)	-0.431	-0.0016 (0.0094)	-0.1684
Constant	12.2784 ** (5.6231)	2.1836	9.8146 *** (2.2187)	4.4237
Time trend	-0.0294 *** (0.0097)	-3.0409	-0.0348 *** (0.0081)	-4.3033
<i>Cointegration relationship testing</i>				
F-Bounds test	3.6409		4.28 **	
t-Bounds test	-3.6233		-3.64	

Note: See notes for Table 4.2 and Table 4.1.

There are some interesting findings displayed in Table 4.10. First, rent prices have no contemporaneous relationship with income inequality; instead, there is a dynamic change in income inequality from a rent price shock over two years from the initial change. In contrast, the relationship between house prices is found to be contemporaneous only. Therefore, it is unlikely that rent prices are driving the initial increase of the income Gini following a positive house price shock. Second, when rent prices are held constant in the model, house prices have no statistically significant effect on the income Gini. The insignificant coefficient suggests that some of the relationship between house prices and income inequality arises from changing rent prices. This is because increasing house prices will not affect the income distribution when rent prices are held constant.

Third, the significant rent price coefficients sum close to zero in model two and -0.21 in model one, giving evidence that when house prices are not controlled for, rent prices do

not significantly impact income inequality in the long-run. This means that rent prices themselves cannot entirely capture the mechanisms of the house price relationship. Forth, rent prices increase income inequality one period after the shock, followed by a correction in the second period after the shock. This is true in models one and two. Therefore, studies that only include one lag of rent prices may miss the model correction and incorrectly conclude that higher rent prices worsen income inequality.

Finally, a nonsensical cointegration relationship is present in model two based on the Bounds test results. Altogether, the results suggest that the rental market drives some of the house prices and income inequality relationship. However, solely rent prices cannot capture the entirety of the relationship. There must be other mechanisms at play that cause an association between house prices and income inequality. To test another channel, the heterogeneity of the house price impact across the wealth distribution is analysed in section 4.2.3.

4.2.3 Heterogeneity Across the Distribution

McGregor et al. (2019) emphasised the importance of considering which properties of the inequality distribution are relevant to a particular study when researching inequality. Researchers can reach differing conclusions by examining the same relationship but alternative properties/measures of income inequality. This may explain the variations in findings from the prior literature and this thesis. For example, while the Gini showed that house prices increase income inequality, the Palma ratio indicates a negative association, and the S80S20 ratio suggests no statistically significant impact resulting from house price shocks. Different comparison groups have led to differing conclusions when analysing the same relationship. To further investigate these disparities, the

income share for each of the ten deciles of the income distribution is regressed using the income inequality control variables.

The results of the ARDL estimations for each decile, where the dependent variable is in log form, are presented in Table 4.11. This table is based on a double-log model; hence, the coefficients indicate the percentage change in the income share of that decile following a one per cent increase in house prices. In other words, the variables are presented in elasticity form and represent the percentage change in the percentage share of NZ income. In addition to the double-log model, a semi-log model was trialled where the income share is left in levels, and the house price variable is in logarithmic form. The coefficients in a semi-log model offer an alternate interpretation and instead estimate the amount that the income share of each decile will increase or decrease following a change in house prices. However, this approach compromises the comparability of the coefficients. For instance, a one per cent increase in the top decile's income share would have a far less meaningful effect than a one per cent increase in the bottom decile's income share. As a result, the implications for each decile are more easily compared using the double-log model. Additionally, the semi-log model yielded very similar results to the double-log model in Table 4.11. Because of these reasons, the semi-log model is included exclusively in Appendix M.

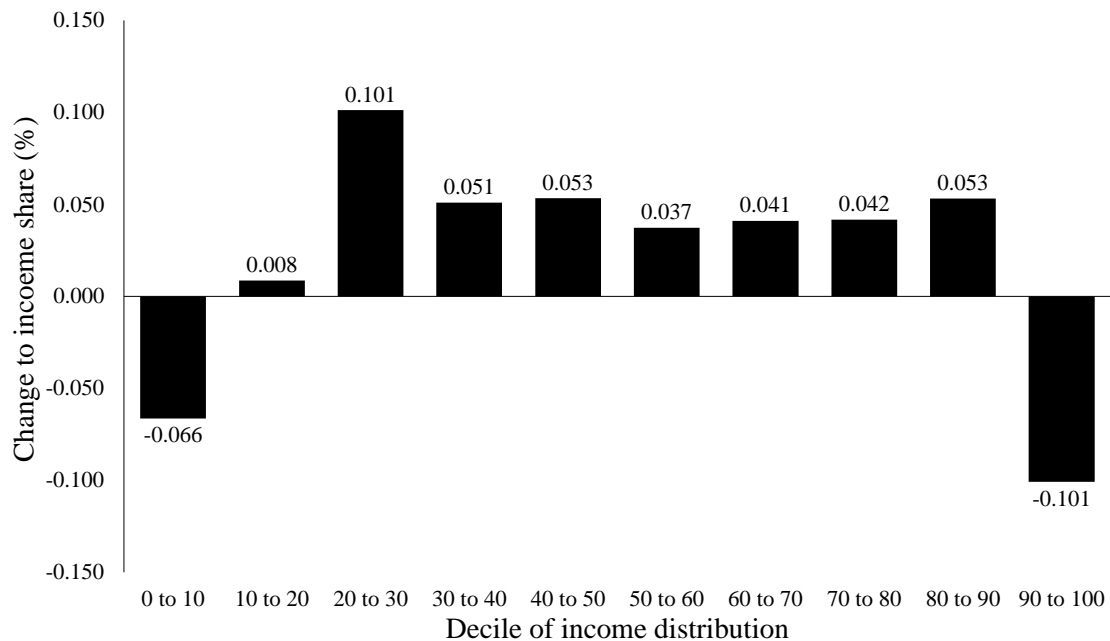
Table 4.11: Change to income share for each decile of the income distribution following an increase in house prices, using the logarithmic form for the dependent variables (double-log model)

Income decile	\sum ARDL coefficients	F-Bounds test	t-Bounds test	Long-run coefficient	Cointegration relationship
0 to 10	-0.0664 ** (0.0289)	6.4062 ***	-6.1703 ***	-0.0462 ** (-0.0148)	Cointegration
10 to 20	0.0085 ** (0.0035)	6.7168 ***	-5.7054 ***	0.0363 *** (0.0071)	Cointegration
20 to 30	0.1011 *** (0.0251)	4.0352 **	-4.8498 **	0.1119 *** (0.0341)	Cointegration
30 to 40	0.0509 ** (0.023)	2.2151	-4.6952 **	0.1297 ** (0.0475)	Inconclusive
40 to 50	0.0533 ** (0.021)	3.7528	-4.0193	0.073 (0.0427)	Inconclusive
50 to 60	0.0372 (0.0324)	2.2954	-2.5419	0.0628 (0.038)	No cointegration

Income decile	Σ ARDL coefficients	F-Bounds test	t-Bounds test	Long-run coefficient	Cointegration relationship
60 to 70	0.041 ** (0.0163)	3.7202	-1.496	0.1 * (0.053)	Inconclusive
70 to 80	0.0416 ** (0.0147)	4.6186 **	-2.9995	0.0322 *** (0.0095)	Nonsensical cointegration
80 to 90	0.053 ** (0.0215)	4.376 **	-3.5845	0.0341 ** (0.0118)	Nonsensical cointegration
90 to 100	-0.1008 ** (0.0417)	2.2049	-1.2558	-0.2136 * (0.1062)	No cointegration

Notes: (i) Each row represents a separate ARDL equation estimation where the dependent variable is the income share of the decile specified in the first column. All dependent variables are in logarithmic form; (ii) coefficients represents the (%) change to each income share following a 1% increase in house prices; (iii) null hypothesis for Bounds test is there is no cointegration relationship in levels ($H_0: \pi_y \cap \{\pi_j\}_{j=1}^k = 0$). Null hypothesis for long-run coefficients is $\pi_{p,j} = 0$; (iv) see notes for Table 4.2.

Figure 4.11: Change in the income share for each decile of the income distribution following an increase in house prices (double-log model)



Note: Values are sourced from the \sum ARDL coefficients in Table 4.11 and still include the statistically insignificant coefficient for the 50 to 60 decile.

Looking at the results in Table 4.11, it can be seen that house prices make a statistically significant difference to the income share of all the deciles except the 50 to 60 per cent of the income distribution. Additionally, a positive (negative) house price shock increases (decreases) the income share of all the deciles except the top and bottom of the distribution. This is because the top and bottom deciles own relatively fewer housing-related assets that can return an income than other deciles. The top decile loses income share as they are not accessing the additional income that can be received from holding a higher proportion of housing-related assets relative to their income, specifically investment properties that can return additional income.

The bottom decile is also not accessing the housing asset income stream but is theoretically paying a higher share of income towards housing-related assets as rent

prices increase. Therefore, the magnitude of the house price coefficient should be greater in absolute terms for the bottom decile than the top. However, the coefficient for the top decile is larger. This suggests that another mechanism is either offsetting the loss of income share for the bottom decile or worsening the loss of income share for the top decile.

Figure 4.12 presents the average property value for different deciles of the income distribution. It shows that when looking at earnings deciles, the bottom decile tends to have a higher property value than the 10 to 60 per cent of the income distribution. This is initially a surprising result. While the bottom income decile typically owns fewer housing assets than other deciles, the assets owned are on average a higher value than the assets within other deciles. Because higher value properties are more likely to accrue greater price increases following a house price shock (McCarthy & Peach, 2004), this value heterogeneity may be offsetting the increase in rental costs the lower deciles experience. This could explain why the top decile experiences a greater loss of income share in Table 4.11, not the bottom decile as theoretically expected. This supports the work of Vale and Camões (2022) who argue the relationship depends on the specific countries portfolio allocation across the income distribution.

Furthermore, when comparing property values across the income after housing cost deciles, this heterogeneity becomes less. However, the bottom decile still has a similar average property value to the 10 to 40 per cent of the after housing costs distribution. Overall, these results suggest that disproportionate rental costs and property values together explain some of the mechanisms in the house price and income inequality relationship.

Figure 4.12: The average house price of different income and income after housing deciles from 2015 to 2021



Note: Data is sourced from the Stats NZ IDI. For a more granular breakdown of the information in this figure, see the link in Appendix A.

A cointegration relationship is present for three deciles at the bottom of the income distribution. The rest of the cointegration tests are either inconclusive, nonsensical, or confident that no cointegration is present. That likely drives the lack of cointegration in the previous estimations, except for the Palma ratio. Three of the five deciles included in the Palma ratio have a clear cointegrating relationship present, likely driving the cointegration for only this income inequality measure.

The sum of the ARDL house price coefficients from Table 4.11 have been plotted in Figure 4.11. The 50 to 60 decile is included despite the coefficient not being statistically different from zero; still, Figure 4.11 offers a comparison of the relative magnitudes of the house price coefficients across the income distribution and Table 4.11 should be used for comparing statistical significance. It can be seen from Figure 4.11 that heterogeneity in the impact of house prices across the income distribution is present. The 20 to 30 decile benefits the greatest from increasing house prices, while the top

decile of the distribution experiences an equivalent loss in their income share. There is no apparent reason why the 20 to 30 decile experiences the greatest gain. The top and bottom 20 per cent of the distribution experience a change of income share within 0.01 of each other, which is why the house price coefficient in the S80S20 model is not statistically different from zero. The bottom 40 per cent of the decile experiences a gain in income share greater than the loss of the top ten per cent of the distribution, which is why the house price coefficient in the Palma ratio is negative and less than one in absolute terms.

There appears to be an inverted U-curve relationship prevalent in Figure 4.11, supporting the work of Vale and Camões (2022), but not an overly well-behaved one. There is a steep increase in the impact of house prices moving from the bottom decile to the 20 to 30 decile, followed by a shallower decrease down to the top decile of the distribution. There is evidence that a good proportion of the house price and income inequality relationship is explained by the heterogeneity in property value across the income distribution, but not all of it. The graph in Figure 4.11 highlights the importance of target groups for inequality research, as different measures will yield very different results because of this heterogeneity.

4.3 Loan-to-Value Ratio Restrictions

Few studies have considered the impact of LVR restrictions on the income distribution (Frost & van Stralen, 2018; Malovana et al., 2023; Ndou & Mokoena, 2019) and none have analysed solely NZ in their research. However, NZ presents a unique opportunity to examine how LVRs affect income inequality using an approach similar to (Park & Kim, 2022). Table 4.12 shows the ARDL model from Table 4.2 with an LVR dummy

variable included as an additional control. The LVR acts like a structural break dummy variable by itself, so the (multiplicative) structural break variables from Table 4.2 are omitted from this model. Table 4.12 shows that introducing an LVR restriction in NZ has a statistically significant and positive impact on income inequality, matching the previous international research (Frost & van Stralen, 2018; Malovana et al., 2023; Ndou & Mokoena, 2019). The impact on income inequality is irrelevant to the specifics of the LVR policy or how tight the limits are⁹. Introducing an LVR increases the income Gini by approximately 1.02 (where the income Gini is bounded between 0 and 100) when all else is constant. Furthermore, when the introduction of LVRs is held constant, the impact of house prices on the income Gini becomes smaller than what is estimated in Table 4.2. However, this value is closer to what is found in previous studies (Gholipour et al., 2016).

⁹ This is only true in a NZ context to date, where the specifics of the LVR restrictions have changed by relatively small amounts in comparison to when the policy was first introduced. These small changes have made a minimal impact to the effect of LVR restrictions on income inequality. It could be true that changing the LVR restrictions by large amounts, such as changing the policy so it only impacts a small minority of people, would change whether introducing LVR restrictions still impacts income inequality.

Table 4.12: Loan-to-value ratios included in the income inequality ARDL model

Variable	Coefficient	t-statistic
ln(Income Gini (-1))	0.4424 *** (0.1273)	3.4751
ln(House prices)	0.1187 ** (0.0561)	2.1175
LVR	0.0234 ** (0.0110)	2.1177
ln(Real GDP per capita)	1.957 *** (0.5412)	3.616
Population PC	0.0023 (0.0713)	0.0325
Unemployment rate	0.0249 ** (0.0109)	2.2856
Unemployment rate (-1)	0.0312 *** (0.0087)	3.603
Foreign investment	0.0028 (0.0029)	0.9597
ln(Trade volume)	0.4156 *** (0.1173)	3.5427
Inflation rate	-1.8502 ** (0.7025)	-2.6337
Constant	5.9245 *** (2.0357)	2.9103
Time trend	-0.0326 *** (0.0093)	-3.5086
<i>Model diagnostics</i>		
R-squared	0.8865	
Adjusted R-squared	0.8013	
S.E. of regression	0.0354	

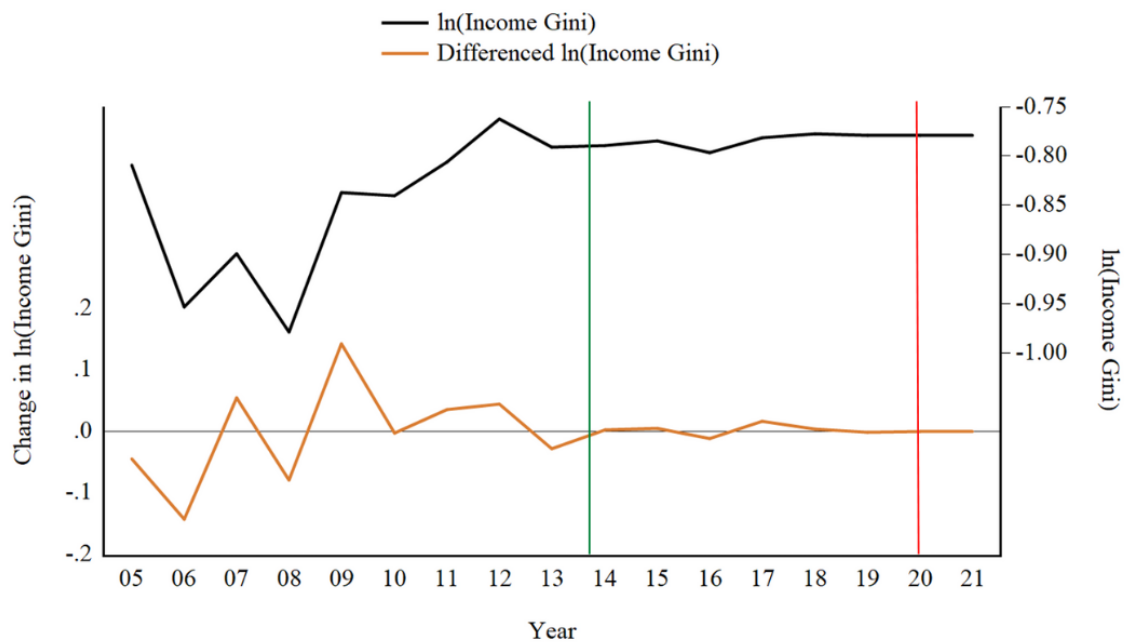
Note: The structural break dummy variables have been excluded as the LVR acts like a structural break dummy by itself, and see notes for Table 4.2.

Similar to Park and Kim (2022), LVRs are also included as a control variable in each of the decile estimations from Table 4.11. It is found that introducing a LVR restriction only has a statistically significant impact on the income share of the 80 to 90 per cent decile of the distribution, holding all else constant. The LVR coefficient for this decile is positive. LVR restrictions limit the amount of low-deposit lending commercial banks can offer, specifically for investment properties like rentals (RBNZ, 2022). Those higher up the income distribution have relatively more disposable income for deposits and, therefore, are less likely to be affected by LVR restrictions. In contrast, those lower down the distribution make up a greater proportion of low-deposit borrowers and will generally be more affected by LVR restrictions. This will disproportionately limit access to housing-related assets that can return income for those lower down the income distribution. This is likely why the 80 to 90 decile experiences a positive change in income share from introducing LVRs. The insignificant coefficients for the other deciles likely arise from the impact being spread over many income distribution groups. Hence, no decile is impacted enough to result in a statistically significant coefficient.

Figure 4.13 compares the NZ income Gini and the change in the income Gini since 2005 to when LVRs were introduced and removed. There is no noticeable difference in income inequality following LVRs being introduced or removed; this means that the results from Table 4.12 are only applicable when all other income inequality determinants are held constant in the model. Figure 4.13 shows NZ house prices and the amount of loans fully backed by residential mortgages in relation to when LVR restrictions are introduced and removed. There is a reasonably distinct, and almost contemporaneous decrease in both variables when LVRs are introduced. However, this is not necessarily a causal relationship as LVRs being introduced and the decreases in these variables could be simultaneously driven by another factor. However, Figure 4.13

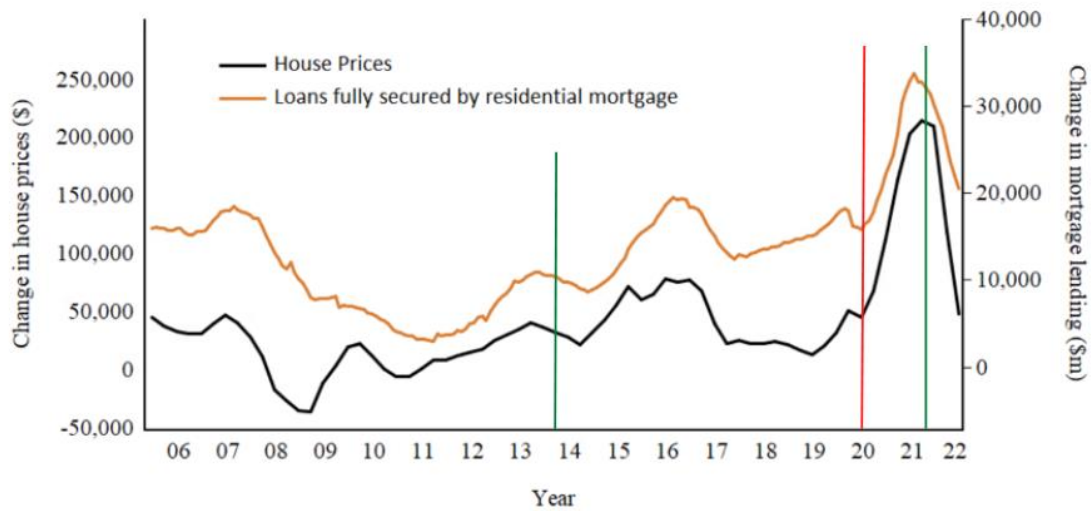
does appear to show that LVRs are imposing liquidity constraints which is reducing the number of mortgages banks can offer. This happens before house prices adjust, which provides some evidence that heterogeneous liquidity constraints could be driving the positive LVR coefficient found in Table 4.12. Altogether, the LVR results do not say anything about the extent of the LVR restrictions on income inequality, purely the impact of introducing any LVR policy, no matter the specifics. Future research should focus on how RBNZ tightening LVR restrictions has impacted the income distribution.

Figure 4.13: NZ income Gini since 2005 in relation to LVR restrictions



Notes: The green vertical line represents LVR restrictions being introduced and the red line represents their removal. The data is sourced from the WID.

Figure 4.14: The relationship between house prices and loans backed fully by residential mortgages



Notes: The green vertical line represents LVR restrictions being introduced and the red line represents their removal. The data is sourced from CoreLogic NZ and RBNZ.

4.4 Summary

When examining the relationship between house prices and income inequality, the groups of interest matter. Different inequality measures can yield unique results, so considering the target of the analysis is essential. Studying dynamics across the entire distribution is a more reliable way to understand the impact of house prices on income inequality. House prices have a heterogeneous effect across the income distribution, resulting in an inverted U-curve relationship between house prices and income inequality. This is driven by disproportionate amounts of housing-related assets across the income distribution, particularly properties that can earn an income like investment properties and rentals, and disproportionate housing-related costs across the income distribution. However, the curve could be more well-behaved, and other mechanisms are likely involved.

There are a variety of other mechanisms that could drive the relationship: (i) the types of properties owned across the income distribution as there may be heterogeneous income returns from different property types; (ii) spatial variation in house price change as where the properties are owned and where house price increases occur could result in different behaviours; (iii) and, heterogeneous liquidity constraints across the income distribution, limiting access to housing assets that yield a return, similar to LVR restrictions. Other impacts may also affect the house price and income inequality dynamics. Future research should focus on the alternative mechanisms of the relationship and how tightening LVR restrictions impacts income inequality. The following chapter considers the impact of house prices on NZ wealth inequality; the results for this analysis are then used concurrently with the results from this income inequality investigation in Chapter 6. Specifically, the model from Table 4.12 is used while also controlling for changes in wealth inequality.

Chapter 5: Wealth Inequality

5.1 Introduction

This thesis so far has examined the significance of the relationship between house prices and inequality, summarised the existing literature on the subject, and outlined the methodology for exploring this relationship within a NZ context. Furthermore, the NZ housing market dynamics with income inequality have been analysed. Specifically, rising house prices and introducing LVRs increase the income Gini. Still, these can have different effects on other measures of income inequality because of the impact heterogeneity across the income distribution.

This chapter considers the dynamics of the NZ housing market with wealth inequality. Specifically, an ARDL model is utilised to evaluate house prices' role, the results of which are analysed through section 5.2. A robustness and sensitivity analysis follow this to ensure the validity of the findings; this is presented throughout section 5.2.1. In section 5.2.2, the mechanisms of this relationship are analysed, and the effect on wealth shares is considered; this gives greater certainty of the house price impact across the wealth distribution. These results are contrasted for house price booms (busts) by seeing the relative effect on wealth inequality of an increase (decrease) in house prices through section 5.2.3. This is concluded with a summary of the wealth inequality analysis in section 5.3.

5.2 Price Changes

When specifying the wealth inequality ARDL model, most control variables are set to a fixed lag length according to the VAR lag order selection that minimises the SIC. However, the lag length for house prices and wealth inequality is selected automatically based on the model that minimises SIC overall. Twelve separate models were estimated, and the SIC for each is shown in Figure 5.1. It can be seen that while many models had a similar SIC, Model 1 in Figure 5.1 was considerably lower. Hence, Model 1 was used for modelling, with the final ARDL equation presented in equation 5.1. The results of this equation estimation are shown in Table 5.1.

$$\begin{aligned} \ln(W_t) = & \alpha_0 + \alpha_1 t + \psi_1 \ln(W_{t-1}) + \psi_2 \ln(W_{t-2}) + \psi_3 \ln(W_{t-3}) + \phi_0 \ln(H_t) \quad (5.1) \\ & + \phi_1 \ln(H_{t-1}) + \phi_2 \ln(H_{t-2}) + \phi_3 \ln(H_{t-3}) + \phi_4 \ln(RGDP_t) + \phi_5 \ln(Shares_t) \\ & + \phi_6 Popl PC_t + \phi_7 Dvelop PC_t + \phi_8 Dvelop PC_{t-1} + \varepsilon_{W,t} \end{aligned}$$

Figure 5.1: The Schwarz information criterion for all of the estimated ARDL wealth inequality models

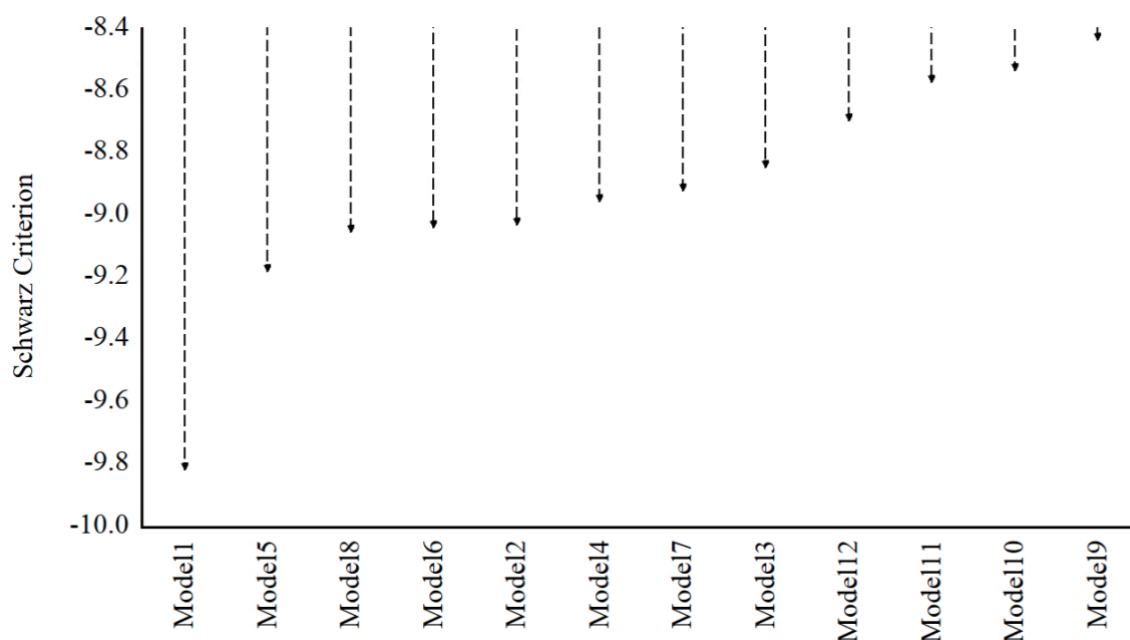


Table 5.1: Results of the ARDL model predicting ln(Wealth Gini)

Variable	Coefficient	t-statistic
ln(Wealth Gini (-1))	-0.109 (-0.185)	-0.588
ln(Wealth Gini (-2))	-0.831 *** (-0.135)	-6.182
ln(Wealth Gini (-3))	-0.558 *** (-0.158)	-3.528
ln(House prices)	-0.0306 *** (-0.006)	-5.493
ln(House prices (-1))	0.004 (-0.006)	0.597
ln(House prices (-2))	0.003 (-0.006)	0.560
ln(House prices (-3))	-0.0238 ***	-5.095

Variable	Coefficient	t-statistic
	(-0.005)	
ln(Real GDP per capita)	-0.0612 **	-2.885
	(-0.021)	
ln(Share prices)	0.0174 ***	5.257
	(-0.003)	
Population PC	-0.002	-0.216
	(-0.008)	
Development PC	0.000	-0.129
	(-0.001)	
Development PC (-1)	0.000	0.801
	(-0.001)	
Constant	10.820 ***	7.026
	(-1.54)	
Time trend	0.00369 ***	7.609
	(0)	
<i>Model diagnostics</i>		
R-squared	0.9382	
Adjusted R-squared	0.8300	
S.E. of regression	0.0011	
Schwarz criterion	-9.8105	

Notes: The standard error is reported in parenthesis underneath the coefficients. HAC standard errors & covariance have been used throughout. () is significant at 10%; (**) significant at 5%; and (***) significant at 1%.*

There are a few cursory things to highlight from Table 5.1. First, increasing house prices results in a contemporaneous decrease in wealth inequality, holding everything else constant. There is another statistically significant decrease for the third period after the initial house price shock. Overall, the sum of all the statistically significant house price coefficients is negative. In other words, an increase in house prices leads to decreased wealth inequality over the four periods from the shock, based on the lagged

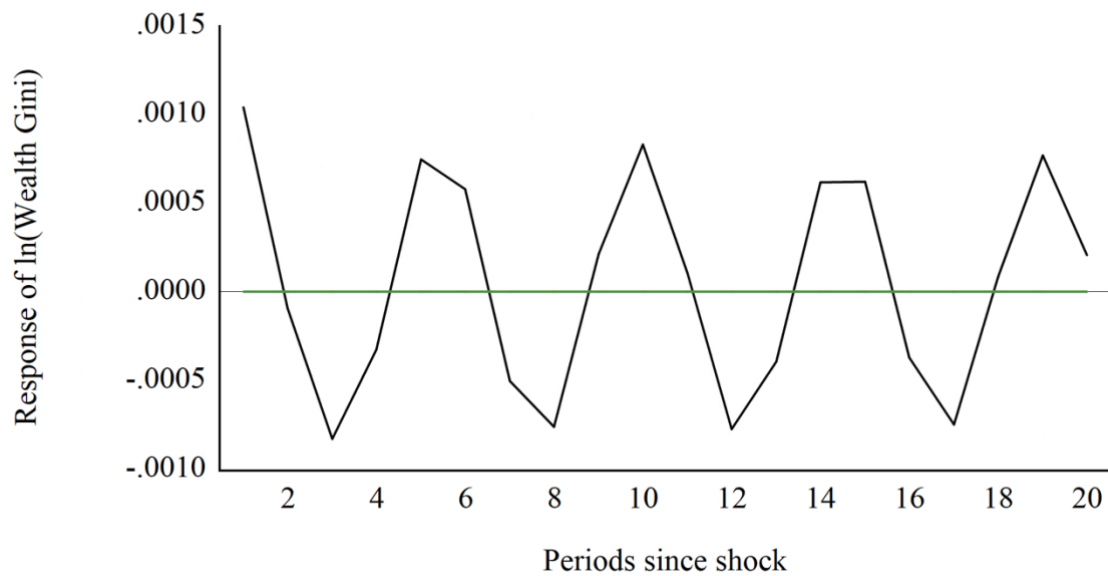
variables. Second, only the second and third lag of wealth inequality makes a statistically significant difference to wealth inequality. There is not necessarily a theoretical reason for this besides a delayed response time for corrections from shocks. This is known as a stabilisation delay and can occur for various factors. For instance, government policies responding to increasing inequality can take time to implement and later have distributional impacts (Alesina & Drazen, 1989), causing a stabilisation delay. Alternatively, human behaviour can be slow to adjust to an economic shock, and human behaviour has been demonstrated by Bechtel et al. (2018) to influence redistribution. The mechanisms of the stabilisation delay for wealth inequality in NZ are unknown but could be an exciting focus for future research. Lastly, real GDP per capita, share prices, and the time trend are statistically significant, at least at the 95 per cent confidence level, and have the theoretically expected sign. Contrastingly, none of the PCs are statistically significant. However, this is a minor issue as they are still controlling for their respective variables' impacts, improving the accuracy of other estimates. The influence of PCs in the model is further explored in section 5.2.1.

Before proceeding further with the model, diagnostic checks were executed. First, the model's dynamic stability was analysed, focusing on whether the model is explosive. An explosive model is one where the influence of past values of wealth inequality on the current value grows larger and larger over time. This can result in an oscillatory process that never dampens -instead, the oscillations continually increase over time. An explosive model would bias the assumption of stationarity for an ARDL model. When considering the statistically significant lagged wealth inequality coefficient in Table 5.1, the sum is larger than one in absolute terms, potentially representing an explosive model that is not dynamically stable. However, when conducting a Wald test, the sum of the

coefficients is not statistically different from negative one (p-value = 0.2463). Therefore, the Wald test result gives some confidence that the model is not explosive.

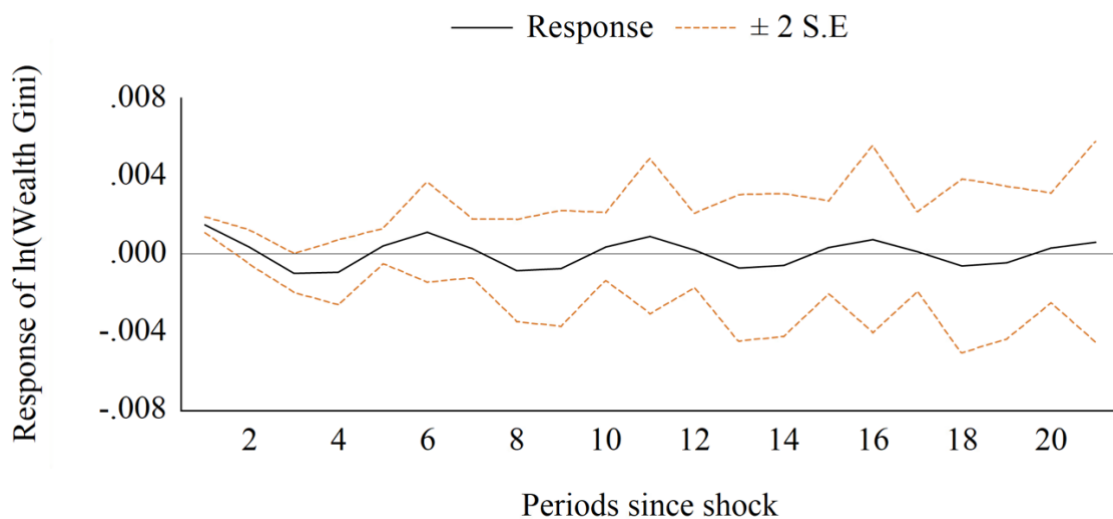
To further investigate dynamic stability, the impulse response function of the wealth Gini following an innovative shock in the wealth Gini is considered. The impulse response function is generated using the ECM and the AR terms of the structural ARDL model, which is displayed in Figure 5.2 and Figure 5.3, respectively. The adjustment process to long-run equilibrium appears to be oscillatory but non-explosive. The oscillations do not dampen within 20 periods from the initial shock, but the amplitude does not become larger. This is further confirmed when considering the inverse root of the AR polynomial [$\varphi^{-1}(L)$ (*where $L = 1, 2, 3$*)] presented in Figure 5.4. All three inverse roots lie within the unit circle, supporting that the wealth inequality model is dynamically stable. However, some inverse roots are very close to the unit circle and almost touching it, indicating that the model is close to explosive. Ultimately, the combination of these three tests offers evidence that wealth inequality's dynamics remain stable over time. Nevertheless, cautioning the reader that the results are on the brink of explosiveness is essential. This warning is especially critical if using the model for forecasting purposes.

Figure 5.2: Response of $\ln(\text{Wealth Gini})$ following a shock to $\ln(\text{Wealth Gini})$ using the ECM



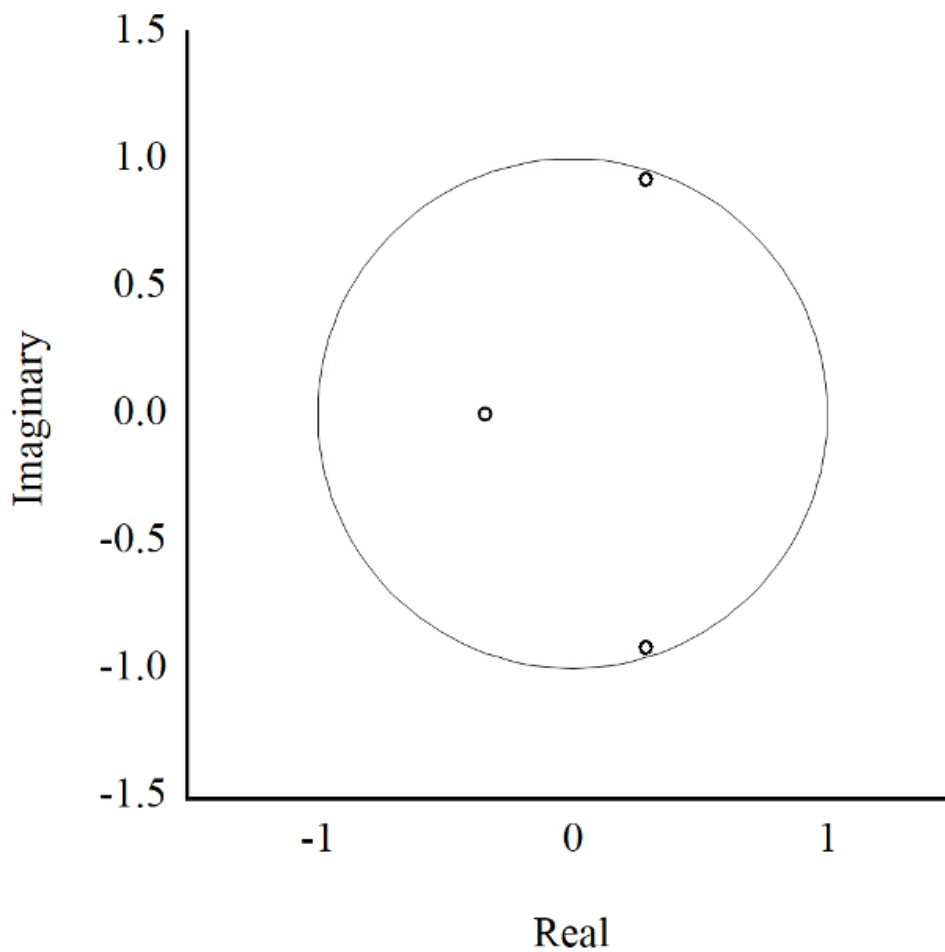
Note: Initial shock is a Cholesky one standard deviation innovation, adjusted for degrees of freedom.

Figure 5.3: Response of $\ln(\text{Wealth Gini})$ following a shock to $\ln(\text{Wealth Gini})$ using the AR structure of the ARDL model



Note: Initial shock is a one standard deviation innovation.

Figure 5.4: The inverse roots of the AR polynomials in the wealth inequality ARDL model



Note: The largest circle represents the unit circle, while the smaller circles represent the inverse root of the AR polynomials $[\varphi^{-1}(L)]$ (where $L = 1, 2, 3$) in equation 5.1.

The second diagnostic check was considering the potential multicollinearity problem. The correlation between all the regressors is shown in Table 5.2 presenting a high correlation between many of these variables. The biggest variables of concern are house prices and real GDP per capita, which cannot be omitted given their importance and commonplace in the previous literature. However, the problem with multicollinearity is that it leads to disproportionately large R-squared values and insignificant regressors. Both appear to be okay when considering the results in Table 5.1; there are many

statistically significant regressors, and the R-squared value is 0.93, which suggests that the model variables explain 93 per cent of the variation in wealth inequality. This matches the R-squared values of other researchers examining wealth inequality and does not appear artificially inflated by multicollinearity. Furthermore, the adjusted R-squared (0.83) is not abnormally lower than the R-squared. Additionally, multicollinearity is also limited by using ARDL models, which involve large amounts of differencing for variables in the CECM and ECM (Giles, 2014). Based on these factors, multicollinearity was assumed to be a minor issue in this analysis.

Next, the actual, fitted, and residual values of the ARDL model are considered, as shown in Figure 5.5. The model does not appear to be overfitted to the sample, and well-behaved residual disturbances are present. The model performed the poorest in 2012 and 2013, where the fitted values of wealth inequality were too low and high, respectively. This is further shown when considering the histogram of residuals in Figure 5.6. The 2012 and 2013 residual values are outliers to the histogram being very far away from the other residuals. These residuals bias the Jarque-Bera test to reject the null hypothesis of normality at commonly used significance levels. When these two outlier residuals are removed, and the Jarque-Bera test is conducted again, the test yields insignificant results at the one per cent significance level and above. These residual outliers are caused by the steep increase in wealth inequality following the GFC and a subsequent abrupt decrease in 2012. This presents potential caution when interpreting values during periods directly following financial crises. However, the model performs well with other steep changes over time, so this issue is assumed to be relatively minor.

The following diagnostic checks involved examining the recursive, CUSUM, and CUSUM-of squares for the residuals in Figure 5.7, Figure 5.8, and Figure 5.9, respectively. This is done to consider the stability of the estimated ARDL model. These figures appear stable as none cross the five per cent significance level or two standard error critical lines. This is especially good considering the small sample size used for the model. The residuals' potential serial correlation and autocorrelation are tested in Table 5.3 and Table 5.4, respectively. The null hypothesis is rejected in very few lag structures in the autocorrelation test and never in the serial correlation test. These excellent results suggest that no additional lags of the dependent variables need to be included. This is further supported by plotting the autocorrelation over time in Figure 5.10; the actual autocorrelation values oscillate over time in a slightly dampening manner, matching the concerns of dynamic stability previously discussed. However, the actual and theoretical values are very similar, indicating that the AR process is adequately accounted for in the ARDL model.

The final diagnostic check is the Breusch-Pagan-Godfrey test for heteroskedasticity, which fails to reject the null hypothesis of homoskedasticity at any level. This suggests that the variances of the model are constant over time. It is important to note that all discussed diagnostics tests are performed on all subsequently predicted models in this chapter but are never discussed or presented as thoroughly again. Given the satisfactory results of the diagnostics testing for this ARDL model, besides the normality of the residuals, the subsequent steps of estimation are proceeded with, beginning with the bounds test for cointegration.

Table 5.2: Correlation matrix of explanatory variables in the ARDL model predicting $\ln(\text{Wealth Gini})$

<i>Variable</i>	1.	2.	3.	4.
1. $\ln(\text{House prices})$	1			
2. $\ln(\text{Real GDP per capita})$	0.9848	1		
3. $\ln(\text{Share prices})$	0.8357	0.8221	1	
4. Population PC	-0.9161	-0.9364	-0.6119	1
5. Development PC	0.5895	0.6421	0.5263	-0.5405

Figure 5.5: The actual, fitted, and residual values of the ARDL model predicting $\ln(\text{Wealth Gini})$

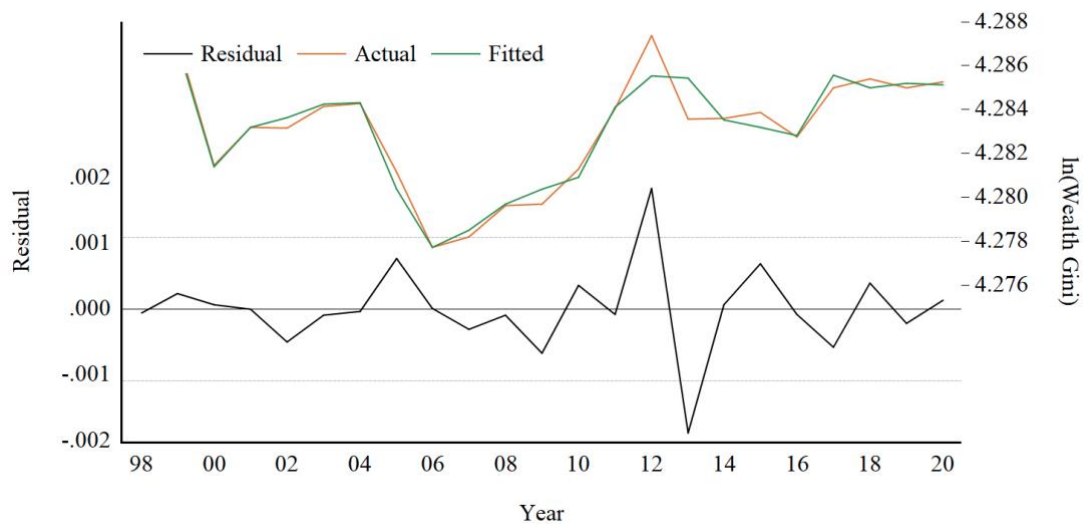
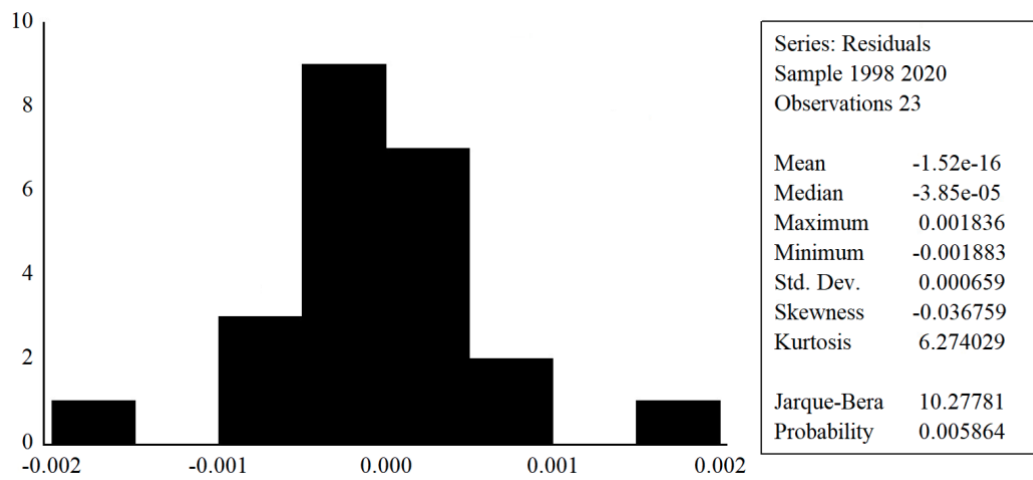


Figure 5.6: Histogram of the residuals from the ARDL model predicting ln(Wealth Gini)



Note: The null hypothesis of the Jarque-Bera test is a normal distribution.

Figure 5.7: The recursive residuals from the ARDL model predicting ln(Wealth Gini)

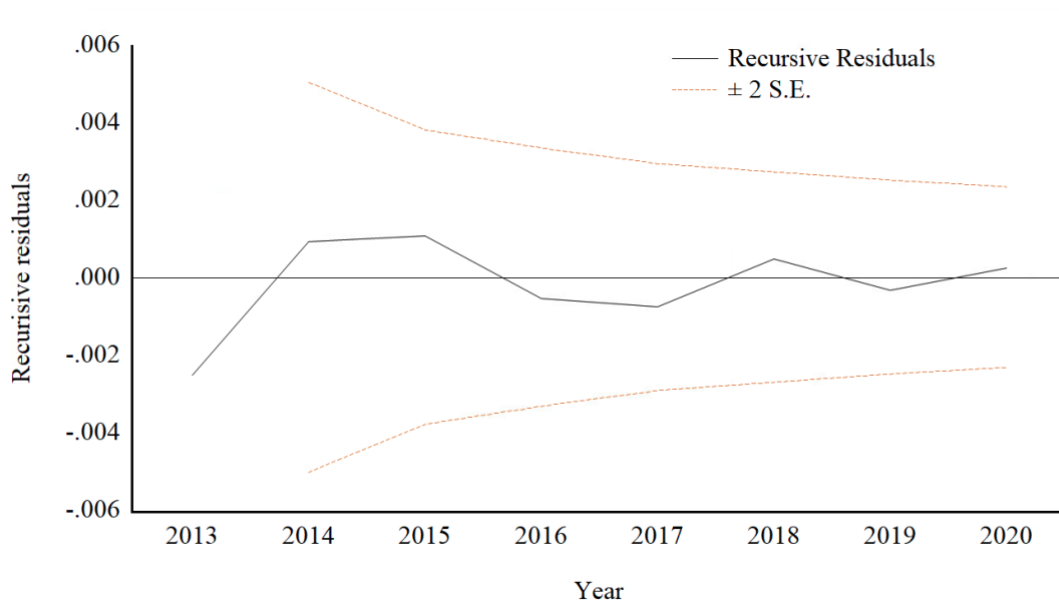


Figure 5.8: The cumulative sum of the residuals from the ARDL model predicting $\ln(\text{Wealth Gini})$

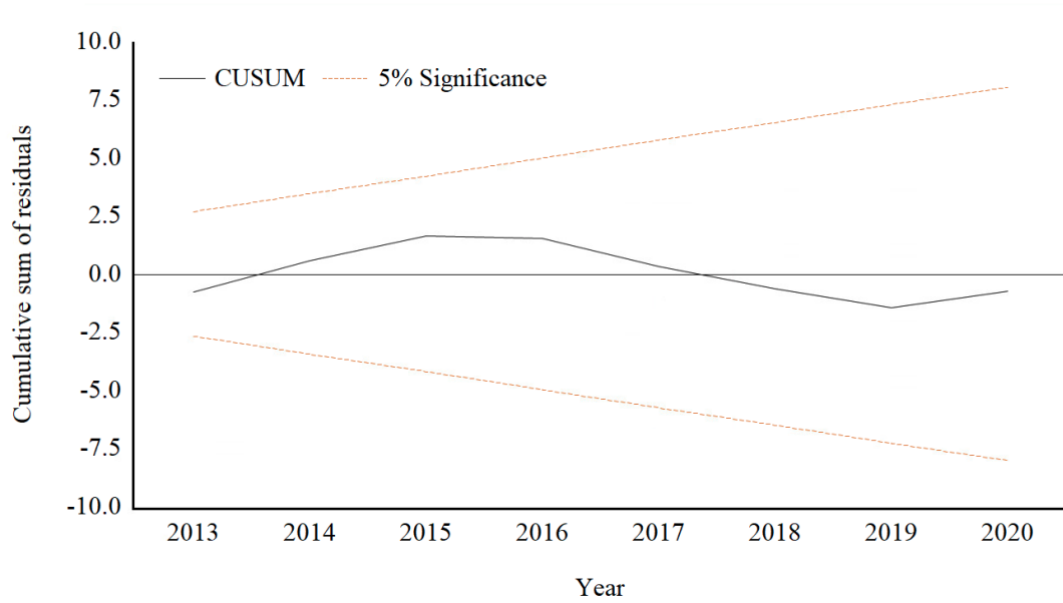


Figure 5.9: The cumulative sum of squared residuals from the ARDL model predicting $\ln(\text{Wealth Gini})$

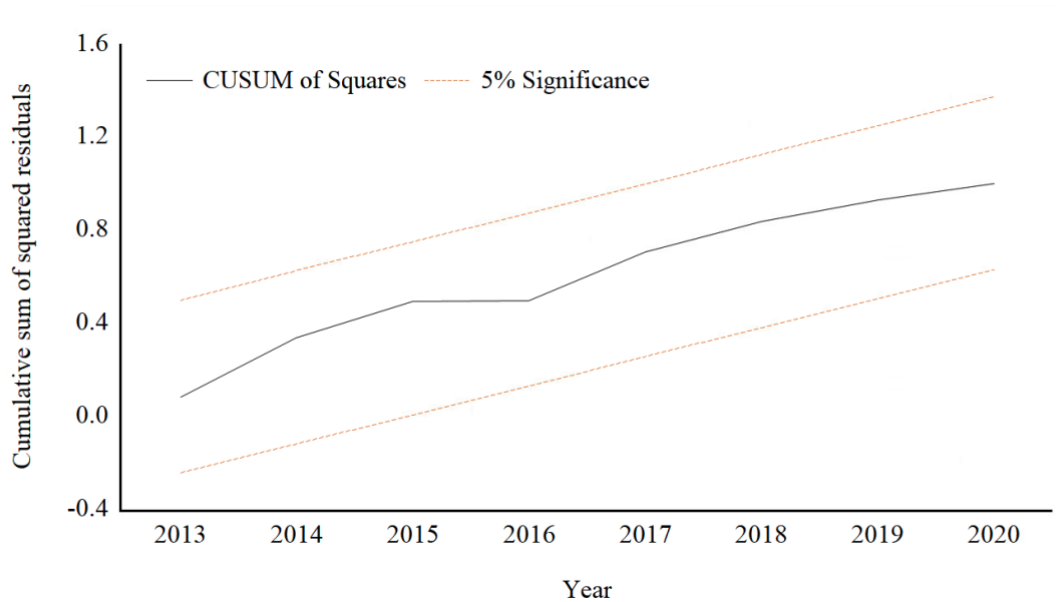


Table 5.3: Serial correlation LM test for the ARDL model predicting ln(Wealth Gini)

Lags	f-statistic	p-value
1	2.6208	0.1495
2	2.3364	0.1777
3	3.8239	0.0914
4	2.4484	0.2035
5	2.0435	0.2953
6	2.5687	0.3065

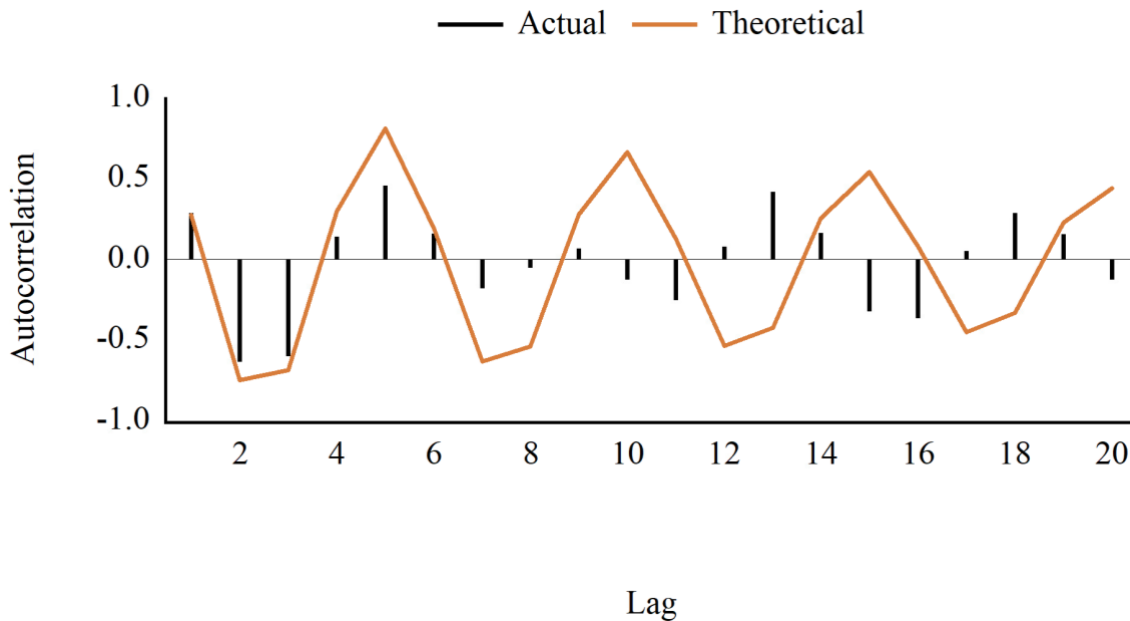
Note: Null hypothesis is no serial correlation up to the specified number of lags.

Table 5.4: Correlogram of residuals for the ARDL model predicting ln(Wealth Gini)

Lags	<i>Residuals</i>		<i>Residuals Squared</i>	
	Q-Stat	p-value	Q-Stat	p-value
1	5.0594 **	0.024	3.794 *	0.051
2	5.207 *	0.074	3.9989	0.135
3	5.5236	0.137	4.0176	0.26
4	6.1867	0.186	4.1401	0.387
5	6.8722	0.23	4.5126	0.478
6	7.7217	0.259	5.2754	0.509
7	7.9161	0.34	5.6751	0.578
8	8.4994	0.386	5.7097	0.68
9	8.5458	0.48	5.9856	0.741
10	8.5458	0.576	6.0394	0.812
11	8.8555	0.635	6.1854	0.861
12	8.9457	0.708	6.5162	0.888

Notes: Null hypothesis is no autocorrelation up to specified lag level and () is significant at 10%; (**) significant at 5%; and (***) significant at 1%.*

Figure 5.10: The autocorrelation over time in the wealth inequality ARDL model



The results of the cointegration relationship testing are presented in Table 5.5. For the F-Bounds test, it can be seen that the null hypothesis is rejected for all of the critical values, no matter the order of integration, significance level, or sample size. That is conclusive evidence that a cointegration relationship is present at levels between the explanatory variables and wealth inequality. When considering the t-Bounds test, the null hypothesis is rejected for every significance level. According to EViews (2017), this provides evidence that it is not a nonsensical cointegrating relationship between the variables. Therefore, these test results suggest that the regressors are bound with wealth inequality in the long-run. These results indicate a cointegration relationship is present; thus, the long- and short-run dynamics can be estimated, presented in Table 5.6 and Table 5.7, respectively.

Table 5.5: Cointegration testing for the derived equations from the ARDL model predicting ln(Wealth Gini)

Significance level	I(0)	I(1)
<i>Pesaran et al. F-bounds critical values</i>		<i>Asymptotic: n=1000</i>
10%	2.75	3.79
5%	3.12	4.25
2.50%	3.49	4.67
1%	3.93	5.23
<i>Narayan F-bounds critical values</i>		<i>Finite Sample: n=35</i>
10%	3.087	4.277
5%	3.673	5.002
1%	5.095	6.77
		<i>Finite Sample: n=30</i>
10%	3.157	4.412
5%	3.818	5.253
1%	5.347	7.242
<i>t-Bounds test critical values</i>		<i>Asymptotic: n=1000</i>
10%	-3.13	-4.21
5%	-3.41	-4.52
2.50%	-3.65	-4.79
1%	-3.96	-5.13
<i>Test statistic values</i>		
Test type	Value	Decision
F-statistic	10.3361	Cointegrated
t-statistic	-7.6662	Cointegrated

Note: Null hypothesis for Bounds test is there is no cointegration relationship in levels ($H_0: \pi_y \cap \{\pi_j\}_{j=1}^k = 0$).

Table 5.6: Estimated long-run coefficients using the ARDL approach (dependent variable = $\ln(\text{Wealth Gini})$)

Variable	Coefficient	t-statistic
$\ln(\text{House prices})$	-0.019 *** (0.0015)	-13.0592
$\ln(\text{Real GDP per capita})$	-0.0245 ** (0.0097)	-2.5128
$\ln(\text{Share prices})$	0.007 *** (0.0013)	5.2858
Population PC	-0.0007 (0.0031)	-0.2195
Development PC	0.0001 (0.0002)	0.5366

Note: See notes for Table 5.1.

Table 5.7: Estimated short-run coefficients using the ARDL approach (dependent variable = $\Delta \ln(\text{Wealth Gini})$)

Variable	Coefficient	t-statistic
$\Delta \ln(\text{House prices})$	-0.0307 *** (0.0038)	-7.9772
$\Delta \ln(\text{House prices } (-1))$	0.0206 *** (0.0041)	5.0263
$\Delta \ln(\text{House prices } (-2))$	0.0239 *** (0.0042)	5.7017
$\Delta \ln(\text{Wealth Gini } (-1))$	1.3892 *** (0.173)	8.0321
$\Delta \ln(\text{Wealth Gini } (-2))$	0.5575 *** (0.1317)	4.2342
$\Delta \text{ Development PC}$	-0.0001 (0.0003)	-0.3629
ECT	-1.2711 *** (0.1428)	-10.0388
Constant	10.8206 *** (1.0767)	10.0494
Time trend	0.0037 *** (0.0004)	9.2944
<i>Model diagnostics</i>		
R-squared	0.9193	
Adjusted R-squared	0.8634	
S.E. of regression	0.0009	
Schwarz criterion	-10.4921	

Note: See notes for Table 5.1.

Examining the long-run coefficients in Table 5.6, all variables are statistically significant, at least at the five per cent significance level, excluding the PCs - this matches the results of the original ARDL model. In the long-run, a ten per cent increase in house prices results in a 0.19 per cent decrease in wealth inequality, holding all else constant¹⁰. To put that into perspective, in the last 26 years, there have only been five yearly changes to wealth inequality, more negative than -0.19 per cent. It would be a relatively large decrease in wealth inequality by NZ standards, where it has experienced minimal change since 1995. This is without considering that annual house price increases have been considerably more extensive than ten per cent in the last three years.

Relative to the previous literature, 0.19 is a low estimate. Symes (2022) estimated an equivalent rise in house prices to decrease the wealth Gini by 0.7 per cent. However, Symes only considers the impact of house prices over one year, whereas, in this thesis, 0.19 represent a long-run coefficient. Therefore, the divergence between the estimates could be driven by a different contemporaneous and long-run impact of house prices on wealth inequality. Additionally, examining the other two statistically significant coefficients shows that an increase in real GDP per capita leads to decreased wealth inequality in the long-run, *ceteris paribus*. In contrast, increasing share prices worsen wealth inequality in the long-run, *ceteris paribus*. Both of these estimates match the findings of other studies (Adam & Tzamourani, 2016; Arrigoni, 2022; Bagchi et al., 2019; Bivens, 2015; Kartashova & Zhou, 2021; Kuhn et al., 2020; O'Farrell & Rawdanowicz, 2017)

¹⁰ The wealth Gini variable is represented in logarithmic form in this model. Therefore, the coefficient represents a 0.19 per cent decrease in the Gini coefficient, i.e., a percentage decrease of a percentage variable (where the Gini is bounded between 0 and 100).

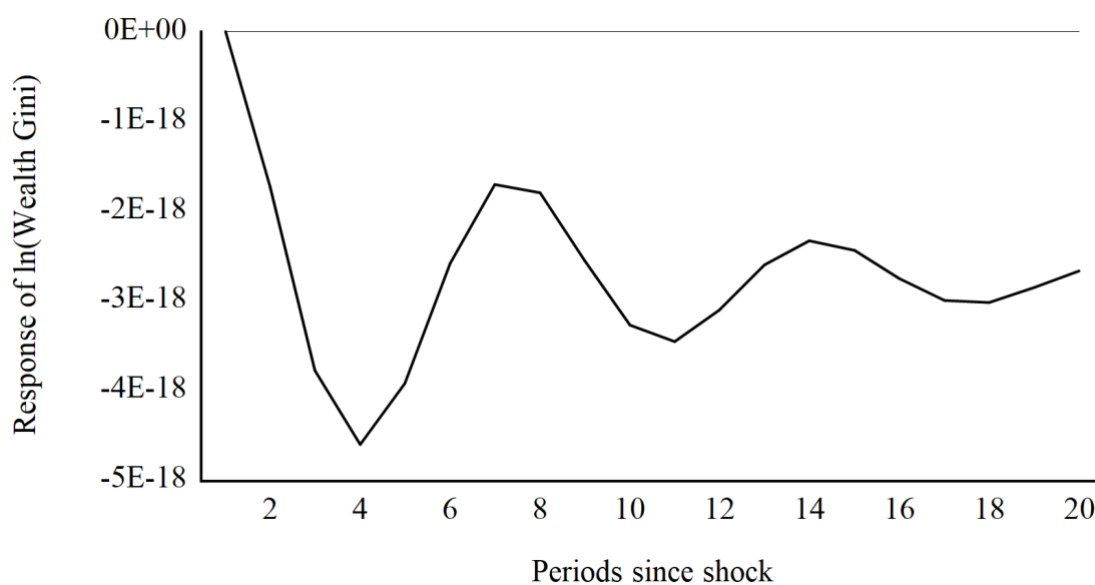
When considering the short-run coefficients in Table 5.7, all variables are statistically significant except for the PCs, matching the long-run estimates. The ECT is statistically significant and negative, as theoretically expected. This supports the presence of a long-run cointegration relationship between the variables and validates the error correction representation. However, the ECT is very large, with the value being greater than one in absolute terms. This suggests that an innovative shock to the system results in a large overcorrection in subsequent periods. The error correction process is a wealth Gini that fluctuates above and below the long-run value, giving an oscillatory adjustment process following convergence to long-run equilibrium. This matches the previous dynamic stability results.

A variety of potential mechanisms could drive the oscillatory process. First, going from one oscillation's peak (trough) to the following peak (trough) takes anywhere from four to six years, as shown in Figure 5.2 and Figure 5.3. Therefore, the long period could relate to political cycles, as NZ elections occur every three years. Second, speculation in the NZ economy, particularly the housing market, could drive changes followed by overcorrections. Speculation could be related to how households adjust their portfolios in response to asset price shocks in NZ, which is discussed more extensively in section 5.2.3. Third, fiscal or monetary policy adjustment could drive the oscillations in response to economic factors. The fluctuations appear particularly crucial for monetary policy, which tends to follow similar cycles. Ultimately, the mechanisms behind the discovered oscillatory process could not be tested in this thesis but should be the focus of future research.

When looking at house prices in the short-run, a ten per cent positive change in house prices results in a 0.307 per cent negative change to wealth Gini in the same period,

ceteris paribus¹¹. This is greater than the long-run value, which is why there is a correction to wealth inequality in the subsequent periods as it corrects to its long-run equilibrium. The accumulated impulse response function shown in Figure 5.11 allows viewing these corrections visually. After a positive house price shock, wealth inequality decreases for the first four years. After the fourth year, it increases again, beginning the oscillatory process of convergence to long-run equilibrium. This impulse response function demonstrates an oscillatory dampening process which contributes to some further certainty on the dynamic stability of the model in the long-run. Additionally, it is essential to highlight evidence of a permanent reduction in wealth inequality from this shock, consistent with the statistically significant and negative long-run coefficient for house prices.

Figure 5.11: The accumulated response of $\ln(\text{Wealth Gini})$ following a shock to $\ln(\text{House prices})$

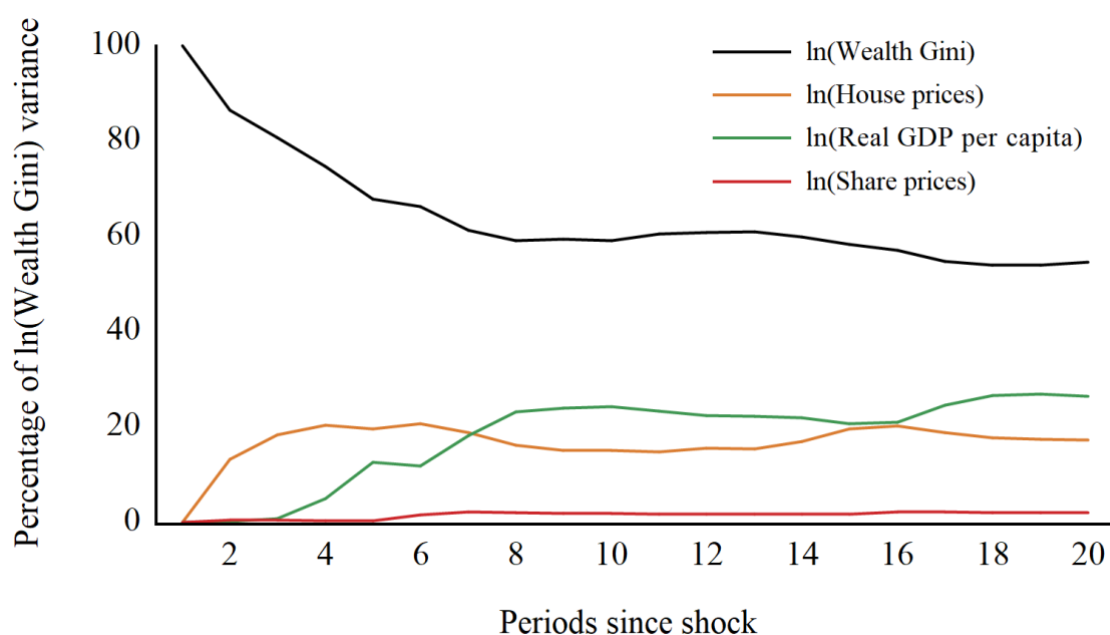


Note: Initial shock is a Cholesky one standard deviation innovation, adjusted for degrees of freedom.

¹¹ The wealth Gini variable is represented in logarithmic form in this model. Therefore, the coefficient represents a 0.307 per cent increase in the Gini coefficient, i.e., a percentage increase of a percentage variable (where the Gini is bounded between 0 and 100).

Performing a variance decomposition of the ECM, shown in Figure 5.12, yields many interesting results. First, it can be seen that previous values of wealth inequality explain the most significant share of variation in wealth inequality following a random shock. This variance contribution does decrease from around 100 per cent in the initial periods and steadies to about 60 per cent after 20 periods. However, past values of wealth inequality remain the most significant factor in explaining the variation in wealth inequality. Second, around 20 per cent of the variation in wealth inequality is explained by shocks to house prices from periods three to six; during this period, house prices explain the second-largest amount of variation in wealth inequality. However, house prices are overtaken by real GDP per capita from the seventh period onwards and finish as the third most significant contributor to wealth inequality variation. Share prices make very little difference to wealth inequality throughout the process, only increasing slightly; this differs from other studies in which share prices significantly contribute to wealth inequality. The system becomes reasonably stable after around 18 periods which is a long process to stability. This is similar to the impulse response function, which takes a long time to stabilise at approximately 20 periods. This could be related to the oscillatory adjustment, which causes the model to overcorrect each period, increasing the period until stability is reached.

Figure 5.12: Variance decomposition of $\ln(\text{Wealth Gini})$ using the ECM



Note: See Figure 5.11 note.

5.2.1 Sensitivity and Robustness

The wealth inequality model underwent several sensitivity and robustness checks, including an investigation into the direction of causality in the relationship. Table 5.8 displays the results of the Granger pairwise test (Granger, 1969), which indicates a rejection of the null hypothesis that house prices do not Granger cause wealth Gini from lag three to five. Furthermore, the lag structure between the two variables aligns with the results of the ARDL modelling. Although this test does not offer conclusive evidence that house prices cause changes in wealth inequality, it does suggest that the modelling results are not subject to reverse causation or a simultaneous relationship between wealth inequality and house prices. This interpretation is reinforced by conducting a Granger causality test on the VECM (a block exogeneity Wald test) (Granger, 1969), popularised by Sims (1980), which is a multivariate test that also takes the control variables of the equation into account. Table 5.9 presents the block

exogeneity Wald test and reports findings similar to those in Table 5.8. Expressly, the null hypothesis is rejected only for the relationship between house prices and wealth Gini, never the reverse. These two tests provide greater certainty regarding the direction of influence, suggesting that there is no evidence that wealth inequality causes changes in house prices.

Table 5.8: Results of the pairwise Granger causality test between house prices and wealth inequality

Null hypothesis	Lags	Observations	F-statistic
<i>House prices do not Granger cause the wealth Gini</i>	1	26	0.3688
	2	25	0.1395
	3	24	4.9422 ***
	4	23	7.0679 ***
	5	22	3.4275 ***
	6	21	0.9133
<i>The wealth Gini does not Granger cause house prices</i>	1	26	0.1229
	2	25	1.2289
	3	24	0.9132
	4	23	1.1152
	5	22	0.7471
	6	21	1.4570

*Note: Lags are included for the dependent and explanatory variable up the specified length and (***) is significant at the 1% significance level.*

Table 5.9: Results of the block exogeneity Wald test / multivariate Granger causality test based on the VECM between house prices and wealth inequality

Dependent variable	Excluded variable	DoF	Chi-squared
$\Delta \ln(\text{Wealth Gini})$	$\Delta \ln(\text{House prices})$	2	21.2771 ***
$\Delta \ln(\text{House prices})$	$\Delta \ln(\text{Wealth Gini})$	2	5.2585

*Notes: DoF is degrees of freedom, the null hypothesis is the excluded variable does not Granger cause the dependent variable, and (***) is significant at the 1% significance level.*

Multiple alternative model specifications were tested to ensure wealth inequality and house price findings robustness. First, models using two alternative measures of wealth inequality and house prices were considered. In each case, the F-bounds and t-bounds tests yielded a conclusive rejection of the null hypothesis, indicating the presence of cointegration. These results demonstrate that the conclusions drawn from the original model specifications are not overly sensitive to the particular measures chosen for wealth inequality and house prices. Because cointegration is present, models are displayed as long- and short-run dynamics compared to the original findings in Table 5.11 and Table 5.12, respectively. The S80S20 model is in semi-log form, where the dependent variable is in levels due to the negative values of the dependent variable, and the alternative interpretation is noted beneath the table.

When considering the long-run dynamics across different models in Table 5.11, the significance testing and coefficient signs are similar for all models. However, real GDP per capita is not statistically different from zero in models two or four. This may be due to multicollinearity for model four, as the house prices variable and GDP per capita have been adjusted for the same inflation variable, resulting in some association. There is no apparent reason why real GDP per capita is no longer statistically significant when the Palma ratio is used as the dependent variable. Nevertheless, this only suggests that real GDP per capita does not influence the wealth ratio between the top ten and bottom 40 per cent of the distribution.

Table 5.11 shows that the house price coefficient is greater when the Palma ratio is the dependent variable¹². This suggests that an increase in house prices will decrease the gap between the top ten per cent and the bottom 40 per cent more than lower the Gini. Because the house price variable is negative when regressed on the Palma ratio, the house price variable decreases the wealth share of the top decile or bottom 40 per cent of the distribution, but not both. Contrastingly, the house price variable is positive when the dependent variable is the S80S20 ratio. This means that house prices either increase the wealth share of the top 20 and bottom 20 per cent of the distribution or decrease the wealth share of both. The change in wealth share of these deciles cannot be contrasted as the house price variable coefficient would be negative in model 3. Additional modelling is provided in section 5.2.2, which explains the driving forces of these behaviours.

An increase in house prices in real terms has a slightly larger impact on the wealth Gini than an increase in nominal house prices. This makes logical sense as it impacts homeowners more meaningfully than house price increases resulting from rising inflation. In contrast, an increase in the value-to-income ratio has a lesser impact on the wealth Gini than house prices. That is likely since increases in the value-to-income ratio can be driven by a rise in house prices, a decrease in average wages, or some combination of the two. A reduction in average wages is unlikely to make the wealth

¹² Caution is advised when considering the magnitude of coefficients when the dependent variable is a ratio of wealth share. The bottom decile generally has a negative net wealth share. Therefore, if this decile increases their wealth share, the ratio overall will increase (as the denominator is decreasing); *ceteris paribus*. An increase in an inequality ratio generally represents rising inequality, so the wealth share change for the bottom deciles is misrepresented. Therefore, comparing the relative magnitudes of the coefficients for ratio models should be done sparingly. Instead, the sign of the coefficients should be primarily examined.

distribution more equitable, which likely explains why the magnitude is less than the house price variable.

The short-run dynamics in Table 5.12 show that all four models are similar. All house price variables have the same sign and significance; however, the magnitude is initially larger when predicting the Palma ratio than the Gini, just like the long-run coefficients. Relatively more extensive corrections are seen in the following periods for the Palma ratio model. The magnitudes are smaller for the housing affordability and real house price measures in the same period when regressed against the wealth Gini; this also matches the long-run coefficients. The corrections in subsequent periods are also more minor for real house prices than the nominal house price variable, leading to a greater magnitude for the long-run coefficient. The ECT is alike in all models showing the same oscillatory convergence to the long-run equilibrium. Every other coefficient is comparable except for the Development PC variable, which is only statistically significant in model two.

An essential aspect of ensuring the model's robustness is determining the control variables' role. Four control variables were included, which creates 24 different combinations of control variable specifications¹³. Appendix O specifies the combinations and presents the ARDL estimates for all 24. Table 5.10 provides a statistical summary of the long-run coefficients across these 24 models. It is noteworthy that house prices have a statistically significant impact on wealth inequality in 22 out of 24 models, with the only two insignificant models occurring when no control variables

¹³ There are 24 unique combinations if the control variable can only take on the fixed lag length specified by the VAR lag order selection that minimises the SIC. If the control variables can take on different lag structures, there would be more than 24 possible combinations.

are included or when real GDP per capita is the only control variable. Furthermore, most model specifications reject the null hypotheses of the F- and t-Bounds tests. Across all 24 models, the house price coefficients are negative. The estimates' average, median, and mode are only slightly lower than the 0.019 per cent estimate from the primary model specification. Notably, removing or adding the principal components to the model has little effect on the sign or significance of the house price variable, but it does slightly increase its magnitude. In other words, controlling for the LCH and financial development in the model reveals that house prices affect wealth inequality more considerably than when omitted. Taken together, these findings suggest that the relationship between house prices and wealth inequality is robust to various alternative model specifications.

Table 5.10: A summary of the long-run coefficients for all 24 of the wealth inequality control variable combinations

Measure	Value
Mean	-0.01765
Median	-0.01635
Mode	-0.01635
Minimum	-0.02949
Maximum	-0.01147
Number of statistically significant long-run coefficients	22
Number of statistically significant F-Bounds tests	21
Number of statistically significant t-Bounds tests	19
Number of models	24

Notes: Null hypothesis for Bounds test is there is no cointegration relationship in levels ($H_0: \pi_y \cap \{\pi_j\}_{j=1}^k = 0$). Null hypothesis for long-run coefficients is $\pi_j = 0$; A significant test result is a rejection of the null at the 5% significance level.

Table 5.11: Estimated long-run wealth inequality coefficients using the ARDL approach for a range of model specifications

<i>Model</i>	<i>(1)</i>		<i>(2)</i>		<i>(3)</i>		<i>(4)</i>		<i>(5)</i>	
<i>Dependent variable:</i>	<i>ln(Wealth Gini)</i>		<i>ln(Wealth Palma)</i>		<i>Wealth S80S20</i>		<i>ln(Wealth Gini)</i>		<i>ln(Wealth Gini)</i>	
Variable	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
ln(House prices)	-0.019 ***	-13.0592	-0.0841 ***	-7.4562	3.7024 ***	6.027				
	-0.0015		(0.0113)		(0.6143)					
ln(Real house prices)							-0.0194 ***	-10.7049		
							(0.0018)			
ln(Value-to-income)									-0.0184 ***	-9.7262
									(0.0019)	
ln(Real GDP per capita)	-0.0245 **	-2.5128	-0.0747	-1.6023	4.7275 **	2.3712	-0.0133	-1.1497	-0.0256 **	-2.908
	-0.0097		(0.0466)		(1.9938)		(0.0116)		(0.0088)	
ln(Share prices)	0.007 ***	5.2858	0.0296 ***	2.5978	-1.3434 ***	-3.6578	0.0068 ***	4.4159	0.0071 ***	5.1925
	-0.0013		(0.0114)		(0.3673)		(0.0015)		(0.0014)	
Population PC	-0.0007	-0.2195	0.025	1.1215	-1.3283	-1.3111	0.0031	0.9727	-0.0014	-0.3987
	-0.0031		(0.0223)		(1.0131)		(0.0032)		(0.0035)	
Development PC	0.0001	0.5366	-0.0015	-0.7393	-0.0288	-0.3348	0	0.084	0.0002	0.796
	-0.0002		(0.0021)		(0.086)		(0.0003)		(0.0003)	

Notes: See notes for Table 5.1. Additionally, the coefficients for model (3) are interpreted as a the change to the dependent variable from a percentage change ($p\%$) in house prices is calculated as $\hat{\beta} \cdot \log([100 + p]/100)$.

Table 5.12: Estimated short-run wealth inequality coefficients using the ARDL approach for a range of model specifications

<i>Model:</i>	<i>(1)</i>		<i>(2)</i>		<i>(3)</i>		<i>(4)</i>		<i>(5)</i>	
<i>Dependent variable:</i>	<i>ln(Wealth Gini)</i>		<i>ln(Wealth Palma)</i>		<i>Wealth S80S20</i>		<i>ln(Wealth Gini)</i>		<i>ln(Wealth Gini)</i>	
Variable	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Δ ln(House prices)	-0.0307 ***	-7.9772	-0.1423 ***	-5.3122	4.468 ***	4.1633				
	(-0.0038)		(0.0268)		(1.0732)					
Δ ln(House prices (-1))	0.0206 ***	5.0263	0.0839 ***	3.5859	-4.8594 ***	-3.6792				
	(-0.0041)		(0.0234)		(1.3208)					
Δ ln(House prices (-2))	0.0239 ***	5.7017	0.0759 **	3.1545	-5.6501 ***	-4.9617				
	(-0.0042)		(0.0241)		(1.1388)					
Δ ln(Real house prices)							-0.0268 ***	-6.8812		
							(0.0039)			
Δ ln(Real house prices (-1))							0.0201 ***	4.7717		
							(0.0042)			
Δ ln(Real house prices (-2))							0.0226 ***	5.3242		

<i>Model:</i>	(1)		(2)		(3)		(4)		(5)	
<i>Dependent variable:</i>	<i>ln(Wealth Gini)</i>		<i>ln(Wealth Palma)</i>		<i>Wealth S80S20</i>		<i>ln(Wealth Gini)</i>		<i>ln(Wealth Gini)</i>	
Variable	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
$\Delta \ln(\text{Value-to-income})$							(0.0042)		-0.0289 ***	-8.3517
$\Delta \ln(\text{Value-to-income}(-1))$									(0.0035)	
$\Delta \ln(\text{Value-to-income}(-2))$									0.0244 ***	6.1401
									(0.004)	
$\Delta \ln(\text{Wealth Gini} (-1))$	1.3892 ***	8.0321					1.3471 ***	7.4715	1.3233 ***	8.2822
	(-0.173)						(0.1803)		(0.1598)	
$\Delta \ln(\text{Wealth Gini} (-2))$	0.5575 ***	4.2342					0.5213 ***	3.8036	0.5273 ***	4.2292
	(-0.1317)						(0.1371)		(0.1247)	
$\Delta \ln(\text{Wealth Palma} (-1))$			1.1065 ***	6.0419						
			(0.1831)							
$\Delta \ln(\text{Wealth Palma} (-2))$			0.4852 ***	3.5725						
			(0.1358)							
$\Delta \ln(\text{Wealth Palma} (-1))$					1.2707 ***	7.1043				
					(0.1789)					
$\Delta \ln(\text{Wealth Palma} (-2))$					0.5361 ***	3.9773				
					(0.1348)					
ECT	-1.2711 ***	-10.0388	-1.2866 ***	-8.2577	-2.6022 ***	-9.4574	-1.5009 ***	-9.4328	-1.364 ***	-10.4215
	(-0.1428)		(-0.1769)		(0.2751)		(-0.1651)		(0.1268)	
$\Delta \text{Development PC}$	-0.0001	-0.3629	-0.0059 **	-2.8606	0.1722 *	1.8439	-0.0003	-0.7854	-0.0002	-0.8062
	(-0.0003)		(0.0021)		(0.0934)		(0.0003)		(0.0003)	
Constant	10.8206 ***	10.0494	8.7135 ***	8.3004	-199.6424 ***	-9.4216	11.0138 ***	9.4418	9.7781 ***	10.4352
	(-1.0767)		(1.0498)		(21.1899)		(1.1665)		(0.937)	
Time trend	0.0037 ***	9.2944	0.0153 ***	7.5478	-0.7981 ***	-9.5956	0.0025 ***	8.378	0.0028 ***	9.3082
	(-0.0004)		(0.002)		(0.0832)		(0.0003)		(0.0003)	
<i>Model diagnostics</i>										
R-squared		0.9193		0.8804		0.9075		0.9078		0.9273
Adjusted R-squared		0.8634		0.7977		0.7738		0.844		0.8770

Note: See notes for Table 5.11.

5.2.2 Heterogeneity Across the Distribution

McGregor et al. (2019) highlighted that when conducting any inequality research, it is essential to consider what properties of the inequality distribution matter to the specific study. While the answer may differ for each researcher's goal, it can lead to different conclusions when testing the same relationship. This may be the reason for the variation in findings amongst the previous literature. For example, Di and Travers et al. focused primarily on the difference between homeowners and non-homeowners. Other research compared wealth changes across the entire distribution using the Gini's or wealth share ratios. This difference in comparison groups can lead to different conclusions when examining the same relationship. This thesis has already found contrasting magnitudes when using the Gini instead of the Palma ratio and the positive sign when using the S80S20 ratio. The differences for alternative measures are more substantial for the income inequality results in Chapter 4. To further explore these differences across the wealth distribution, an ARDL regression is employed, regressing the wealth share for the ten deciles of the wealth distribution.

Table 5.13: Change to wealth share for each decile of the wealth distribution following an increase in house prices, using the logarithmic form for the dependent variables (double-log model)

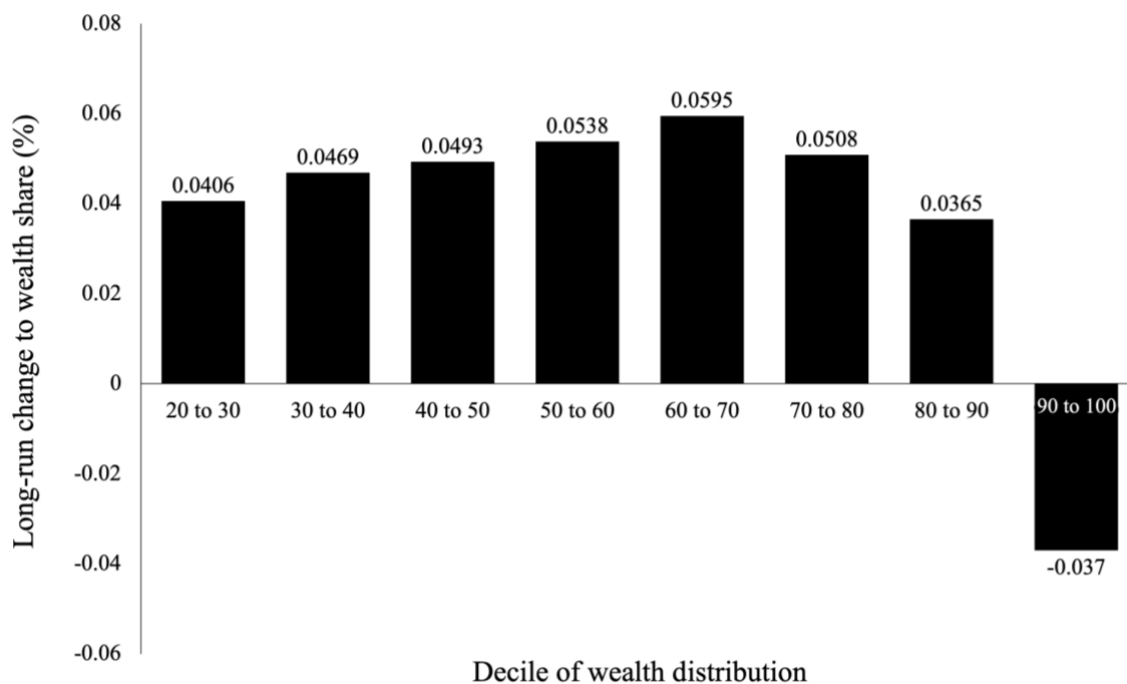
Wealth decile	Long-run change to wealth share (%)	F-Bounds test-statistic	t-Bounds test-statistic
20 to 30	0.0406 *** (0.008)	7.116 ***	-5.8764 ***
30 to 40	0.0469 *** (0.0048)	9.853 ***	-7.2971 ***
40 to 50	0.0493 *** (0.0042)	13.4354 ***	-8.5728 ***
50 to 60	0.0538 *** (0.0038)	14.0654 ***	-8.7085 ***
60 to 70	0.0595 *** (0.0059)	12.218 ***	-8.001 ***
70 to 80	0.0508 *** (0.0036)	11.0977 ***	-7.8138 ***
80 to 90	0.0365 *** (0.0035)	9.9298 ***	7.5081 ***
90 to 100	-0.037 *** (0.0029)	11.5662 ***	-7.9768 ***

Notes: (i) Each row represents a separate ARDL equation estimation where the dependent variable is the wealth share of the decile specified in the first column. All dependent variables are in logarithmic form; (ii) change represents the long-run (%) change to each wealth share following a 1% increase in house prices; (iii) bottom two deciles cannot be estimated due to negative values or a lack of variation in the dependent variable; (iv) null hypothesis for Bounds test is there is no cointegration relationship in levels ($H_0: \pi_y \cap \{\pi_j\}_{j=1}^k = 0$). The null hypothesis for long-run coefficients is $\pi_{P,j} = 0$; (v) see notes for Table 5.1.

The results of the ARDL estimations for each decile, where the dependent variable is in logarithmic form, are presented in Table 5.13. Since this table represents a double-log model, the coefficients indicate the long-run percentage change in the wealth share of each decile following a one per cent increase in house prices, i.e., the variables are in

elasticity form. However, it is essential to note that the bottom decile could not be included as it cannot be logged, leading to incomparable coefficients as they are not in elasticity form. Moreover, the 10th to the 20th decile is not included due to a lack of variation over time, with a wealth share of 0.29 per cent every year from 1995 to 2021. The long-run changes presented in Table 5.13 should only be considered if the null is rejected for all three tests: the F-Bounds, t-Bounds, and statistical significance of the coefficient tests. As shown in Table 5.13, all eight decile regressions resulted in a decisive rejection of the null for all three tests, indicating that for each decile, a cointegration relationship is present and house prices make a statistically significant difference to the wealth share. However, there are differences in the magnitude and sign across the wealth distribution. These differences are visually presented in Figure 5.13, clearly illustrating the variations across deciles.

Figure 5.13: Change in the wealth share for each decile of the wealth distribution following an increase in house prices (double-log model)



Note: Values are sourced from Table 5.13.

It can be seen from Figure 5.13 that the decile to benefit the most from an increase in house prices is the 60 to 70 per cent of the distribution; a ten per cent increase in house prices will increase the wealth share of this decile by 0.595 per cent on average, *ceteris paribus*¹⁴. The deciles from 20 per cent to 90 per cent of the distribution all experience a change in wealth share that is very similar and within a standard error of each other. All deciles experience a positive shift in wealth share except for the highest decile, which undergoes a decrease. This result is in line with the literature that suggests the middle of the distribution primarily increases their wealth through housing. In contrast, the top ten per cent generally increases their wealth through equities. Because equity prices are held constant in the model, and other deciles are growing their share of NZ wealth, the top decile experiences an overall decrease in their wealth share. This is not necessarily because they have decreased their net wealth but because they own a lesser proportion of NZ's overall wealth following an increase in house prices, as other deciles have increased their proportion of NZ's overall wealth. These results provide supporting evidence that the inverted U-curve relationship exists in NZ, which matches the findings of Symes (2022) and Rashbrooke et al. (2017).

The true inverted U-curve using NZ data from Rashbrooke et al. (2021) is presented in Figure 5.14 for 2015 and 2018. It is essential to note that the values in this figure do not consider housing assets held in a trust due to the complex makeup of trusts. A method approximating housing assets in trusts was trialled and supplied in Appendix N. However, this alternative method primarily only changes the percentage of housing-

¹⁴ This is a percentage increase in the wealth share which is itself a percentage. In other words, it is a percentage increase in the percentage of overall NZ wealth owned.

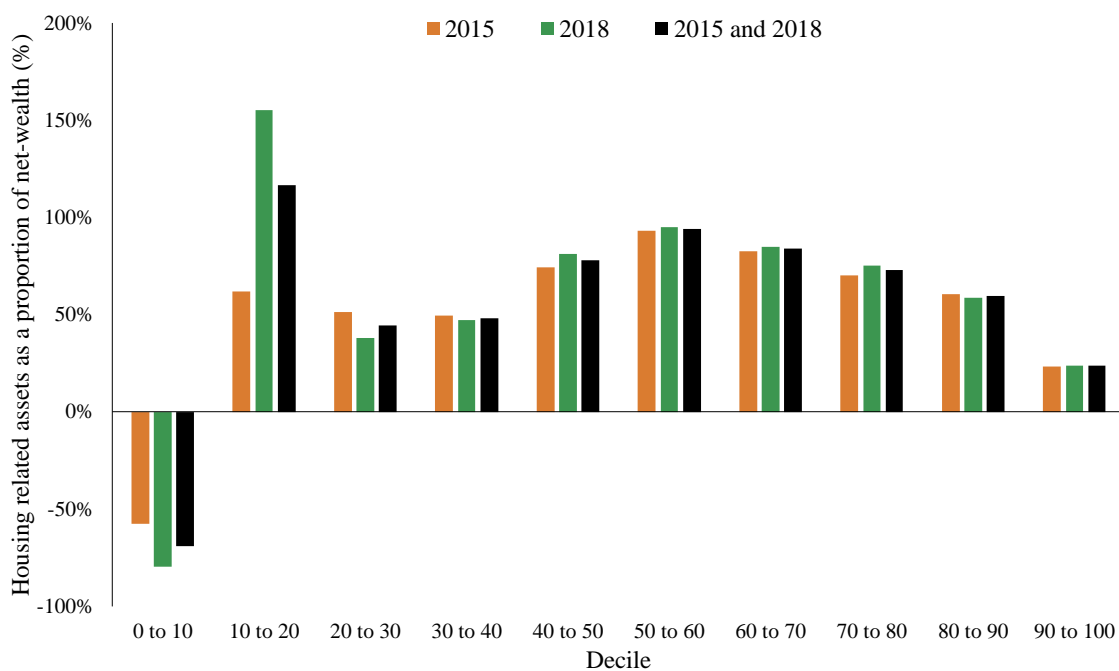
related assets for the top decile. Overall, the difference between the two graphs is minimal.

It is important to note how different the bottom two deciles in Figure 5.14 look compared to the other eight. On average, households in the bottom decile have fewer assets than debt, leading to an overall negative net worth. This is why their percentage of housing-related assets is less than zero. Furthermore, for a household with a negative net worth, increasing their net worth while the quantity of housing-related assets remains constant will increase their overall percentage of housing-related assets. This contrasts with a household with a positive net worth where the change would decrease its proportion of housing-related assets. This behaviour of ratios overinflates the proportion of housing-related assets a negative net worth household owns. This behaviour can also lead to a proportion of housing-related assets greater than 100 per cent of a household's net worth. This occurs when the net worth has surpassed zero but has yet to increase above the value of the housing-related assets. Because the bottom two deciles contain households with a negative net worth, this leads to a higher proportion of housing-related assets for these deciles than initially expected. The reader should know that a household with a negative net worth can increase its proportion of housing-related assets without acquiring more housing. While the proportion increases, the household would not be more sensitive to changes in house prices. Therefore, caution should be taken when considering the bottom two deciles in Figure 5.14 concerning house price shocks.

Additionally, it is notable that the decile with the greatest proportion of net wealth in housing (50 to 60 per cent) does not necessarily experience the greatest change in wealth share from a house price shock, as shown in Figure 5.13. An additional factor

may play a role in offsetting the marginal impact of housing for this decile. Nonetheless, the inverted U-curve relationship appears to be a strong driver of the equalising effects of house price changes on wealth distributions, as evident from the close resemblance between Figure 5.13 and Figure 5.14.

Figure 5.14: The inverted U-curve of housing related assets across the wealth distribution in NZ from 2015 to 2018



Notes: The calculations for this figure are done using data from Rashbrooke et al. (2021). Housing assets held in trusts are not included in the calculations, although this primarily impacts the top decile of the distribution. A brief discussion of the calculations, along with an alternative method that considers trusts, is provided in Appendix N. Caution is advised for the bottom two deciles. Please read the discussion in the above paragraphs for an explanation of this phenomenon.

In addition to the double-log model, where both house prices and wealth inequality is logarithmic, a linear-log or semi-log model was estimated where the dependent variable is in levels, and the house price variable is logged. This has the added benefit of estimating the change in the bottom decile. Furthermore, it provides an alternative interpretation of the coefficients, representing the nominal change in the wealth share of

each decile following a house price shock. However, it reduces the comparability of the coefficients in terms of implications for a decile. For instance, a one per cent increase in the wealth share of the top decile is a less meaningful impact than a one per cent increase in the wealth share of the bottom decile. Thus, the double-log model is better suited to show the relative impact of a house price shock on a specific decile's wealth share, as the coefficients represent elasticities. The results of the ARDL modelling for the semi-log model are shown in Table 5.14.

All linear-log models show a firm rejection of the three null hypotheses. The bottom decile has a small and negative coefficient; when house prices increase by ten per cent, the wealth share of the bottom decile is expected to decrease by 0.00165, all else held constant¹⁵. This aligns with the theory that the bottom of the distribution owns relatively less wealth in housing-related. Like the top decile, this does not necessarily provide evidence that the bottom decile has less wealth due to a house price increase. However, it does suggest that the overall proportion of NZ wealth the bottom decile owns is decreasing as other deciles increase their share of NZ wealth. This is a relatively small change, and the top decile experiences the majority of the loss in wealth share.

The coefficients from Table 5.14 are plotted in Figure 5.15 to present the relative magnitudes visually. Because the coefficients are not in elasticity form, the resulting curve looks starkly different from Figure 5.13. Despite this, it explains similar mechanisms. First, the positive impact of house prices on the wealth distribution primarily occurs around the middle of the distribution. There are positive increases in

¹⁵ The wealth share variable is represented in levels in this model. Therefore, the coefficient represents a 0.00165 per cent decrease in the wealth share in nominal terms. In other words, this is not a percentage change of a percentage variable like in other instances.

the wealth share of 20 to 90 per cent of the distribution, the same as before. Second, there is a decrease in wealth share for the top and bottom deciles of the distribution. However, the reduction for the top decile is far more significant than the increase for any other decile. This matches the results from Figure 5.13. The 80 to 90 decile experiences the largest nominal increase in wealth share of any decile. However, in elasticity form, the 60 to 70 per cent decile experiences the most significant increase in wealth share. The difference stems from the relative proportion of wealth share each decile generally owns. On average, the 60 to 70 decile owns seven per cent of NZ's wealth throughout the sample period compared to around 16 per cent for the 80 to 90 decile. Therefore, when house prices increase by ten per cent, the 0.017 per cent increase in wealth share for the 60 to 70 decile will make a comparatively greater difference than the 0.025 per cent increase in wealth share for the 80 to 90 decile¹⁶.

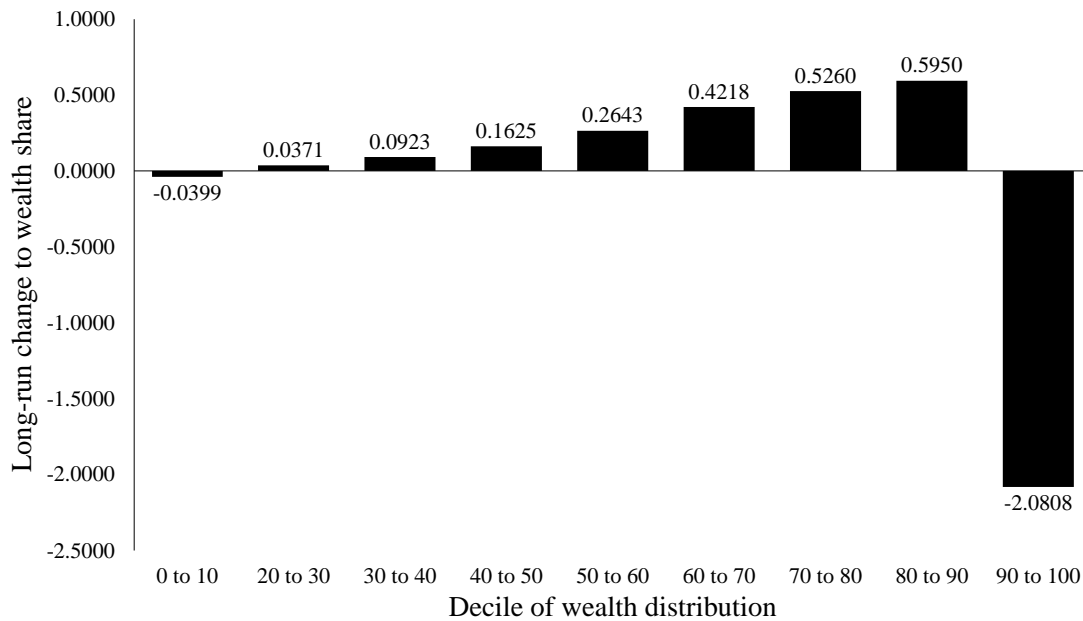
¹⁶ Please note that the nominal change in a semi-log model is calculated by: $\hat{\beta} \cdot \log([100 + p]/100)$. Where $\hat{\beta}$ is the estimated coefficient and p is the percentage change in house prices.

Table 5.14: Change to wealth share for each decile of the wealth distribution following an increase in house prices, using the nonlogarithmic form for the dependent variables (semi-log model)

Wealth decile	Long-run coefficient	F-Bounds test	t-Bounds test
0 to 10	-0.0399 *** (0.0075)	8.7017 ***	-6.519 ***
20 to 30	0.0371 *** (0.0073)	7.1522 ***	-5.887 ***
30 to 40	0.0923 *** (0.0095)	9.8376 ***	-7.2911 ***
40 to 50	0.1625 *** (0.0138)	13.48 ***	-8.5879 ***
50 to 60	0.2643 *** (0.0183)	14.1243 ***	-8.7272 ***
60 to 70	0.4218 *** (0.0414)	12.2458 ***	-8.01 ***
70 to 80	0.526 *** (0.0379)	11.1314 ***	-7.8258
80 to 90	0.595 *** (0.0562)	9.976 ***	-7.5248 ***
90 to 100	-2.0808 *** (0.1618)	11.5452 ***	-7.996 ***

Notes: (i) Each row represents a separate ARDL equation estimation where the dependent variable is the wealth share in levels for the decile specified in the first column; (ii) the coefficient is for the explanatory variable of house prices; (iii) the long-run change to the dependent variable from a percentage change (p%) in house prices is calculated as $\hat{\beta} \cdot \log([100 + p]/100)$; (iv) null hypothesis for Bounds test is there is no cointegration relationship in levels ($H_0: \pi_y \cap \{\pi_j\}_{j=1}^k = 0$); (v) see notes for Table 5.1.

Figure 5.15: Change in wealth share for each decile of the wealth distribution following a house price increase using a semi-log model



Note: Values are sourced from Table 5.14.

Little is known about housing's impact on the ten to 20 per cent decile through regression estimation. While this decile has not experienced any change in wealth share in 25 years, it is inconclusive to claim that house prices do not affect their wealth share. Other factors balance offset the impact of house prices, but this cannot be estimated using a regression approach. In Table 5.11, an increase in house prices resulted in a positive impact on the S80S20 ratio. Because the share of wealth for the top 20 per cent decreases overall, according to Table 5.14, the bottom 20 per cent must also experience a decrease in wealth share to achieve a positive coefficient for the S80S20 model. This suggests that the ten per cent to 20 per cent decile either experiences a reduction in their wealth share from an increase in house prices, a positive change with a coefficient smaller than 0.0399, or zero change.

Approximately estimating the actual coefficient for the ten to 20 per cent decile was trialled using the results from other regressions. Three thoughts of logic were used: (i) if the change to the S80S20 ratio from a house price increase is known along with the change to the other three deciles, the fourth one could be calculated; (ii) if the change to the Palma ratio and the four other deciles in the formula is known, the fifth could be calculated; (iii) if in the long-run, deciles gaining more of NZ's overall wealth resulted in other deciles losing some of their wealth shares, the missing decile could be approximated as the value that makes the sum of long-run changes equal to zero. This works on the logic that wealth redistribution is initially a zero-sum game. Wealth creation is not a zero-sum game, as new wealth can be created without others decreasing their wealth; however, because the sum of all deciles' wealth share is bounded between zero and 100 per cent, a group increasing the proportion of overall NZ wealth has to decrease another group(s) share of overall wealth. While these three methods were used to estimate the missing decile, it could not reach a consistent answer across the methods, so it was discounted.

5.2.3 Asymmetries

It is crucial to examine whether the association between house prices and wealth inequality remains consistent during negative shocks, especially following the NZ house price decline experienced since February 2022. To test for asymmetries in the relationship between house prices and wealth inequality, a NARDL model is used. The findings of the Wald test for the NARDL approach are presented in Table 5.15, indicating significant differences between positive and negative changes in house prices in the short-run. Further analysis of this dynamic is conducted by presenting the results of the short-term NARDL model in Table 5.16.

Table 5.15: Wald test for the wealth inequality NARDL estimates

Inequality	Wald test long-run	Wald test short-run	Conclusion
Wealth	-0.0584 (0.0669)	-0.1239 ** (0.04734)	Long-run symmetry and short-run asymmetry

Notes: The test is for a null hypothesis of symmetry; specifically, the short-run tests if $H_0: \sum_{r=0}^u \delta_r^+ = \sum_{z=0}^h \delta_z^-$ and the long-run tests if $H_0: \frac{\theta^+}{\pi_y} = \frac{\theta^-}{\pi_y}$, using values from equation 3.10. Standard error reported in parenthesis underneath test coefficients. (**) is significant at 5%.

Table 5.16: The wealth inequality model NARDL results

Variable	Coefficient	t-statistic
$\Delta \ln(\text{House prices})$ \oplus	-0.0276 *** (0.0039)	-7.0059
$\Delta \ln(\text{House prices } (-1))$ \oplus	0.0059 (0.0044)	1.3546
$\Delta \ln(\text{House prices } (-2))$ \oplus	0.0567 *** (0.0058)	9.8375
$\Delta \ln(\text{House prices})$ \ominus	0.0866 *** (0.0081)	-9.6653
$\Delta \ln(\text{House prices } (-1))$ \ominus	-0.0477 *** (0.0092)	4.099
$\Delta \ln(\text{Wealth Gini } (-1))$	1.5196 *** (0.1271)	11.96
$\Delta \ln(\text{Wealth Gini } (-2))$	0.6567 *** (0.1027)	6.394
$\Delta \text{Development PC}$	0.0025 *** (0.0003)	8.1397
ECT	-2.6579 *** (0.1894)	-14.0367
Constant	10.9183 *** (0.7779)	14.0351
Time trend	0.004 *** (0.0003)	14.1459

Notes: (\oplus) Represents the short-run (%) change to the wealth Gini following a 1% increase in house prices, while (\ominus) is for a 1% negative change. Also, see notes for Table 5.1.

Based on the results from Table 5.16, there is no difference in the sign for a positive or negative house price shock, i.e., an increase (decrease) in house prices results in an

initial reduction (expansion) of the wealth Gini in the short-run¹⁷. However, there is a difference in the magnitudes of these effects. A negative house price shock leads to a more considerable percentage change in the wealth Gini than a comparative positive shock in house prices. This implies a non-linear relationship between house prices and wealth inequality in the short-run. Interestingly, this result is only present in the short-run, and the magnitudes are statistically equivalent in the long-run. This implies that over time, the economy converges to a steady state in which the relationship between house prices and inequality becomes stable and predictable; the response of wealth inequality to a house price shock becomes equivalent regardless of the direction of the shock in the long-run. This provides evidence that rigidities may be present in the NZ economy in the short-run.

Rigidities in the economy can take various forms. Some common rigidities for wealth inequality include institutional barriers or a lack of intergenerational mobility (Aiyar & Ebeke, 2020) that may prevent groups from benefiting fully from the house price shock. In a NZ context, de Roiste et al. (2021) also provide evidence that rigidities are present when considering housing and wealth. They found a similar asymmetry when considering the impact of house prices on the wealth effect, finding that a negative shock to house prices results in a more significant change to the marginal propensity to consume than a positive shock. This provides additional evidence that there may be

¹⁷ This is because the interpretations for NARDL models change compared to traditional models. For instance, the $\Delta \ln(\text{House prices})^+$ coefficient is interpreted as the change to wealth inequality following a one per cent *increase* in house prices. Because this coefficient is negative, increasing house prices lead to decreasing wealth inequality in the same period. Furthermore, the $\Delta \ln(\text{House prices})^-$ coefficient is interpreted as the change to wealth inequality following a one per cent *decrease* in house prices. Because this value is positive, a decrease in house prices increases wealth inequality in the same period. Therefore, the directionality for positive and negative shocks is still the same as predicted using an ARDL model.

asymmetries in the relationship between wealth inequality and housing in New Zealand. To further test which groups are driving this asymmetry, the decile regressions from Table 5.13 are repeated utilising a NARDL approach.

Table 5.17: Wald test for NARDL decile estimates

Decile	Wald-test long-run	Wald-test short-run	Conclusion
20 to 30	-0.1991 (0.1580)	-0.2539 (0.1821)	Symmetry
30 to 40	-0.0373 (0.1966)	-0.3108 * (0.1781)	Symmetry
40 to 50	-0.33 (0.3842)	-0.24 (0.2290)	Symmetry
50 to 60	0 (0.2498)	-0.3841 ** (0.1837)	Long-run symmetry and short-run asymmetry
60 to 70	-0.0049 (0.2687)	-0.4835 ** (0.2217)	Long-run symmetry and short-run asymmetry
70 to 80	-0.0117 (0.2250)	-0.3688 (0.1907)	Symmetry
80 to 90	-0.183 -0.1707	-0.2014 (0.1461)	Symmetry
90 to 100	0.0040 (1.66)	0.1673 ** (0.0833)	Long-run symmetry and short-run asymmetry

Note: See notes for Table 5.15

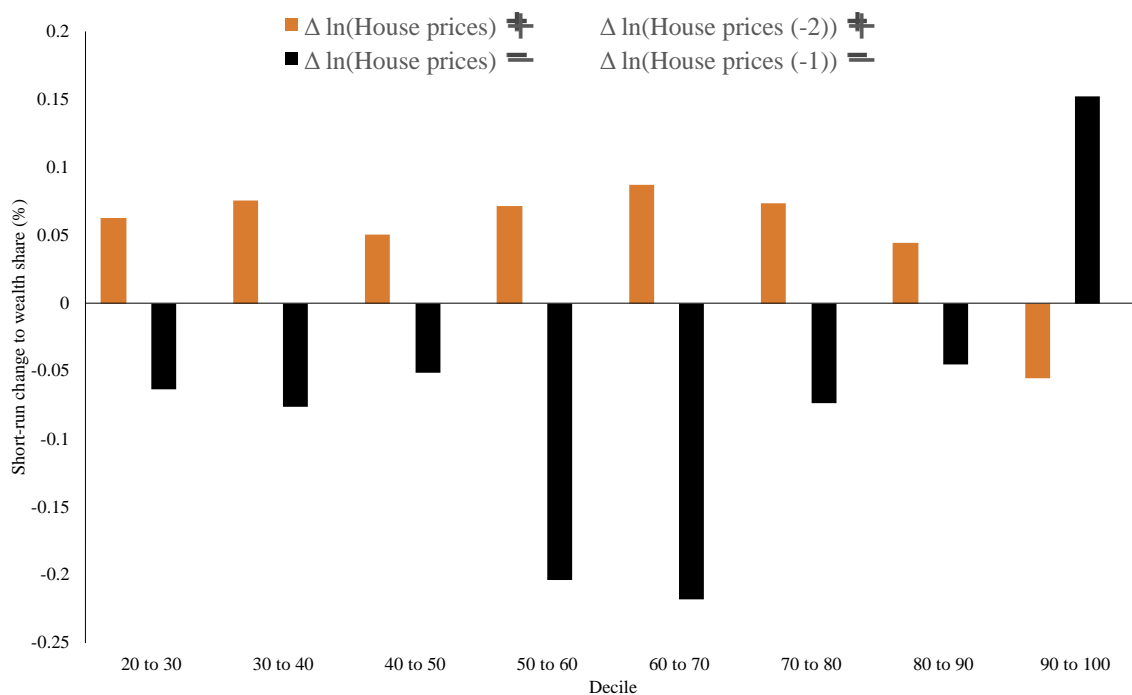
The result of the NARDL decile Wald tests is presented in Table 5.17, showing symmetry in the short- and long-run for most deciles. However, there is a short-run asymmetry for three of the deciles that stabilise in the long-run, driving the previous results in Table 5.16. A similar story is shown with the NARDL decile estimates in Table 5.18. The positive and negative coefficients are comparable for most deciles except for the distributions 50 to 60 per cent, 60 to 70 per cent, and the top decile. For those three deciles, the magnitude is more prominent for a negative housing price shock

than a positive shock. This is seen more quickly by graphing the coefficients, as shown in Figure 5.16. Orange values represent the change in wealth share from a positive shock to house prices, while black represents a negative shock. The lighter colour represents the correction in subsequent periods. The $\Delta \ln(\text{House prices } (-1)) \oplus$ values are excluded from the figure due to their statistical insignificance. In Figure 5.16, an inverted U-curve relationship is present for the black and orange series, similar to Figure 5.15. However, the curve is flatter for positive shocks to house prices. The middle 50 to 70 per cent of the distribution experience a more significant loss in their wealth share when house prices decrease than the gain they would achieve from an increase. Conversely, the top decile earns a greater improvement in wealth share from a negative shock to house prices than what they would lose from a positive shock.

A potential explanation for this phenomenon could come from the work of Martínez-Toledano (2020). Martínez-Toledano found wealthier individuals can more readily reshuffle their portfolio to contain more or less housing-related assets depending on whether house prices increase or decrease. More significant adjustment frictions at the lower ends of the distribution could exist for various reasons. First, reshuffling housing assets can be costly; there are high transaction costs, such as property taxes, real estate agent fees, lawyer fees, and closing costs. Second, middle-income individuals often have comparatively more limited access to credit, making it harder to finance new purchases. Third, housing represents a more significant proportion of overall wealth for those in the middle of the distribution, creating a greater reluctance to sell housing assets. Finally, related to the reluctance to sell, realised losses represent a proportionally more significant share of overall wealth for those lower down the wealth distribution. This can cause some individuals to hold onto assets they have already made a loss on and exhibit non-optimal behaviours (Shefrin & Statman, 1985).

Therefore, the asymmetry in the short-run could result from heterogeneity in portfolio adjustment friction across the wealth distribution. During adverse house price shocks, wealthier individuals may adjust their portfolios quicker to contain fewer housing-related assets than those in the middle of the distribution. This results in a greater loss of overall wealth for those in the middle of the distribution and a significant gain for the top of the distribution. Similarly, wealthy individuals can reshuffle their portfolios during a positive shock to contain greater housing-related assets. This means that while the middle of the wealth distribution still experiences a gain in overall wealth share, it is offset by the top deciles portfolio reshuffling. However, why this asymmetry only exists in the long-run remains explained. It is interesting for future research to focus on why this rigidity exists solely in the short-run.

Figure 5.16: Relative magnitudes for the wealth inequality NARDL results across different deciles



Note: Values are sourced from Table 5.18.

Table 5.18: Wealth inequality NARDL results for different deciles

Explanatory variable	$\Delta \ln(\text{House prices}) \text{+}$		$\Delta \ln(\text{House prices } (-1)) \text{+}$		$\Delta \ln(\text{House prices } (-2)) \text{+}$		$\Delta \ln(\text{House prices}) \text{—}$		$\Delta \ln(\text{House prices } (-1)) \text{—}$	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
20 to 30	0.0633 *** (0.0137)	4.6373	-0.0009 (0.0135)	-0.0667	-0.1094 *** (0.016)	-6.8189	-0.0734 *** (0.0179)	4.2384		
30 to 40	0.0759 *** (0.0127)	5.9779	-0.0099 (0.0147)	-0.6694	-0.1274 *** (0.0173)	-7.3634	-0.0649 *** (0.0119)	7.5638	0.1007 ** (0.0296)	-3.4091
40 to 50	0.051 *** (0.0119)	4.2761	-0.0003 (0.0135)	-0.0187	-0.1194 *** (0.015)	-7.9801	-0.0491 *** (0.0121)	10.4013	0.1863 *** (0.0295)	-6.3069
50 to 60	0.0717 *** (0.0122)	5.8946	-0.024 (0.0137)	-1.7565	-0.1652 *** (0.017)	-9.7296	-0.2036 *** (0.0396)	9.1903	0.0971 ** (0.0288)	-3.3746
60 to 70	0.0872 *** (0.013)	6.7178	-0.014 (0.0145)	-0.9646	-0.2075 *** (0.0193)	-10.7364	-0.2179 *** (0.0456)	10.2599	0.1188 *** (0.0305)	-3.8995
70 to 80	0.0735 *** (0.011)	6.6839	-0.0127 (0.0123)	-1.0316	-0.1614 *** (0.0161)	-10.0292	-0.0648 *** (0.0179)	10.0506	0.1127 *** (0.0259)	-4.3553
80 to 90	0.0446 *** (0.0084)	5.2837	-0.002 (0.0095)	-0.216	-0.0951 *** (0.011)	-8.6247	-0.0435 *** (0.0114)	11.3626	0.093 *** (0.0106)	-6.7639
90 to 100	-0.0559 *** (0.0081)	-6.8657	0.0116 (0.0091)	1.2749	0.1184 *** (0.0119)	9.9284	0.1527 *** (0.0274)	-9.8641	-0.0793 *** (0.0191)	4.1555

Notes: (i) Each row represents a separate ARDL equation estimation where the dependent variable is specified in the first column. All dependent variables are in logarithmic form; (ii) (**+**) represents the long-run (%) change to each wealth share following a 1% positive shock to house prices, (**—**) is for a negative shock ; (iii) the bottom two deciles cannot be estimated due to negative values or a lack of variation in the dependent variable; (iv) see notes for Table 5.1.

5.3 Summary

There is empirical evidence to support the theory that wealth inequality decreases as house prices increase in a NZ environment. This finding is robust to a wide range of alternative model specifications. However, the effect of house prices on wealth inequality is not homogeneous across the wealth distribution, and the heterogeneity becomes more pronounced when house prices decrease instead of increase. Therefore, policymakers should consider the target groups of interest when using the results of this analysis. If the goal is to lower the wealth Gini, house price increases are desirable. However, if the aim is to close the wealth gap between homeowners and non-homeowners, increasing house prices is unlikely to achieve this outcome. In the next chapter, the wealth inequality model used in this study is expanded to account for earnings inequality in NZ.

Chapter 6: Income and Wealth Inequality

6.1 Introduction

Throughout this thesis so far, the importance of the relationship between house prices and inequality has been analysed. A summary of the existing literature has been presented, and the methodology for investigating the relationship within a NZ context has been outlined. In addition, the dynamics of the NZ housing market concerning income and wealth inequality have been considered separately. House prices and the introduction of LVRs are found to increase the income Gini, but their effects on other measures of income inequality may differ. This is due to the heterogeneity in the impact of house price shocks across the income distribution. A similar heterogeneity is observed when considering wealth inequality. Although, unlike income inequality, the heterogeneity in the wealth distribution becomes more pronounced during a negative shock to house prices rather than an increase. Furthermore, introducing LVRs does not appear to have a statistically significant effect on wealth inequality as it does on income inequality.

This chapter undertakes a novel approach to supplement the previous analyses by concurrently examining income and wealth inequality. This is an approach infrequently done in the prior literature. In section 3.3.3, the relationship between income and wealth inequality is discussed; the connection arises because earnings inequality impacts wealth accumulation, leading to wealth inequality. But the opposite direction of the relationship also exists - wealthier individuals have more time and financial resources than less wealthy individuals to invest in education, increasing their human capital and

resulting in higher income. Additionally, they earn more significant returns on their assets than less wealthy individuals, contributing to income inequality.

To account for this relationship, two techniques are used. First, a seemingly unrelated regression (SUR) model is used to obtain an efficiency gain of the estimates by controlling for the contemporaneous correlation of the error terms in the income and wealth inequality models; this approach is analysed throughout section 6.2. Throughout section 6.3, income inequality is included as an explanatory variable in the wealth inequality equation, creating a system of equations. However, to overcome the potential endogeneity issue for this equation, a 2SLS approach is used with two unique instruments. Next, the robustness and validity of the findings for the system of equations are considered in section 6.4, followed by a summary of all the results in section 0.

6.2 Contemporaneous Error Correlation

An efficiency gain can be achieved when a contemporaneous correlation between the error terms of two equations is present. This is achieved through a SUR approach, where the estimation process accounts for the common disturbances by estimating the equations jointly and exploiting the shared information between equations (Srivastava & Giles, 1987). However, a SUR approach is only appropriate if there is a correlation between the error terms; otherwise, separate OLS/ARDL equations would be more efficient. The error terms of the wealth and income inequality equations have a reasonably high correlation of 0.76. However, Anselin (2016) recommends using a likelihood ratio (LR) test to see if the error terms are contemporaneously related. The formula used to calculate the LR is given in equation 6.1, where $\sum_t \hat{\sigma}_{t,\varepsilon,OLS}^2$ is the sum of

error variances for each equation in an OLS/ARDL estimation and $\hat{\Sigma}^{IFGLS}$ is the determinant residual covariance estimated from the SUR. The LR follows a chi-squared (χ^2) distribution, with the χ^2 critical value given in equation 6.2. Because the LR_{stat} (838) is greater than the $\chi^2_{critical}$ (406) in absolute terms, the null hypothesis of no contemporaneous relationship between the error terms of each equation is rejected (p-value = 0.00001). Therefore, the SUR method is an appropriate approach to achieve an efficiency gain of the equation estimates.

$$LR = t \left(\ln \sum_t \hat{\sigma}_{t,\varepsilon,OLS}^2 - \ln \left| \hat{\Sigma}^{IFGLS} \right| \right) \quad (6.1)$$

$$LR_{stat} = 29 \cdot (\ln(4.8963 \times 10^{-7} + 0.000789) - \ln|3.4 \times 10^{-10}|) = -838.76$$

$$\chi^2_{critical} = 456, \left(\text{where } DoF = \frac{t(t-1)}{2} = 406 \right) \quad (6.2)$$

Table 6.1: Comparison of the ARDL and SUR for predicting ln(Income Gini)

<i>Model</i>	<i>(1)</i>		<i>(2)</i>	
<i>Estimation method</i>	<i>ARDL</i>		<i>SUR</i>	
Variable	Coefficient	t-statistic	Coefficient	t-statistic
ln(Income Gini (-1))	0.4424 *** (0.1273)	3.4751	0.2826 ** (0.1303)	2.1693
ln(House prices)	0.1187 ** (0.0561)	2.1175	0.1563 ** (0.0619)	2.527
LVR	0.0234 ** (0.0110)	2.1177	0.0028 ** (0.0013)	2.1309
ln(Real GDP per capita)	1.957 *** (0.5412)	3.616	1.9275 *** (0.5609)	3.4366
Population PC	0.0023 (0.0713)	0.0325	-0.1606 (0.0987)	-1.6265
Unemployment rate	0.0249 ** (0.0109)	2.2856	0.0406 *** (0.0139)	2.9146
Unemployment rate (-1)	0.0312 *** (0.0087)	3.603	0.0313 *** (0.0112)	2.803
Foreign investment	0.0028 (0.0029)	0.9597	0.0054 (0.0032)	1.6636
ln(Trade volume)	0.4156 *** (0.1173)	3.5427	0.366 *** (0.1024)	3.575
Inflation rate	-1.8502 ** (0.7025)	-2.6337	-0.167 (0.7161)	-0.2333
Constant	5.9245 *** (2.0357)	2.9103	4.5932 * (2.2676)	2.0256
Time trend	-0.0326 *** (0.0093)	-3.5086	-0.0417 *** (0.0108)	-3.8593
<i>Model diagnostics</i>				
R-squared	0.8865		0.8645	
Adjusted R-squared	0.8013		0.7629	
S.E. of regression	0.0354		0.0387	

Notes: The ARDL model (1) is replicated from Table 4.12. The standard error is reported in parenthesis underneath the coefficients. HAC standard errors & covariance have been used throughout. (*) is significant at 10%; (**) significant at 5%; and (***) significant at 1%.

Table 6.2: Comparison of the ARDL and SUR approaches for predicting ln(Wealth Gini)

<i>Model</i>	<i>(3)</i>		<i>(4)</i>		<i>(5)</i>	
<i>Estimation method</i>	<i>ARDL</i>		<i>SUR</i>		<i>SUR</i>	
Variable	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
ln(Wealth Gini (-1))	-0.109 (-0.185)	-0.588	0.0369 (0.1077)	0.3429	-0.291 *** (0.0645)	-4.5134
ln(Wealth Gini (-2))	-0.831 *** (-0.135)	-6.182	-0.7818 *** (0.1284)	-6.0866	-0.6378 *** (0.072)	-8.8593
ln(Wealth Gini (-3))	-0.558 *** (-0.158)	-3.528	-0.3093 *** (0.0996)	-3.1051	-0.4956 *** (0.0606)	-8.1747
ln(House prices)	-0.0306 *** (-0.006)	-5.493	-0.025 *** (0.006)	-4.1625	-0.0156 *** (0.0034)	-4.592
ln(House prices (-1))	0.004 (-0.006)	0.597	0.0117 ** (0.0045)	2.6251	0.0036 (0.0025)	1.4728
ln(House prices (-2))	0.003 (-0.006)	0.560	-0.0092 * (0.0045)	-2.0137	0.0086 *** (0.0025)	3.4764
ln(House prices (-3))	-0.0238 *** (-0.005)	-5.095	-0.0135 *** (0.0041)	-3.2799	-0.0264 *** (0.0023)	-11.3419
ln(House prices (-4))					-0.0139 *** (0.0028)	-4.9376
ln(House prices (-5))					0.0235 *** (0.003)	7.9254
ln(Real GDP per capita)	-0.0612 ** (-0.021)	-2.885	-0.0399 *** (0.0137)	-2.916	-0.0445 *** (0.0076)	-5.8408
ln(Share prices)	0.0174 *** (-0.003)	5.257	0.0146 *** (0.0032)	4.6106	0.0152 *** (0.0017)	8.856
Population PC	-0.002 (-0.008)	-0.216	-0.0017 (0.0062)	-0.2714	0.0157 *** (0.0035)	4.4491
Development PC	0.000 (-0.001)	-0.129	0.0001 (0.0005)	0.2074	-0.0008 *** (0.0002)	-3.583
Development PC (-1)	0.000 (-0.001)	0.801	0.0005 (0.0004)	1.2049	0.0007 *** (0.0002)	3.0991
Constant	10.820 *** (-1.54)	7.026	8.9164 *** (0.8372)	10.6507	10.3454 *** (0.5541)	18.672
Time trend	0.00369 *** (0)	7.609	0.0025 *** (0.0003)	8.0671	0.0019 *** (0.0003)	5.7898
<i>Model diagnostics</i>						
R-squared	0.9382		0.8985		0.9655	
Adjusted R-squared	0.8300		0.7518		0.8915	
S.E. of regression	0.0011		0.0013		0.0009	

Note: The ARDL model (3) is replicated from Table 5.1. The standard error is reported in parenthesis underneath the coefficients. HAC standard errors & covariance have been used throughout. () is significant at 10%; (**) significant at 5%; and (***) significant at 1%.*

A comparison of the SUR models with the original ARDL models is given for income and wealth inequality in Table 6.1 and Table 6.2, respectively; the original ARDL models replicated here are from Table 4.12 and Table 5.1, respectively. The income inequality estimates for the SUR in Table 6.1 shows a change in the estimated coefficients for many variables compared to the ARDL. Most importantly, the impact of past values of income inequality and LVRs has decreased. In contrast, house prices have a greater effect on income inequality than initially predicted. However, the impact is still less than when LVRs are not held constant in the model, estimated to be 0.1803 in Table 4.2. Additionally, the adjusted R-squared of model two has decreased relative to model one. Overall for income inequality, there is evidence that when the contemporaneous correlation of the errors is considered, the magnitudes of coefficients will change. Still, the sign and significance remain largely the same.

When comparing models three and four from the wealth inequality estimates in Table 6.2, the SUR model results in several statistically significant house price variables that are insignificant in the original ARDL model. This is driven by the decreased variance that arises from the efficiency gain of a SUR, which results in higher t-statistics and a greater probability that the null hypothesis is rejected. Because SUR alters significance testing, additional lags of house prices were trialled to see if they make a statistically significant difference to wealth inequality, given in model five. House prices were found to have a statistically significant impact on wealth inequality over five periods from the initial shock, longer than originally predicted¹⁸.

¹⁸ Caution is advised with this result because selecting a model that minimises the overall SIC when using a SUR approach is currently impossible. Therefore, the original model could still accurately represent the relationship.

The coefficients in Table 6.2 show an oscillatory adjustment process to equilibrium, like in section 5.2. The sum of statistically significant house price coefficients is -0.054, -0.036, and -0.024 for models three, four, and five, respectively. While that does appear considerably different at the outset, each model shows various representations of the oscillatory process to the long-run equilibrium. This is because each model has a different number of statistically significant lags, altering the sum of the coefficients. The models may generate similar estimates of the long-run impact of house prices on wealth inequality. Furthermore, the long-run coefficient of -0.019, estimated in Table 5.6 appears somewhat consistent using both ARDL and SUR approaches. However, comparing models three and four suggests that the long-run coefficient will be lower in absolute terms than 0.019 when using a SUR approach.

6.3 The Combined Inequality Impact

An alternative approach to the SUR is to create a system of equations where the dependent variable of one equation features as an explanatory variable in the other. However, this could not be executed for the income inequality model given the low number of observations for wealth inequality, as discussed more extensively in section 3.3.4. In contrast, the wealth inequality ARDL model, where earnings inequality is considered, could be estimated and is provided in Table 6.3. The ARDL model selection shows that income inequality has no contemporaneous impact on wealth inequality but increases wealth inequality over the subsequent two periods after the initial shock. This aligns with the theory that unequal wealth accumulation arising from earnings inequality impacts will take some adjustment period and will not occur immediately. Furthermore, the house price variable becomes contemporaneous only when controlling for earnings inequality in the equation.

Table 6.3: Predicting ln(Wealth Gini) with an ARDL model and two alternative 2SLS models while controlling for income inequality

<i>Estimation method</i>	<i>ARDL</i>		<i>2SLS</i>		<i>2SLS</i>	
<i>IV used:</i>			<i>Income Gini lagged</i>		<i>Bartik instrument</i>	
Variable	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
ln(Wealth Gini (-1))	-0.4818 ** (0.186)	-2.5905	-0.8654 (0.7815)	-1.1074	-0.4317 (0.2999)	-1.4397
ln(Wealth Gini (-2))	-0.8089 *** (0.2392)	-3.3825	-0.9097 ** (0.3795)	-2.3971	-0.7958 ** (0.2786)	-2.8562
ln(Wealth Gini (-3))	-0.3116 ** (0.0964)	-3.2326	-0.4089 * (0.208)	-1.9659	-0.299 * (0.1384)	-2.1594
ln(House prices)	-0.0191 ** (0.0072)	-2.6301	-0.0201 ** (0.0088)	-2.3005	-0.0189 ** (0.0078)	-2.4118
ln(Income Gini)	0.0092 (0.0086)	1.0705	0.0046 (0.0092)	0.4944	0.0098 (0.0103)	0.9572
ln(Income Gini (-1))	0.0237 *** (0.0049)	4.8351	0.0424 (0.04)	1.0605	0.0212 (0.0121)	1.7586
ln(Income Gini (-2))	0.0234 * (0.0118)	1.987	0.0305 (0.0212)	1.4377	0.0225 (0.014)	1.6126
ln(Real GDP per capita)	-0.0343 (0.0229)	-1.4959	-0.0327 (0.0271)	-1.203	-0.0345 (0.0233)	-1.4784
ln(Share prices)	0.0122 *** (0.0034)	3.5697	0.0125 ** (0.0041)	3.0742	0.0121 ** (0.0037)	3.239
Population PC	-0.0099 (0.009)	-1.0994	-0.0151 (0.0175)	-0.8639	-0.0092 (0.0099)	-0.9286
Development PC	-0.0018 (0.001)	-1.8316	-0.002 * (0.001)	-2.0389	-0.0018 (0.001)	-1.6807
Development PC (-1)	0.0013 ** (0.0005)	2.4062	0.0017 (0.0011)	1.5917	0.0012 * (0.0006)	2.1798
Constant	11.1739 *** (1.6304)	6.8533	13.6906 ** (5.4264)	2.5229	10.8455 *** (2.757)	3.9338
Time trend	0.0015 ** (0.0006)	2.4879	0.0015 * (0.0007)	2.1818	0.0015 ** (0.0006)	2.4408
<i>Model diagnostics</i>						
R-squared	0.9318		0.8896		0.9311	
Adjusted R-squared	0.8332		0.7300		0.8315	
S.E. of regression	0.0011		0.0014		0.0011	

Note: See notes for Table 6.1.

In the ARDL model of Table 6.3, the effect on wealth inequality from increasing house prices has become more complicated. When house prices change, wealth inequality directly decreases through the mechanisms discussed in Chapter 5. However, wealth inequality also increases through the augmentation of income inequality, as income inequality exacerbates wealth inequality in the long-run. As such, the effect of house prices on wealth inequality will be the combined impact of these two channels. The calculation for the combined effects is given in equation 6.3 and expanded upon in equation 6.4 to consider that when house prices increase by one per cent¹⁹, the income Gini is expected to rise by 0.1563, *ceteris paribus*, as demonstrated in Table 6.1. A one per cent rise in income inequality, all else equal, will increase wealth inequality by 0.0471 per cent over two years from the initial change. Therefore, a 0.1563 per cent increase in income inequality resulting from a house price shock will increase wealth inequality by 0.00074 per cent. Additionally, the one per cent increase in house prices will directly decrease wealth inequality by 0.0191 per cent. Therefore, the combined effect of a one per cent increase in house prices from both these channels is -0.018 per cent, a slight reduction in magnitude from the long-run coefficient of -0.019 estimated in Table 5.6.

$$\frac{\partial \ln(\textit{Wealth Gini})}{\partial \ln(\textit{House prices})} = (-0.0191 \cdot \partial \ln(\textit{House prices})) + \quad (6.3)$$

$$\left((0.0237 + 0.0234) \cdot \frac{\partial \ln(\textit{Income Gini})}{\partial \ln(\textit{House prices})} \right)$$

¹⁹ For all of the coefficients reported in this paragraph, the dependent variable is represented in logarithmic form in the model. Therefore, the coefficient represents the percentage change in the Gini coefficient, i.e., a percentage increase of a percentage variable (where the Gini is bounded between 0 and 100).

$$\frac{\partial \ln(\textit{Wealth Gini})}{1\%} = (-0.0191 \cdot 1\%) + 0.0471 \cdot (0.1563 \cdot 1\%) \quad (6.4)$$

$$\frac{\partial \ln(\textit{Wealth Gini})}{1\%} = -0.0191 + 0.0007362 = 0.01836$$

Equation 6.4 shows that when controlling for earnings inequality, the effect of house prices on wealth inequality is similar. However, this model does not consider the potential endogeneity arising from the income inequality variable being included in the wealth inequality model. It can be seen from Table 6.3 that when using an IV to mitigate this endogeneity, the effect of income inequality on wealth inequality is not significantly different from zero in all periods. Additionally, the house price coefficient experiences little change in magnitude or statistical significance across the three models. Both results provide evidence that the effect of house prices on the wealth Gini is robust to earnings inequality and close to -0.019 in the long-run.

6.4 Sensitivity and Robustness

One typical robustness check for modelling is testing the influence of the control variables. However, this has mostly already been done in sections 4.2.1 and 5.2.1. For the wealth inequality model, control variables were found to have only a minor influence on the house price estimates. Therefore, it is assumed that the control variables are unlikely to largely influence the estimates in Table 6.2 or Table 6.3. For the income inequality model, the combination of control variables has a negligible impact on the magnitudes of the house price estimates. Still, it primarily changes the results of the significance testing. Three variables consistently drive this change to significance testing. Therefore, it is assumed that these three variables will have a

similar impact on the statistical significance in the SUR model of Table 6.1. These assumptions were tested on a comparatively smaller number of control variable combinations and proved true. Therefore, when considering the impact of different control variables on the models in this chapter, readers should refer to the testing presented in Appendix L and Appendix O.

A variety of testing is undertaken on the 2SLS models in Table 6.3. First, the extent of the potential endogeneity issue is tested. This is done using the Durbin–Wu–Hausman test for endogeneity and the block exogeneity Wald test shown in Table 6.5 and Table 6.4, respectively. The block exogeneity Wald test gives evidence of potential simultaneity as the dependent variables are statistically significant in the other dependent variable models²⁰. In contrast, the endogeneity test shows that no combination of potentially endogenous regressors in either model ever rejects the null hypothesis of exogeneity. This indicates that endogeneity is a minor issue in the model or that the instruments do not explain the exogenous variables well.

Furthermore, looking at the weak instruments test in Table 6.6, there does appear to be at least a five per cent bias due to weak instruments in the first stage equation. However, the bias can be as high as ten per cent for some potentially endogenous variables. While the instruments are statistically significant in the first-stage equations, caution should be advised that the IVs may not adequately solve the potential endogeneity issue. However, this is dependent on each individual's relative bias preference. Future research should aim to trial alternative instruments for this model. The final test undertaken on

²⁰ Neither Gini is statistically significant in the house price model, providing evidence that the simultaneity is a minor issue. However, caution should be advised as this model is likely missing essential control variables.

the IVs is the Eichenbaum, Hansen and Singleton instrument orthogonality test. This test failed to reject the null hypothesis for both models. This shows that the instruments satisfy the orthogonality requirement and are valid instruments in this sense.

Table 6.4: Results of the block exogeneity Wald test / multivariate Granger causality test based on the VECM between house prices , income and wealth inequality

Excluded variable(s)	Chi-squared	DoF
<i>Dependent variable: $\Delta \ln(\text{Wealth Gini})$</i>		
$\Delta \ln(\text{House prices})$	15.599 ***	2
$\Delta \ln(\text{Income Gini})$	7.274 **	2
All	23.741 ***	4
<i>Dependent variable: $\Delta \ln(\text{Income Gini})$</i>		
$\Delta \ln(\text{Wealth Gini})$	7.411 **	2
$\Delta \ln(\text{House prices})$	1.529	2
All	8.775 *	4
<i>Dependent variable: $\Delta \ln(\text{House prices})$</i>		
$\Delta \ln(\text{Wealth Gini})$	2.849	2
$\Delta \ln(\text{Income Gini})$	2.025	2
All	3.053	4

*Notes: DoF is degrees of freedom, the null hypothesis is the excluded variable does not Granger cause the dependent variable, "all" refers to excluding the other two variables in the equation besides the dependent variable, and (***) is significant at 1% significance level.*

Table 6.5: Durbin–Wu–Hausman endogeneity test of the income Gini variables in the 2SLS models

Variable	Difference in J-stats	p-value
<i>Lagged income Gini model</i>		
ln(Income Gini)	0.1716	0.679
ln(Income Gini (-1))	0.4898	0.484
ln(Income Gini (-2))	0.0261	0.872
ln(Income Gini) & ln(Income Gini (-1))	0.5844	0.747
ln(Income Gini) & ln(Income Gini (-2))	2.8630	0.239
ln(Income Gini (-1)) & ln(Income Gini (-2))	0.9907	0.609
All income Gini variables	3.4191	0.331
<i>Bartik Gini model</i>		
ln(Income Gini)	0.5272	0.468
ln(Income Gini (-1))	0.6740	0.412
ln(Income Gini (-2))	1.4293	0.232
ln(Income Gini) & ln(Income Gini (-1))	1.1873	0.552
ln(Income Gini) & ln(Income Gini (-2))	2.7228	0.256
ln(Income Gini (-1)) & ln(Income Gini (-2))	1.4702	0.480
All income Gini variables	2.9164	0.405

Note: The null hypothesis is the specified variable(s) is (are) exogenous.

Table 6.6: Testing for the relative bias of weak instruments in the 2SLS models

Variable	Cragg-Donald F-statistic
<i>Lagged income Gini model</i>	
ln(Income Gini)	13.2035
ln(Income Gini (-1))	9.534
ln(Income Gini (-2))	10.958
<i>Bartik Gini model</i>	
ln(Income Gini)	13.1173
ln(Income Gini (-1))	11.0803
ln(Income Gini (-2))	8.3597
<i>Test critical values (for relative bias size)</i>	
5%	16.85
10%	10.27
20%	6.71
30%	5.34

Notes: The null hypothesis is that a bias exists (up to a maximum of the specified level) from the 2SLS model in predicting the specified variable due to weak instruments. The critical values are sourced from Table 1 in Stock and Yogo (2002).

6.5 Summary

There is reasonable evidence that a relationship exists between income and wealth inequality. Furthermore, an efficiency gain can be achieved by accounting for this connection. In contrast, the system of equations approach makes a minimal difference to the impact of house prices on wealth inequality. Additionally, there remains to be doubt about the effectiveness of the IVs in mitigating the potential endogeneity issue. However, regardless of the adequacy of the IVs, the system of equations still constitutes

a minor difference from estimating the equations separately. While future research should trial other IVs to mitigate this endogeneity, the primary focus should be on the efficiency gain achieved by utilising a SUR when modelling this relationship.

The following chapter considers the results of this chapter alongside the findings from the entire thesis. The conclusions are summarised, some implications for policymakers are outlined, and indications of where future research should focus are more extensively discussed.

Chapter 7: Conclusion

7.1 Findings

This study contributes to the housing and economic inequality literature. Regarding the New Zealand (NZ) wealth distribution, it is found that an increase in house prices has a statistically significant and negative impact on wealth inequality. Specifically, a ten per cent increase in house prices leads to a decrease in the wealth Gini coefficient of approximately 0.19 per cent on average, *ceteris paribus*. These results are robust to various alternative specifications, including alternative inequality measures, house price measures, combinations of control variables, and controlling for earnings inequality. A ten per cent increase in house prices, *ceteris paribus*, also decreases the wealth Palma ratio by -0.084 per cent and increases the S80S20 ratio by 0.076. The positive coefficient for the S80S20 ratio is driven by decreasing wealth share for the top and bottom 20 per cent of the wealth distribution but a more substantial reduction for the wealthiest NZers. Therefore, these results both give evidence of an equalising effect of house prices on wealth distributions.

The analysis reveals that the effect of house prices on wealth inequality varies depending on the decile of the wealth distribution, driving the different signs for the three inequality measures. This is because of the heterogeneity of housing-related assets owned across the net wealth distribution. Furthermore, NZ demonstrates the inverted U-curve relationship of housing-related assets across the net worth distribution commonly seen in the previous literature. The 60 to 70 per cent of the wealth distribution experiences the greatest increase of wealth share of any decile from an increase in house

prices, while the top ten per cent experiences the greatest reduction in wealth share from rising house prices. The opposite is valid for a negative house price shock.

Positive and negative house price shocks do not equally impact the NZ wealth distribution. The gain in wealth share the top ten per cent experiences from a reduction in house prices is more prominent than their loss following an increase in house prices in the short-run. This asymmetry is also present for the 50 to 70 per cent of the distribution. The asymmetry arises due to heterogeneity in the ability of different deciles to adjust their portfolios in response to a positive or negative house price shock. Higher deciles have more liquidity to reshuffle their portfolio following a negative house price shock, offsetting some of the reduction in wealth share. In contrast, lower deciles are less able to reshuffle housing assets. It remains unknown why this symmetry exists solely in the short run, and the relationship is symmetric in the long-run.

The results are mixed regarding the relationship between house prices and income inequality. A ten per cent increase in house prices, *ceteris paribus*, is expected to increase the income Gini coefficient by approximately 1.2 per cent and decrease the income Palma ratio by 2.1 per cent but have no statistically significant effect on the income S80S20 ratio. The top ten per cent of the income distribution experiences the greatest reduction in income share from rising house prices, matching the wealth inequality results. In contrast to the wealth distribution, the 20 to 30 per cent of the income distribution experiences the greatest increase in the income share of any decile from an increase in house prices.

In addition to housing asset value heterogeneity, the rental market plays a vital role in the housing and income relationship mechanisms. Increased rent price drive

disproportionate housing costs for those lower on the income distribution and simultaneously increase income returns for those higher up the income distribution. This is because low-income earners make up a more significant proportion of renters, while higher-income earners make up more landlords. Therefore, the effect of house prices on the bottom decile of the distribution is expected to be greater than the effect on the top decile. However, the opposite result is found, suggesting other mechanisms offset the change in income shares for the bottom of the income distribution or accentuate the change for the top. The heterogeneity in the value of housing-related assets across the income distribution partly drives these differences. Nonetheless, the income inequality inverted U-curve relationship is not well-behaved, and there appear to be additional mechanisms in the relationship besides value heterogeneity and rental prices still to be found.

The house price and income inequality relationship is reasonably robust to alternative specifications. Real house prices, nominal house prices, and housing affordability all exhibit the same relationship. In contrast, the control variables included in the model impact the statistical significance of the house price variable. Excluding real GDP per capita, unemployment, and inflation from the model can considerably change the significance testing for the house price variable. However, the estimated coefficient does not change substantially, and it is always a positive estimate for the income Gini coefficient even when not significantly different from zero.

The income inequality estimates are slightly larger than what is reported in the previous literature, while the wealth inequality estimates are less than other papers' findings. The income inequality relationship is dynamically stable, and adjustment occurs within only a few periods. Furthermore, the autoregressive distributed lag (ARDL) model proposes

that there is only a contemporaneous impact on income inequality following a house price increase. However, the rental market hypothesis cannot drive this behaviour, as rent prices have no contemporaneous relationship with the income Gini coefficient. In contrast, the wealth inequality model is less dynamically stable, and the system's stability is not fully achieved after 20 periods from the initial shock.

Controlling for the two inequality measures concurrently makes a minimal difference to the effect of house prices on wealth inequality. A ten per cent increase in house prices leads to a 0.18 per cent decrease in the wealth Gini coefficient as opposed to a 0.19 per cent decrease. However, when mitigating the endogeneity issue of this equation, there is no difference in the house price estimate from controlling earnings equality in the wealth inequality equation.

However, an efficiency and accuracy gain is achieved by accounting for joint disturbances of each equation in the model. The likelihood ratio test was statistically significant, confirming that a contemporaneous correlation between the income and wealth inequality disturbances is present. Accounting for this in the model results in more accurate estimates with lower variance. The lower variance alters the statistical testing of the wealth inequality model, but there is not much difference in the magnitude of the house price coefficient. In contrast, house prices' effect on the income Gini coefficient is estimated to be higher when accounting for the common disturbance of each equation.

Principal components do not change the sign or significance of the house price variable. However, they control for multiple variables' impacts simultaneously and could be used for accuracy gains in future research. Finally, the analysis shows that introducing loan-

to-value ratios (LVR) has no statistically significant effect on wealth inequality. However, introducing LVRs increases the income Gini coefficient by 0.1 in the same period, all else equal. When controlling for LVRs in the model, the effect of house prices on the income Gini coefficient becomes lower and more in line with the previous literature. It is the preferred model specification to account for LVRs.

To summarise, the answers to the initial research questions outlined in section 1.2 are:

(i) an increase in house prices improves wealth inequality and primarily exacerbates income inequality; (ii) the effect on wealth inequality is different for a negative shock house price compared to a positive shock; (iii) the impact of house prices is heterogeneous across the income and wealth distribution; (iv) for the income distribution, the biggest winner in terms of income share from a positive house prices shock is the 20 to 30 per cent of the distribution, while the biggest loser is the top decile. For the wealth distribution, the top decile is also the biggest loser, while the 60 to 70 per cent of the distribution gains the most wealth share from a positive house price shock; (v) house price estimates are reasonably robust to controlling for both forms of inequality concurrently (vi) an efficiency gain for the estimates can be achieved by accounting for the joint disturbances of the error terms in each model (vii) LVRs increase income inequality but do not impact wealth inequality.

7.2 Policy Implications

The findings of this analysis contribute to a better understanding of the complex relationships between house prices, wealth inequality, and income inequality in NZ. The results suggest that policies addressing wealth and income inequality should consider the impact of housing. Different measures are needed to address the diverse

distributional effects of changes in house prices across wealth and income distributions. Unlike much of the previous literature, estimates of the impact for every decile of the distributions are provided in this thesis. Therefore, using this information, policymakers can calculate the effect of house prices on any inequality measure of interest. That way, the results are not specific to the target group of solely this analysis, increasing the generalisability.

The analysis shows that policymakers need to respond quickly to house price shocks. The effect on income inequality primarily occurs within one year. The later response of rent prices may accentuate the initial impact to a maximum of four years from the initial shock. In contrast, the wealth inequality adjustment in response to house price shocks occurs over considerably extended periods. However, this does not mean policymakers can act slower if wanting to target wealth inequality following a house price shock. That is because a contemporaneous change to the wealth distribution is experienced following a house price shock. Therefore, policymakers wanting to offset the increases in wealth inequality following a reduction in house prices must act quickly, as higher wealth inequality can lead to higher wealth inequality in subsequent periods. Because the asymmetry results from the differing abilities of deciles to reshuffle portfolios, policies that help groups more easily increase (decrease) housing assets in response to shocks may help alleviate wealth inequality.

Because the house price and income inequality relationship only partially arises from rent prices, policymakers should be aware that policies offsetting rental costs will only partially mitigate the effect of house prices on income inequality. Finally, introducing LVRs, no matter the extent of the restrictions is found to have a positive association with income inequality. This should be a consideration for policymakers in the future.

LVRs affect who can access mortgages for residential properties based on relative deposit size, inhibiting some groups from reaping the benefits associated with housing-related assets. Therefore, policymakers should consider which groups are primarily impacted by LVRs and the extent of the restrictions, as different LVR policies may affect income inequality differently. Additionally, policies aimed at improving access to credit are likely to offset the impact of LVRs on income inequality. Furthermore, policies making it easier for low-income earners to access housing-related assets could help equalise wealth distributions.

7.3 Future Research

The international literature has a consensus that rising house prices equalise wealth distributions. However, that is not to suggest that future researchers should not continue to analyse house prices and wealth inequality in NZ or abroad. Future research should focus on the specific groups affected by changing house prices. For example, it is known that between-decile wealth inequality decreases in response to rising house prices, but what about within-decile wealth inequality? Are specific groups within deciles disproportionately impacted by house prices, such as different ethnicities, genders, or other age groups? Additionally, because the relationship is driven by the allocation of housing-related assets across the distribution, is there a threshold of homeownership rates where the negative association will no longer exist or become positive? If the number of NZ properties owned by households outside NZ increased, would the relationship still hold?

Moreover, the asymmetries between house prices and wealth inequality discovered in this paper should be further investigated. What drives the rigidities present, and why do

these only exist in the short-run? Furthermore, other papers should continue exploring the relationship between wealth inequality and LVRs. While this paper found that introducing an LVR has no statistically significant impact on the NZ wealth distribution, this does not consider the extent of the LVR policies. LVR restrictions of differing ‘tightness’ may have contrasting implications for wealth inequality that are not discovered using a regression discontinuity in time approach.

This thesis provides evidence that rising house prices increase the income Gini coefficient and have varying impacts on other inequality measures. Unlike some of the literature, the analysis only supports that direction of causality. However, the complete mechanisms of the house price and income relationship are still a puzzle, and future work should primarily focus on what else may be driving the relationship. In particular, why does the 20 to 30 per cent of the income distribution experience the greatest benefit from rising house prices? One potential mechanism for future research to explore is policy interventions that offset rising rent costs, potentially benefiting the income share of the 20 to 30 per cent decile. However, future research should consider a diverse range of potential mechanisms.

For studies examining either income or wealth inequality, there is a range of gaps in the present knowledge. For instance, the house price and economic disparities relationship may vary across regions or cities. This could lead to asymmetries in the relationship between inequality from increased house prices in one NZ city compared to another. Future research could consider the role of spatial variation when examining the house price and economic inequality relationship. Additionally, a model that considers the dynamics of the house price increases would bring value to the existing literature. For example, is the effect on economic inequality the same for a house price increase driven

by increased demand from investors and speculators as opposed to a house price shock primarily caused by owner-occupiers?

When considered directly in the same equation, wealth and income inequality did not alter the house price relationship. However, there could be an indirect relationship between the two inequalities that future research could consider. As house prices increase, the income Gini coefficient worsens, making it harder for some groups of the income distribution to save for a house deposit due to a reduction in relative income. At the same time, house prices have increased, so the total deposit needed for a residential property has risen in nominal terms. This can disproportionately impact the ability of some groups of the income distribution to access housing-related assets. Owning housing assets has been shown to improve net wealth; therefore, the disproportionate ability to save for a deposit could inhibit some groups from reaping the benefits of owning housing-related assets. This could result in income inequality indirectly accentuating wealth inequality in the long-run. Thus, the house price relationship could still depend on the connection between income and wealth inequality, and future research should continue exploring this area.

Additionally, this is among the few studies to utilise a seemingly unrelated regression (SUR) to model economic inequality and house prices. Still, the approach will have valuable efficiency gains for other countries estimating the same relationship. The SUR approach should be regularly used in future studies to improve the accuracy of estimates. This potentially included re-estimating the behaviours in countries previously analysed.

In conclusion, the relationship between housing and economic inequality is intricate. Heterogeneous impacts across the income and wealth distributions create unique behaviours and contrasting results when examining alternative distribution properties. Nevertheless, the current academic literature offers a unique opportunity to explore the relationship further. As the New Zealand housing market experiences a decline in prices, the first annual decrease seen since 2010, there is a golden opportunity for researchers to delve deeper into the relationship between housing and economic inequality. In particular, to test the validity of the asymmetries using data of a negative house price shock. Many questions and puzzles still need to be answered in the literature, and it is up to researchers to seize the opportunity and expand the understanding of this critical issue.

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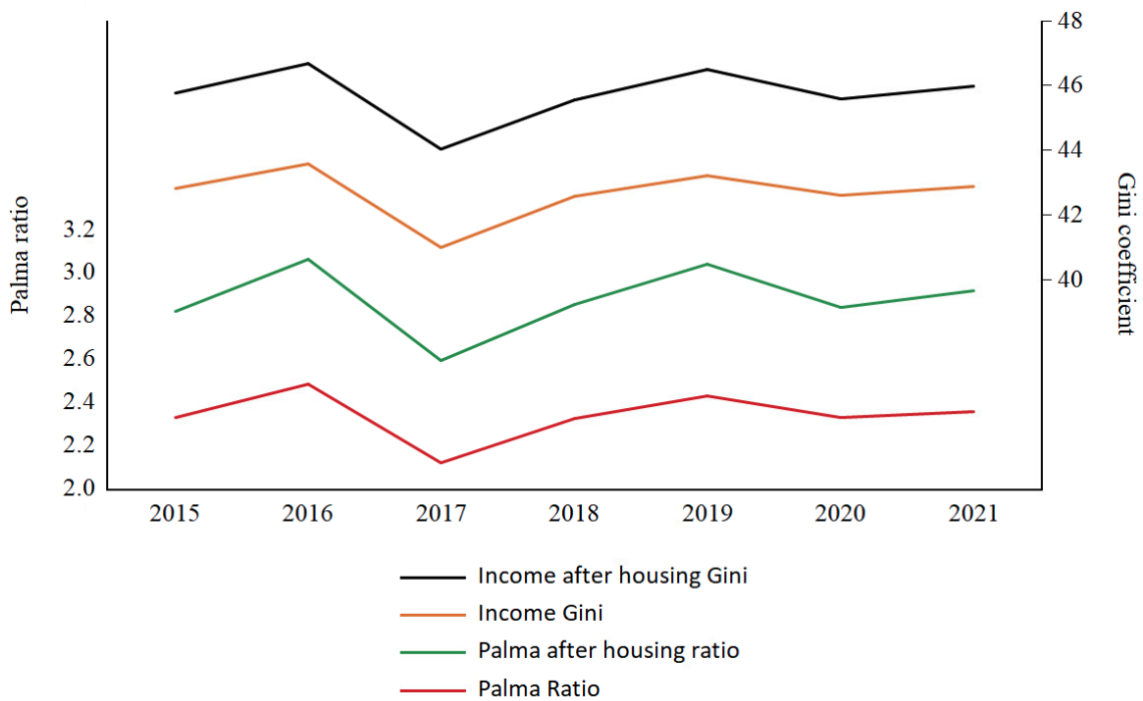
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Appendix A: Income Distribution Related Granular Data

Dustmann et al. (2018) Dustmann et al. (2018) highlighted the importance of calculating inequality measures before and after considering housing costs. The authors argue that this is done too infrequently in the current literature. To compensate for this and provide these measures in a NZ context, the Gini coefficient and Palma ratio before and after housing costs are considered have been provided in Figure A-1. It is important to note that these are calculated using the Household Economic Survey from the Stats NZ IDI. This can create two potential issues. First, the HES can have a high sample error, particularly for the bottom decile of the income distribution. See the work of Rashbrooke et al. (2021) for a more thorough discussion of this issue. Sometimes, the bottom decile had to be excluded from the calculation due to the high sample error, biasing some inequality measure estimates. Second, the values presented in Figure A-1 are calculated from a sample, not the whole population. Therefore, they may differ from the values presented throughout this thesis.

For readers wanting to calculate other inequality measures, or consider more granular data on other factors related to income and housing, see [here](#). Additionally, for readers wanting to more thoroughly examine the data used for Table 4.9 and Figure 4.12, use this [link](#). Please contact the author for any questions regarding this supplied data.

Figure A-1: The income Gini and Palma ratio before and after housing costs are considered from 2015 to 2021



Note: Data is sourced from the StatsNZ IDI. There is a large sample error for some of these calculation and in some instances, data points had to be omitted. This may bias some of the estimates.

Appendix B: Interpolated Data Results

As an alternative method of dealing with variables of a different frequency, the low-frequency data (annual) was interpolated to be the same frequency as the highest (quarterly). This serves as a robustness check to the results from the primary analysis. The results of the ARDL regressions using interpolated data are given for wealth and income inequality in Table B-1 and Table B-2, respectively. The results are somewhat comparable to the findings of the primary method. In particular, the house price coefficients have the same sign and statistical significance. It suggests that if the low-frequency data points were interpolated, the outcomes would have been similar to the primary analysis. However, there might have been some differences in the coefficients' magnitudes.

Table B-1: The wealth inequality ARDL model using interpolated low-frequency data with the high-frequency data (dependent variable = $\ln(\text{Wealth Gini})$)

Variable	Coefficient	t-statistic
$\ln(\text{Wealth Gini} (-1))$	-0.109 (-0.185)	-0.588
$\ln(\text{Wealth Gini} (-2))$	-0.831 *** (-0.135)	-6.182
$\ln(\text{Wealth Gini} (-3))$	-0.558 *** (-0.158)	-3.528
$\ln(\text{House prices})$	-0.0306 *** (-0.006)	-5.493
$\ln(\text{House prices} (-1))$	0.004 (-0.006)	0.597
$\ln(\text{House prices} (-2))$	0.003 (-0.006)	0.560
$\ln(\text{House prices} (-3))$	-0.0238 *** (-0.005)	-5.095
$\ln(\text{Real GDP per capita})$	-0.0612 ** (-0.021)	-2.885
$\ln(\text{Share prices})$	0.0174 *** (-0.003)	5.257
Population PC	-0.002 (-0.008)	-0.216
Development PC	0.000 (-0.001)	-0.129
Development PC (-1)	0.000 (-0.001)	0.801
Constant	10.820 *** (-1.54)	7.026
Time trend	0.00369 *** (0)	7.609

Model diagnostics

R-squared	0.9382
Adjusted R-squared	0.8300
S.E. of regression	0.0011

Notes: The standard error is reported in parenthesis underneath the coefficients. HAC standard errors & covariance have been used throughout. () is significant at 10%; (**) significant at 5%; and (***) significant at 1%.*

Table B-2: The income inequality ARDL model using interpolated low-frequency data with the high-frequency data (dependent variable = ln(Income Gini))

Variable	Coefficient	t-statistic
ln(Income Gini (-1))	1.6129 *** (0.1628)	9.9087
ln(Income Gini (-2))	-0.6441 * (0.3332)	-1.9333
ln(Income Gini (-3))	-0.1806 (0.3112)	-0.5805
ln(Income Gini (-4))	-0.0489 (0.1846)	-0.2648
ln(Income Gini (-5))	0.255 * (0.1421)	1.7947
ln(House prices)	0.1456 *** (0.0395)	3.6871
ln(Real GDP per capita)	0.0085 (0.0386)	0.2201
Population PC	-0.012 *** (0.0039)	-3.0769
Unemployment rate	-0.0112 (0.0073)	-1.547
Unemployment rate (-1)	0.0094 (0.0069)	1.3655
Foreign investment	-0.0007 (0.0005)	-1.4097
ln(Trade volume)	-0.0052 (0.0092)	-0.5728
LVR	-0.0311 ** (0.0121)	-2.5759
LVR (-1)	0.0803 *** (0.0145)	5.5236
Inflation rate	-0.5045 * (0.0145)	-1.7687

Variable	Coefficient	t-statistic
	(0.2853)	
Constant	1.7876 ***	3.3463
	(0.5342)	
Time trend	0.0031 ***	3.5558
	(0.0009)	
<i>Model diagnostics</i>		
R-squared	0.9818	
Adjusted R-squared	0.9752	
S.E. of regression	0.0110	

Note: See notes for Table B-1.

Appendix C: MIDAS Results

A MIDAS regression was employed as a substitute technique for handling variables with varying frequencies. Conducting a MIDAS regression is a robustness check on the primary analysis results. The results of the MIDAS regressions are given for wealth, and income inequality in Table C-1 and Table C-2, respectively; the estimates share similarities to the primary approach, but there are many discrepancies between using a MIDAS regression as opposed to an ARDL model; it implies that utilising a MIDAS regression may have resulted in some differences compared to the primary analysis.

Table C-1: Predicting ln(Wealth Gini) with a MIDAS regression

Variable	Coefficient	t-statistic
ln(Wealth Gini (-1))	0.6173 *** (0.1936)	3.1885
ln(House prices)	0.0566 *** (0.0166)	3.4013
ln(House prices (-1))	-0.1936 *** (0.0523)	-3.7007
ln(House prices (-3))	0.3126 *** (0.092)	3.4
ln(House prices (-4))	-0.1627 *** (0.0535)	-3.0409
ln(Real GDP per capita (-3))	0.1051 *** (0.029)	3.6308
ln(Real GDP per capita (-4))	-0.0917 ** (0.0402)	-2.2837
ln(Share prices)	-0.0167 *** (0.0051)	-3.2656
Population PC	0.0142 (0.0119)	1.1925
Development PC	0.0021 *** (0.0007)	3.2225
Constant	1.6213 (0.9406)	1.7236
<i>Model diagnostics</i>		
R-squared	0.7712	
Adjusted R-squared	0.6077	
S.E. of regression	0.0016	

Notes: The standard error is reported in parenthesis underneath the coefficients. (*) is significant at 10%; (**) significant at 5%; and (***) significant at 1%.

Table C-2: Predicting ln(Income Gini) with a MIDAS regression

Variable	Coefficient	t-statistic
ln(Income Gini (-1))	-0.3647 ** (0.1212)	-3.0098
ln(House prices)	0.2003 * (0.0915)	2.1897
ln(Real GDP per capita)	0.0674 (0.4083)	0.165
Population PC	0.1986 (0.1172)	1.694
Unemployment rate	0.0246 (0.0167)	1.4722
Unemployment rate (-1)	0.0249 * (0.0136)	1.8287
Foreign investment	0.0054 (0.0032)	1.7016
ln(Trade volume)	-0.1847 (0.1294)	-1.4274
LVR	-0.0042 (0.0154)	-0.2716
Inflation rate	-2.1462 (1.2589)	-1.7049
Constant	0.5601 (2.501)	0.224
Time trend	0.0057 *** (0.0015)	3.8959
<i>Model diagnostics</i>		
R-squared	0.9768	
Adjusted R-squared	0.9473	
S.E. of regression	0.0174	

Note: see notes for Table C-1.

Appendix D: Averaged Variable Results

As an alternative method of handling variables with a different frequency, the high-frequency data (quarterly) was averaged to be the same frequency as the lowest (annual). This is instead of using the last quarter of each year, as was done in the primary analysis. The results from this alternative method serve as a robustness check to the findings of the primary analysis. The results of the ARDL models using the averaged variables are given for wealth and income inequality in Table D-1 and Table D-2, respectively. The results share several resemblances to the primary approach, particularly regarding the sign and statistical significance of the variables. This indicates that utilising the annual average values of variables instead of the final data point in each year would have produced comparable results, albeit with some variation in the magnitude of coefficients.

Table D-1: The wealth inequality ARDL model using averaged high-frequency data with the low-frequency data (dependent variable = $\ln(\text{Wealth Gini})$)

Variable	Coefficient	t-statistic
$\ln(\text{Wealth Gini } (-1))$	-0.313 * (0.1619)	-1.9339
$\ln(\text{Wealth Gini } (-2))$	-0.8026 *** (0.215)	-3.7329
$\ln(\text{Wealth Gini } (-3))$	-0.8531 ** (0.2697)	-3.1637
$\ln(\text{House prices})$	-0.0362 ** (0.014)	-2.5853
$\ln(\text{House prices } (-1))$	0.0038 (0.0139)	0.2765
$\ln(\text{House prices } (-2))$	0.0019 (0.0182)	0.1061
$\ln(\text{House prices } (-3))$	-0.0287 ** (0.0114)	-2.5235
$\ln(\text{Real GDP per capita})$	-0.0675 * (0.0304)	-2.2206
$\ln(\text{Share prices})$	0.023 ** (0.0101)	2.2715
Population PC	-0.0055 (0.0139)	-0.3952
Development PC	0.0004 (0.0009)	0.4612
Development PC (-1)	0.0004 (0.0004)	1.1606
Constant	12.9049 *** (2.2205)	5.8118
Time trend	0.0041 *** (0.0005)	8.3171

Model diagnostics

R-squared	0.9000
Adjusted R-squared	0.7557
S.E. of regression	0.0013

Notes: The standard error is reported in parenthesis underneath the coefficients. HAC standard errors & covariance have been used throughout. () is significant at 10%; (**) significant at 5%; and (***) significant at 1%.*

Table D-2: The income inequality ARDL model using averaged high-frequency data with the low-frequency data (dependent variable = ln(Income Gini))

Variable	Coefficient	t-statistic
ln(Income Gini (-1))	0.2513 *** (0.0767)	3.2765
ln(House prices)	0.4232 *** (0.1373)	3.0831
LVR	0.0847 *** (0.0244)	3.4654
ln(Real GDP per capita)	1.9709 ** (0.8644)	2.2802
Population PC	0.4218 *** (0.1185)	3.5581
Unemployment rate	0.1142 ** (0.0427)	2.6745
Unemployment rate (-1)	0.0125 (0.0134)	0.9322
Foreign investment	-0.0001 (0.002)	-0.068
ln(Trade volume)	0.8228 *** (0.2406)	3.42
Inflation rate	0.3509 (0.6652)	0.5275
Constant	11.767 ** (4.9508)	2.3768
Time trend	-0.01 (0.0113)	-0.8882
<i>Model diagnostics</i>		
R-squared	0.9266	
Adjusted R-squared	0.8589	
S.E. of regression	0.0285	

Note: see notes for Table D-1.

Appendix E: Principal Components

Generating a PC is a complex process that requires careful consideration and multiple steps. First, all of the original features are standardised to calculate a new PC. This is necessary because PCA calculations are based on the variation of each of the original variables, and those with larger scales/different units will naturally have different variations, biasing the PCA results. Standardisation will eliminate the effect of different scales between variables, yielding an accurate variation representation as each variable will have a mean of zero and a standard deviation of one. The calculation used for standardisation is shown in equation E. 1, where $x_{s,f}$ is the newly standardised variable for each of the original features, x_f , (where $f = 1, \dots, a$ and $a \geq 2$), μ_f is the mean value of each original feature, and σ_f is the standard deviation of each original feature. This forms a matrix of standardised data points, D_s , where each $x_{n,f,s}$ value is the standardised data point for a given variable and period, t (where $t = 1, \dots, n$).

$$x_{s,f} = \frac{x_f - \mu_f}{\sigma_f} \quad (\text{E. 1})$$

$$D_s = \begin{bmatrix} x_{s,1,1} & x_{s,1,2} & \cdots & x_{s,1,a} \\ x_{s,2,1} & x_{s,2,2} & \cdots & x_{s,2,a} \\ \vdots & \vdots & \ddots & \vdots \\ x_{s,n,1} & x_{s,n,2} & \cdots & x_{s,n,a} \end{bmatrix}$$

Following standardisation, a covariance matrix of the standardised variables is calculated. For a given vector \vec{X} that contains a range of variables ($x_{s,1}, x_{s,2}, \dots, x_{s,a}$), the covariance matrix $[\text{Cov}(\vec{X})]$ can be calculated using the formula outlined in equation E. 2. This makes $\text{Cov}(\vec{X})$ a symmetric matrix as the $\text{Cov}(x_{s,2}, x_{s,1}) = \text{Cov}(x_{s,1}, x_{s,2})$.

$$\text{Cov}(\vec{X}) = \begin{bmatrix} \text{Var}(x_{s,1}) & \text{Cov}(x_{s,1}, x_{s,2}) & \cdots & \text{Cov}(x_{s,1}, x_{s,a}) \\ \text{Cov}(x_{s,2}, x_{s,1}) & \text{Var}(x_{s,2}) & \cdots & \text{Cov}(x_{s,2}, x_{s,a}) \\ \vdots & \vdots & \ddots & \vdots \\ \text{Cov}(x_{s,a}, x_{s,1}) & \text{Cov}(x_{s,a}, x_{s,2}) & \cdots & \text{Var}(x_{s,a}) \end{bmatrix} \quad (\text{E. 2})$$

Then, an eigendecomposition of the covariance matrix is calculated. The general formula for an eigendecomposition is shown in equation E. 3, where A is a matrix, v is an eigenvector, meaning it does not change direction when being multiplied by a particular matrix, and λ is the eigenvalue, which represents by what magnitude the eigenvector changes when multiplied by the covariance matrix. Eigenvectors consist of two values that are orthogonal to each other. The number of eigenvalues is determined by the size of the matrix, where a 2x2 matrix will result in two eigenvalues, a 3x3 matrix will result in three eigenvalues, and so on. There will always be the same number of eigenvalues and eigenvectors. Equation E. 4 is used to precisely calculate eigenvalues for a covariance matrix, where \det is the determinant of a matrix, and I is the identity matrix, which is the same size as the covariance matrix. A distinct eigenvalue for each x_f variable is produced, and by using equation E. 3, each eigenvector can also be calculated.

$$Av = \lambda v \quad (\text{E. 3})$$

$$\det(|\text{Cov}(\vec{X}) - \lambda I|) = 0 \quad (\text{E. 4})$$

The eigenvectors of the covariance matrix are then ordered according to the size of the eigenvalues, with the largest eigenvalue giving the first eigenvector. This forms a matrix of eigenvectors, V , where v_1 is the eigenvector with the highest associated eigenvalue, so it is in the first column, and all subsequent eigenvectors are ordered by decreasing eigenvalues:

$$V = \begin{bmatrix} v_{1,1} & v_{1,2} & \cdots & v_{1,a} \\ v_{2,1} & v_{2,2} & \cdots & v_{2,a} \end{bmatrix}$$

PC scores are calculated by multiplying matrix V by matrix D_s . This produces the PCS matrix, where the first column is referred to as the PC1, the second as PC2, etc. The variance of each column in the PCS matrix is equivalent to the eigenvalue. PCA assumes that because the PC1 column has the highest associated variance and captures almost all of the variance, it retains nearly all of the information from the original features. The subsequent PCs of two and above could be excluded, and PC1 can be used as the new variable in the ARDL model. Alternatively, the researcher can decide to include more than one PC score to capture a more significant amount of variation in the original features. Multiple techniques can be used to determine how many components should be included in the study, such as cross-validation and visual analysis (Leung, 2022). Still, it is highly dependent on the particular study circumstances and making educated decisions as a researcher. Only the first score was included in this thesis, as dimensionality reduction is the primary focus.

$$PCS = V \cdot D_s = \begin{bmatrix} v_{1,1} & v_{1,2} & \cdots & v_{1,a} \\ v_{2,1} & v_{2,2} & \cdots & v_{2,a} \end{bmatrix} \cdot \begin{bmatrix} x_{s,1,1} & x_{s,1,2} & \cdots & x_{s,1,a} \\ x_{s,2,1} & x_{s,2,2} & \cdots & x_{s,2,a} \\ \vdots & \vdots & \ddots & \vdots \\ x_{s,n,1} & x_{s,n,2} & \cdots & x_{s,n,a} \end{bmatrix}$$

$$PCS = \begin{bmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,a} \\ c_{2,1} & c_{2,2} & \cdots & c_{2,a} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n,1} & c_{n,2} & \cdots & c_{n,a} \end{bmatrix}$$

Another way of calculating the PC scores is shown in equation E.5, where ρ_f is the weight assigned to each of the original features, or as it is commonly referred to in PCA, a loading. PCA undertakes a linear maximisation problem to find the optimal ρ_f

values that maximise the variance in PC1. Because this could be achieved by simply choosing larger values for the weights, the algorithm works to the constraint that $\rho_1^2 + \rho_2^2 + \dots + \rho_a^2 = 1$, among a variety of other constraints. Greater weight is assigned to variables that contribute more variance to PC1.

$$\text{PC1} = \rho_1 x_1 + \rho_2 x_2 + \dots + \rho_a x_a = \sum_{f=1}^a \rho_f x_f \quad (\text{E.5})$$

Two unique PCs were made for the analysis, the Population PC and the Development PC. The eigenvalues and eigenvectors of the Population PC are presented in Table E-1, along with the proportion of variation each variable contributes to the final PC. This information has also been provided for the Development PC. However, it is split over two tables. Table E-2 shows the initial PCA using all nine indexes for financial development provided by the IMF. It can be seen in this table that four of the variables account for zero per cent of the total variation. Because of this, those four variables were removed when producing the final PC. Table E-3 presents the final eigenvalues and eigenvectors for the Development PC with the four variables removed.

Table E-1: A summary of how the population principal component was generated

Variable	Value	Cumulative value	Difference	Proportion	Cumulative proportion
Age dependency	1.9553	1.9553	1.0808	0.6518	0.6518
Fertility rate	0.8745	2.8298	0.7043	0.2915	0.9433
Life expectancy	0.1702	3		0.0567	1
<i>Eigenvectors (loadings):</i>					
Variable	PC1	PC2	PC3		
Age dependency	0.6519	-0.3181	0.6884		
Fertility rate	-0.6727	0.1764	0.7186		
Life expectancy	0.3500	0.9315	0.0991		

Table E-2: A summary of the initial financial development principal component analysis

Variable	Value	Cumulative value	Difference	Proportion	Cumulative proportion				
Financial development	4.9524	4.9524	3.3074	0.5503	0.5503				
Financial access depth	1.6449	6.5973	0.5254	0.1828	0.7330				
Financial institutions	1.1195	7.7168	0.4100	0.1244	0.8574				
Financial institutions access	0.7095	8.4264	0.3873	0.0788	0.9363				
Financial institutions efficiency	0.3222	8.7486	0.0708	0.0358	0.9721				
Financial institutions depth	0.2514	9	0.2514	0.0279	1				
Financial market depth	0	9	0	0	1				
Financial markets	0	9	0	0	1				
Financial efficiency depth	0	9		0	1				
<i>Eigenvectors (loadings):</i>									
Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Financial development	0.4423	0.1255	-0.0063	0.0498	0.0965	-0.0409	-0.8119	0.3401	0.0135
Financial access depth	0.3549	-0.2368	-0.1045	-0.4653	0.6002	0.0937	0.1718	-0.0739	0.4319
Financial institutions	0.4140	-0.1919	0.1322	0.1826	-0.1512	-0.3998	-0.1020	-0.7402	-0.0059
Financial institutions access	0.2164	0.0622	0.8135	-0.0259	0.0246	-0.2840	0.2847	0.3530	-0.0002
Financial institutions efficiency	0.1854	-0.5249	0.0566	0.6727	0.1325	0.4287	0.1141	0.1415	-0.0001
Financial institutions depth	0.3390	-0.1456	-0.5286	0.0505	-0.2814	-0.4719	0.3322	0.4119	-0.0002
Financial market depth	0.3815	0.1134	0.0756	-0.2490	-0.6445	0.5423	0.0927	-0.0399	0.2331
Financial markets	0.3948	0.3314	-0.1036	-0.0520	0.2574	0.2199	0.2319	-0.0939	-0.7374
Financial efficiency depth	0.0980	0.6841	-0.1034	0.4767	0.1693	-0.0143	0.1846	-0.0794	0.4639

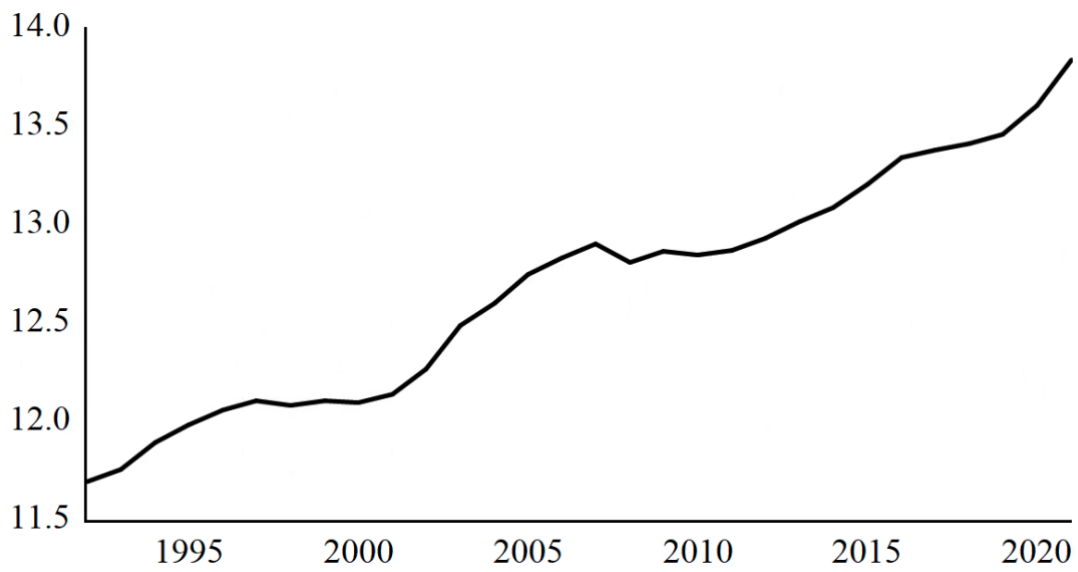
Table E-3: A summary of the final financial development principal component analysis with some indexes removed

Variable	Value	Cumulative value	Difference	Proportion	Cumulative proportion
Financial development	3.1069	3.1069	2.2383	0.6214	0.6214
Financial access depth	0.8686	3.9755	0.1649	0.1737	0.7951
Financial institutions	0.7037	4.6792	0.4457	0.1407	0.9358
Financial institutions access	0.2580	4.9371	0.1951	0.0516	0.9874
Financial institutions efficiency	0.0629	5		0.0126	1
<i>Eigenvectors (loadings):</i>					
Variable	PC1	PC2	PC3	PC4	PC5
Financial development	0.5141	-0.1523	-0.2836	-0.5657	0.5586
Financial access depth	0.4540	0.0923	-0.5796	0.6704	-0.0079
Financial institutions	0.5475	0.0370	0.0819	-0.3142	-0.7704
Financial institutions access	0.3476	-0.6527	0.5632	0.3431	0.1356
Financial institutions efficiency	0.3303	0.7355	0.5097	0.1190	0.2757

Appendix F: Inconclusive Stationarity Testing

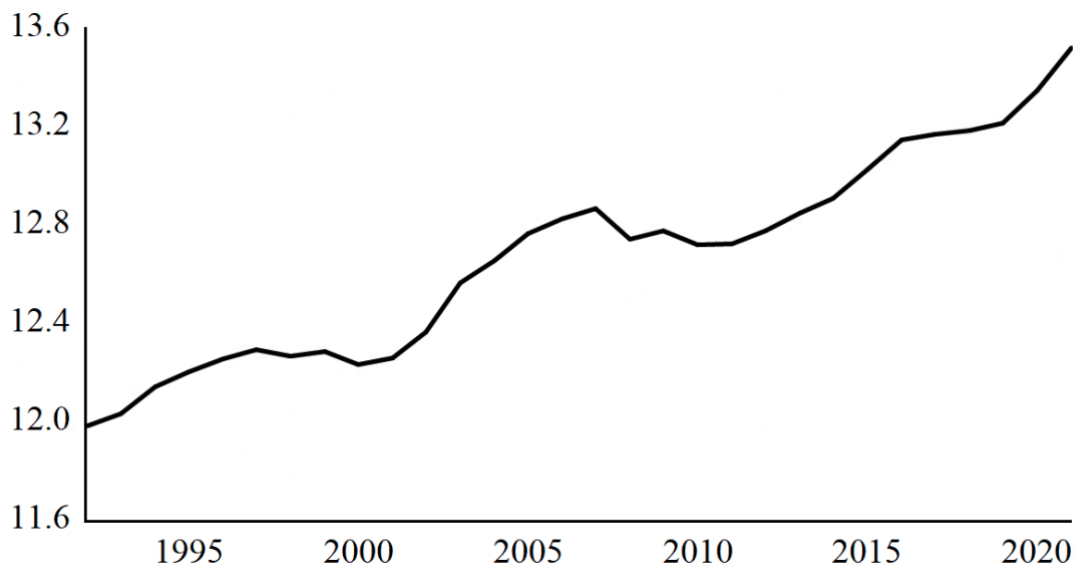
Below are the time series graphs of all the variables for which the unit root testing was inconclusive across the three procedures in section 3.2.4.1. A graph is shown at both levels and the first difference for each variable. The x-variable for all graphs is years, while the y-variable for each graph is titled above. Where the data is sourced from is only noted for the variable in levels and not at first difference.

Figure F-1: ln(House prices) at levels from 1992 to 2021



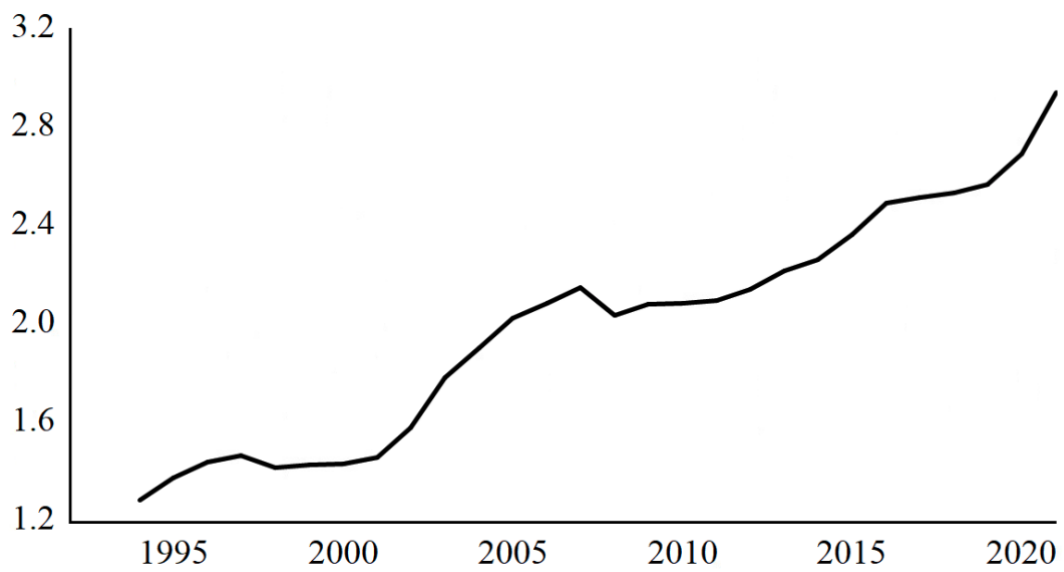
Note: Data is sourced from CoreLogic NZ.

Figure F-2: ln(Real house prices) at levels from 1992 to 2021



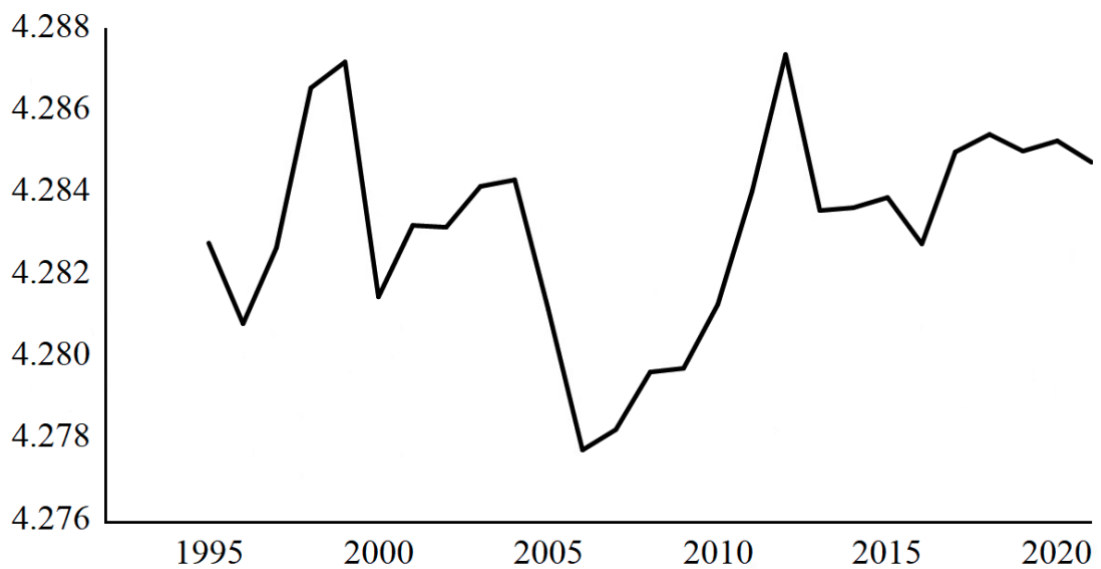
Note: Data is sourced from CoreLogic NZ and RBNZ.

Figure F-3: $\ln(\text{Value-to-income})$ at levels from 1995 to 2021



Note: Data is sourced from CoreLogic NZ and RBNZ.

Figure F-4: $\ln(\text{Wealth Gini})$ at levels from 1995 to 2021



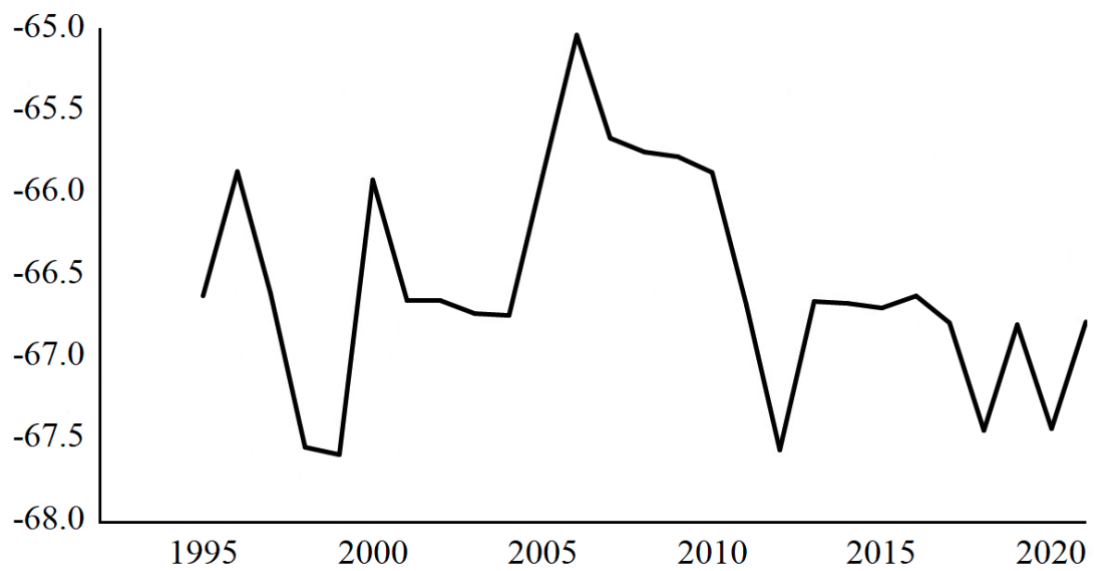
Note: Data is sourced from the WID.

Figure F-5: $\ln(\text{Wealth Palma})$ at levels from 1995 to 2021



Note: Data is sourced from the WID.

Figure F-6: Wealth S80S20 at levels from 1995 to 2021



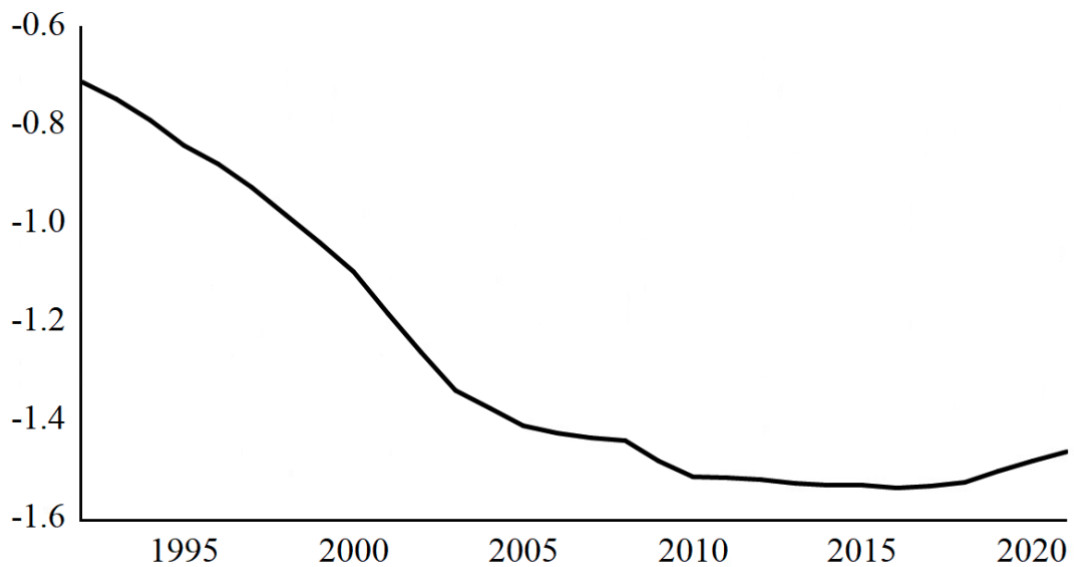
Note: Data is sourced from the WID.

Figure F-7: $\ln(\text{Unemployment rate})$ at levels from 1992 to 2021



Note: Data is sourced from RBNZ.

Figure F-8: Population PC at levels from 1992 to 2021



Note: The population PC is created using the age dependency ratio, fertility rate and life expectancy rate sourced from the World Bank and the UN.

Figure F-9: $\ln(\text{House prices})$ at first difference from 1992 to 2021

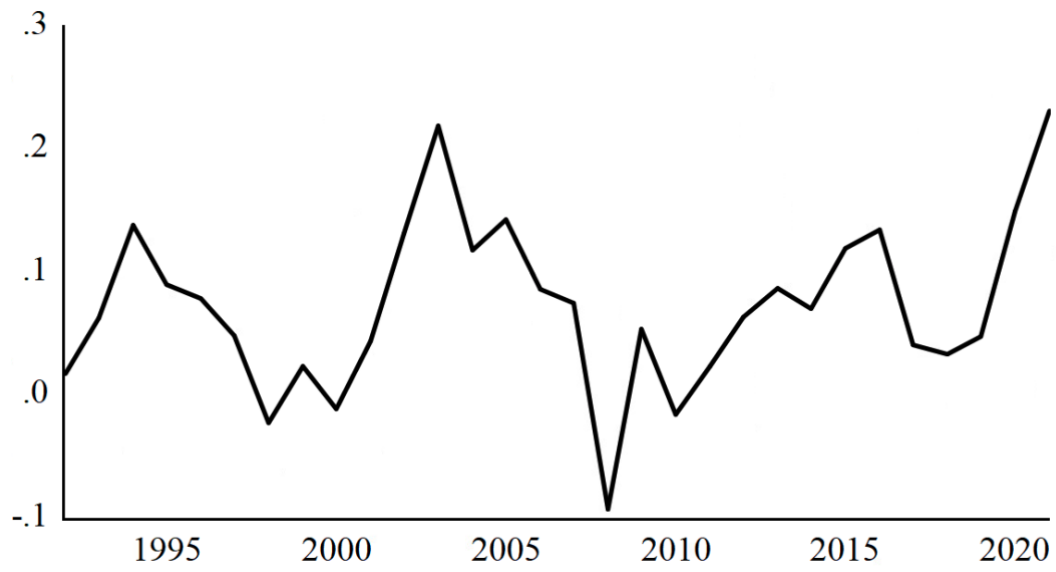


Figure F-10: $\ln(\text{Real house prices})$ at first difference from 1993 to 2021

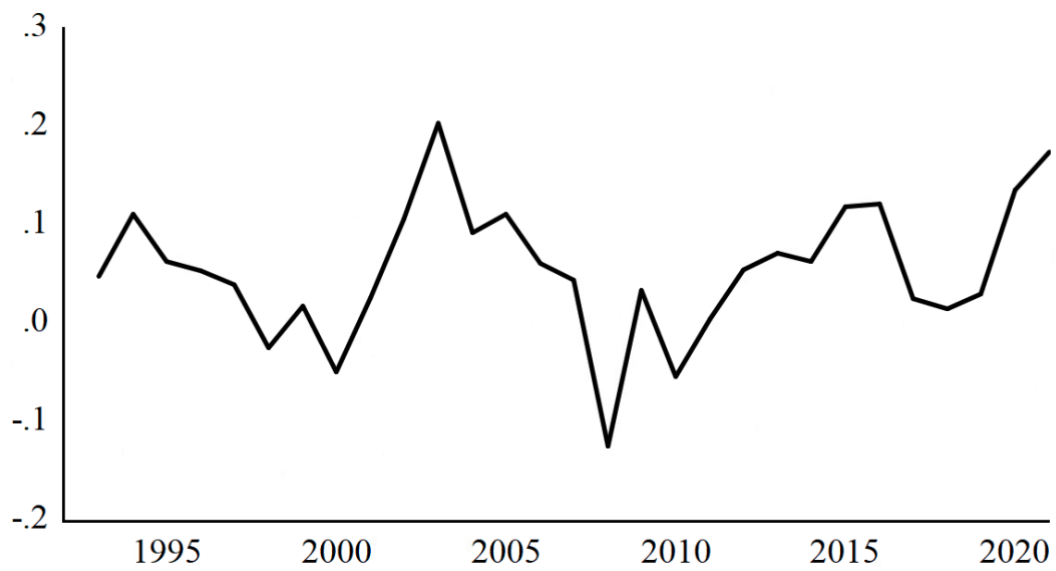


Figure F-11: $\ln(\text{Value-to-income})$ at first difference from 1995 to 2021



Figure F-12: $\ln(\text{Wealth Gini})$ at first difference from 1996 to 2021

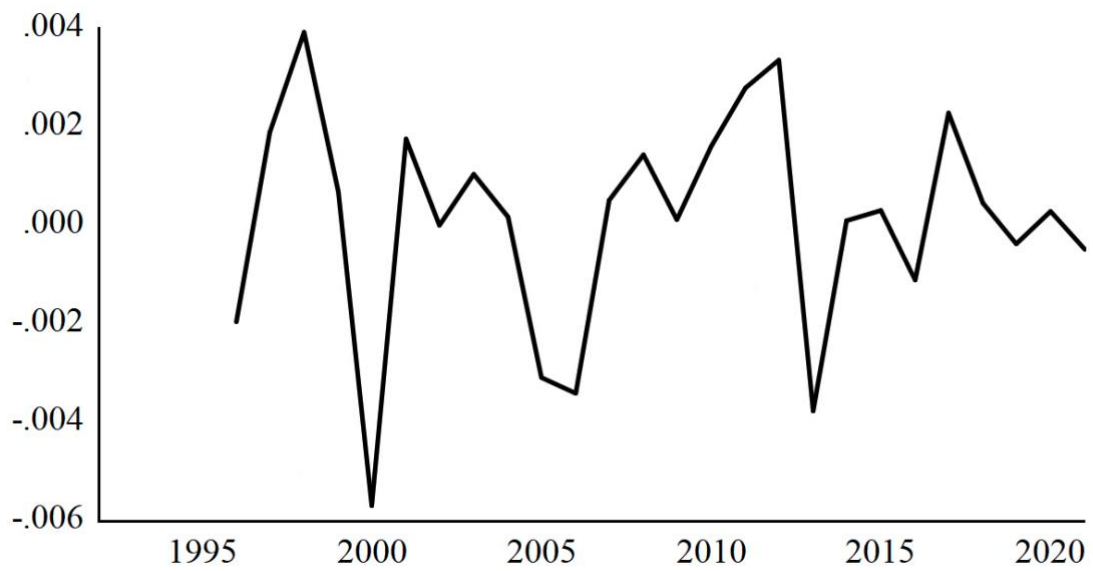


Figure F-13: $\ln(\text{Wealth Palma})$ at first difference from 1996 to 2021

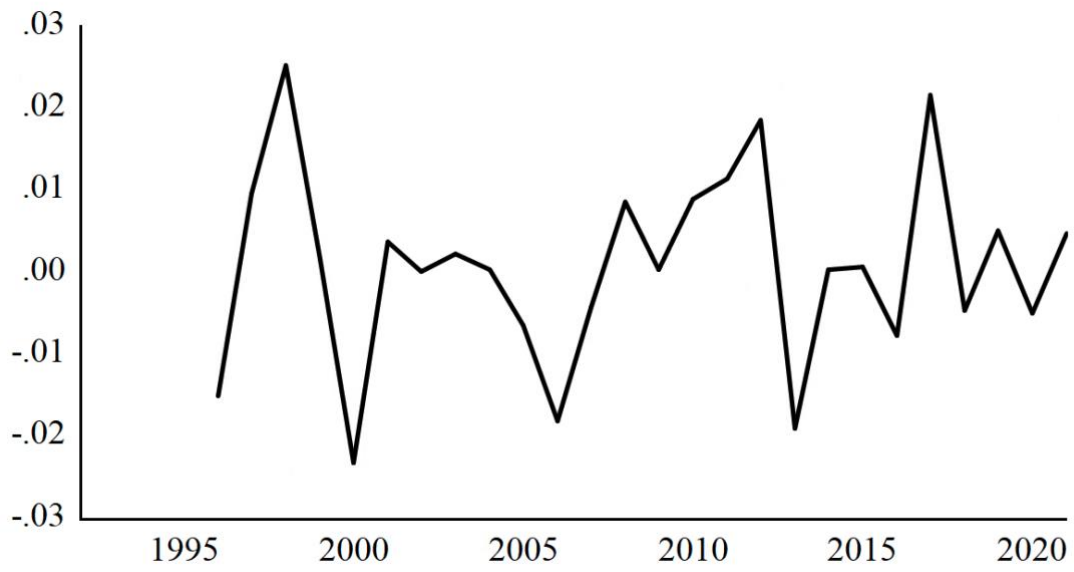


Figure F-14: Wealth S8020 at first difference from 1996 to 2021

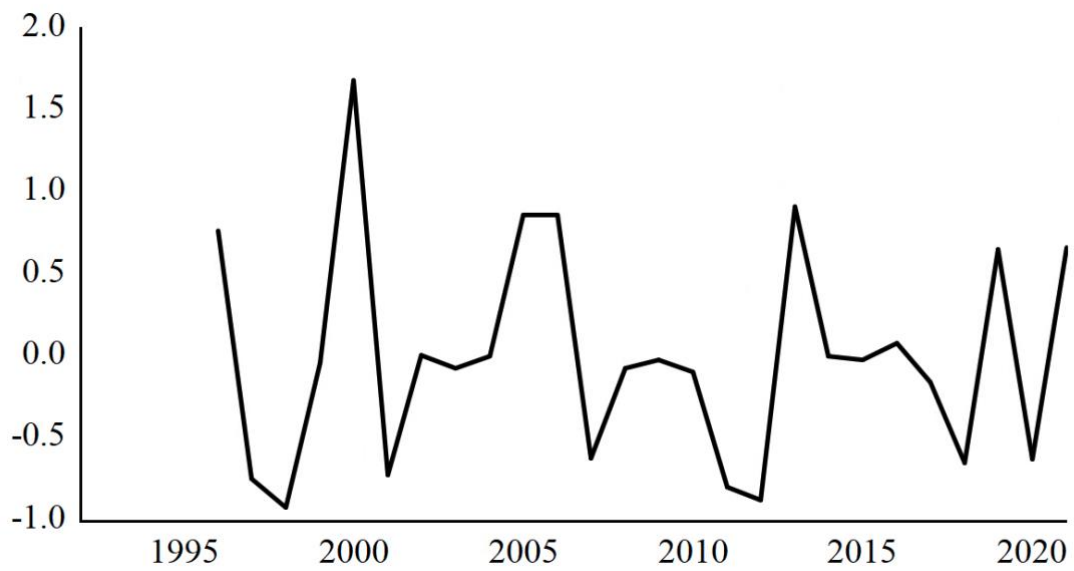
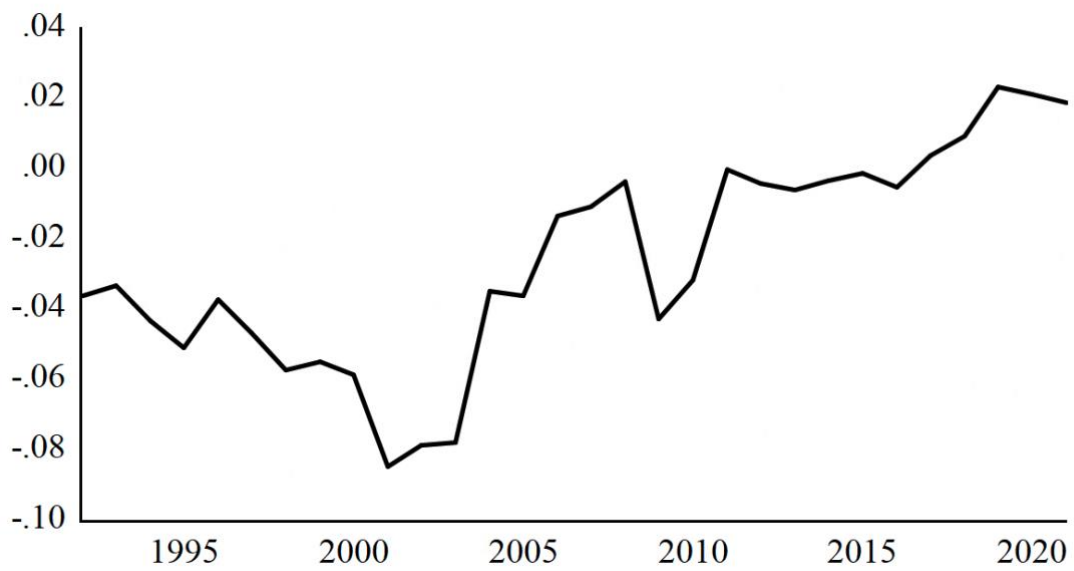


Figure F-15: $\ln(\text{Unemployment rate})$ at first difference from 1992 to 2021



Figure F-16: Population PC at first difference from 1992 to 2021



Appendix G: Income Inequality NARDL Model

A NARDL model was used to examine the presence of asymmetries in the relationship between house prices and income inequality. Table G-1 displays the outcome of the Wald test for the NARDL approach. The results indicate no evidence of asymmetries in the income Gini between positive and negative changes in house prices in the long-run. As for the short-run, conducting a Wald test was impossible since no short-run dynamics were detected in the relationship, as emphasised throughout Chapter 4. The results of the NARDL model are included in Table G-2 and the long-run NARDL estimates are in Table G-3. Both tables show the house price variables as statistically insignificant at the five per cent significance level. Additionally, the positive and negative coefficients are highly similar, leading to the Wald test results seen in Table G-1. Overall, there is reasonable evidence that no asymmetries exist in the income inequality and house price dynamics.

Table G-1: Wald test for the income inequality NARDL estimates

Inequality	Wald test long-run	Conclusion
Income	-0.1672 (1.4908)	Symmetry

Notes: Test is for a null hypothesis of symmetry; specifically, $H_0: \frac{\theta^+}{\pi_y} = \frac{\theta^-}{\pi_y}$, using values from equation 3.10. The short-run is unable to be tested as there are no short-run dynamics present in the house prices and income inequality relationship. Standard error reported in parenthesis underneath test coefficients. () is significant at 10%; (**) significant at 5%; and (***) significant at 1%.*

Table G-2: Income inequality NARDL estimates

Variable	Coefficient	t-statistic
ln(Income Gini(-1))	0.2772 * (0.1429)	1.9395
ln(House prices) \oplus	0.3019 * (0.1547)	1.9513
ln(House prices) \ominus	-0.3742 (0.6612)	-0.566
ln(Real GDP per capita)	1.048 (0.6935)	1.5112
ln(Real GDP per capita (-1))	0.4664 (0.5259)	0.887
Population PC	-0.8929 (0.643)	-1.3887
Population PC (-1)	1.1231 (0.7113)	1.579
Unemployment rate	-0.035 (0.1215)	-0.2883
Unemployment rate (-1)	0.2767 *** (0.087)	3.1818
Foreign investment	0.0046 ** (0.0016)	2.9162
ln(Trade volume)	0.3216 ** (0.1337)	2.4045
Inflation rate	-2.3495 *** (0.7581)	-3.0992
Structural break	-14.3491 (36.089)	-0.3973
Multiplicative structural break	0.0071 (0.018)	0.3968
Constant	5.8103 ** (2.5292)	2.2973
Trend	-0.0347 ** (0.0153)	-2.2706

Notes: (\oplus) represents the (%) change to the income Gini following a 1% increase in house prices, while (\ominus) is for a 1% negative change. Standard error reported in parenthesis underneath test coefficients. (*) is significant at 10%; (**) significant at 5%; and (***) significant at 1%.

Table G-3: Long-run income inequality NARDL estimates

Variable	Coefficient	t-statistic
ln(House prices) †	0.4177 (0.2652)	1.5752
ln(House prices) †	-0.5177 (0.9576)	-0.5406
ln(Real GDP per capita)	2.0953 ** (0.8656)	2.4205
Population PC	0.3185 ** (0.1447)	2.2017
Unemployment rate	0.3344 *** (0.0746)	4.4804
Foreign investment	0.0064 ** (0.0027)	2.4169
ln(Trade volume)	0.4449 * (0.2184)	2.0374

Note: See notes for Table G-2.

Appendix H: Wealth Inequality LVR

Including a dummy variable for when an LVR restriction is in place was trialled in the wealth inequality model. However, it was never found to be statistically significant, no matter the lag structure. The model estimates with the insignificant LVR variable have been presented in Table H-1.

Table H-1: Loan-to-value ratios included in the wealth inequality ARDL model

Variable	Coefficient	t-statistic
ln(Wealth Gini (-1))	-0.0995 (0.1813)	-0.5487
ln(Wealth Gini (-2))	-0.8521 *** (0.1637)	-5.2058
ln(Wealth Gini (-3))	-0.5751 ** (0.171)	-3.3635
ln(House prices)	-0.0303 *** (0.006)	-5.0905
ln(House prices (-1))	0.0027 (0.0075)	0.3592
ln(House prices (-2))	0.0033 (0.006)	0.5485
ln(House prices (-3))	-0.0229 *** (0.0046)	-4.9468
LVR	0.0003 (0.0007)	0.4822
ln(Real GDP per capita)	-0.0656 ** (0.0193)	-3.3948
ln(Share prices)	0.018 *** (0.0036)	5.0501
Population PC	-0.003 (0.0089)	-0.3381
Development PC	-0.0001 (0.0009)	-0.1326
Development PC (-1)	0.0005 (0.0005)	0.9109
Constant	10.919 *** (1.7741)	6.1546
Time trend	0.0037 *** (0.0005)	6.7673

Notes: The standard error is reported in parenthesis underneath the coefficients. HAC standard errors & covariance have been used throughout. () is significant at 10%; (**) significant at 5%; and (***) significant at 1%.*

Appendix I: Quantile Regressions

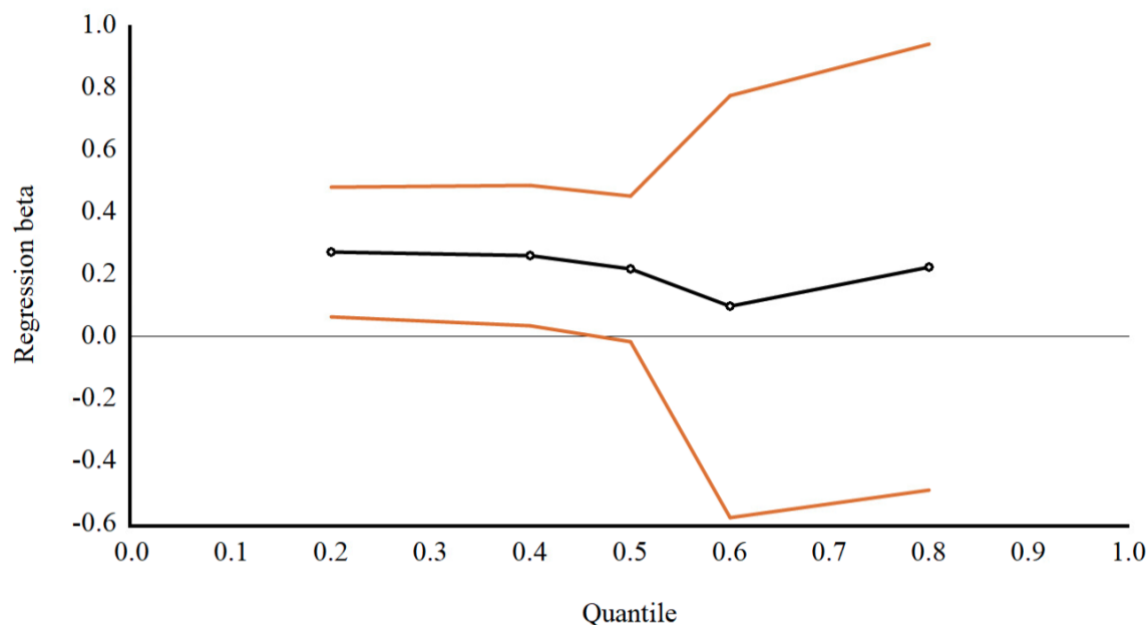
A quantile regression was undertaken on both income and wealth inequality. The same control variables and lags were used from the structural ARDL models specified in Chapter 4 and Chapter 5. However, the Wald test failed to reject the null hypothesis of symmetry across the coefficients. The results for the income inequality regression are shown in Table I-1 and graphically in Figure I-1. The results for wealth inequality are presented in Table I-2 and graphically in Figure I-2. For wealth inequality, house prices and the third lag of house prices are included as these are the x variables of interest that yielded statistically significant estimates. Only house prices in the current period are included for income inequality to show a contemporaneous relationship. Neither table presents the constants or control variables, which were not tested for asymmetry across quantiles of the dependent variables.

Table I-1: Results of the ln(Income Gini) quantile regression

Quantile	Coefficient	t-statistic
0.2	0.2704 ** (0.1062)	2.5463
0.4	0.2594 ** (0.1151)	2.2541
0.5	0.2171 * (0.1188)	1.828
0.6	0.0962 (0.346)	0.278
0.8	0.2223 (0.365)	0.609

Notes: Coefficients are interpreted as the percentage change for that quantile of the Gini. The standard error is reported in parenthesis underneath the coefficients. HAC standard errors & covariance have been used throughout. () is significant at 10%; (**) significant at 5%; and (***) significant at 1%.*

Figure I-1: Graphic representation of the results from the ln(Income Gini) quantile regression



Note: The orange line represents the 95% confidence interval for the beta coefficient.

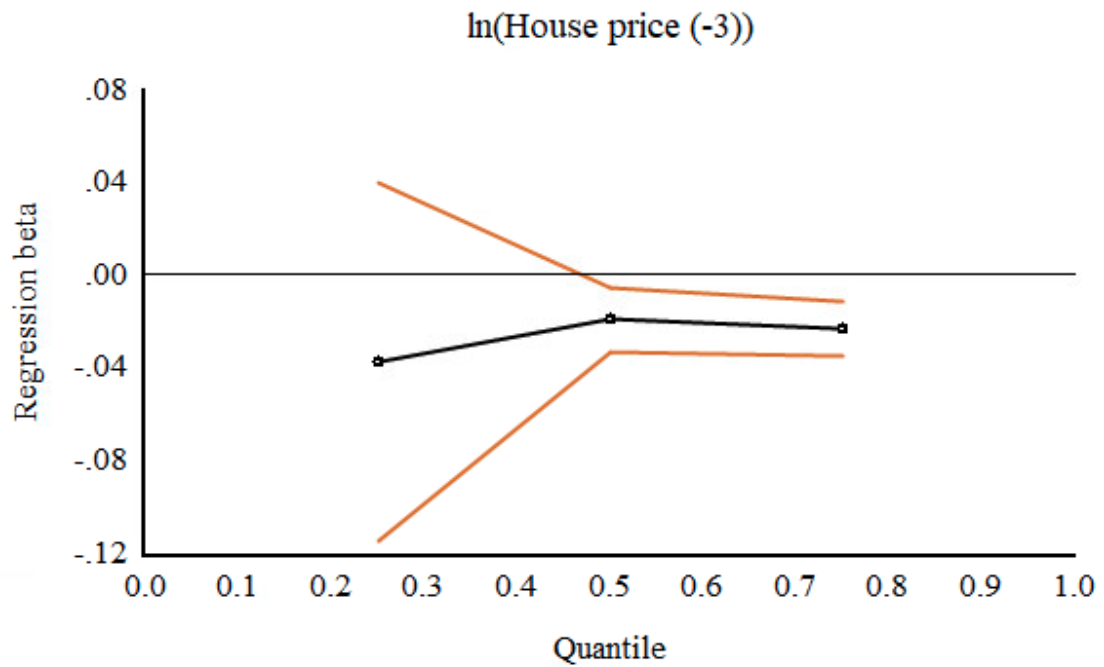
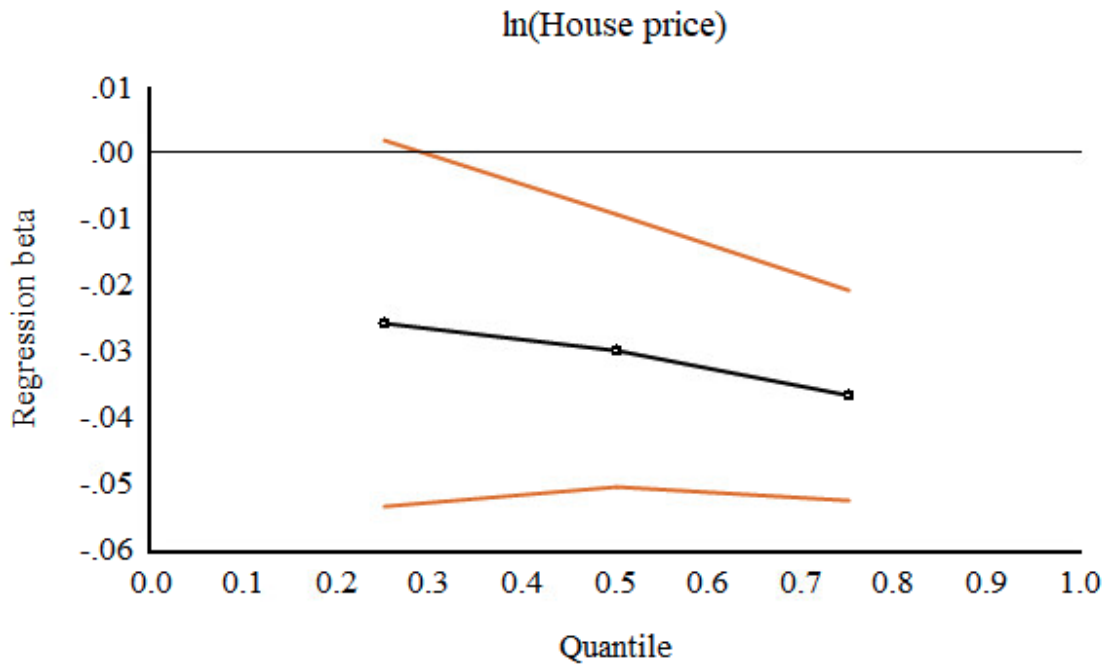
Table I-2: Results of the ln(Wealth Gini) quantile regression

Quantile	Coefficient	t-statistic
<i>ln(House prices)</i>		
0.25	-0.0259 (0.0141)	-1.8286
0.5	-0.03 ** (0.0105)	-2.8408
0.75	-0.0367 *** (0.0081)	-4.5121
<i>ln(House prices (-3))</i>		
0.25	-0.0382 (0.0394)	-0.9682
0.5	-0.02 **	-2.8009

Quantile	Coefficient	t-statistic
	(0.0071)	
0.75	-0.0235 ***	-3.9649
	(0.0059)	

Notes: See notes for Table I-1 and two x variables have been included, house prices and the third lag of house prices as these are the statistically significant estimates.

Figure I-2: Graphic representation of the results from the ln(Wealth Gini) quantile regression



Note: See notes for Figure I-1.

Appendix J: Income Inequality Bartik Instruments

Bartik instruments have gained increased attention in economic literature and are considered valuable tools for mitigating endogeneity issues (Goldsmith-Pinkham et al., 2020). As a result, their use is becoming more commonplace. Bartik instruments for NZ income inequality data have been made freely available for other researchers to facilitate their more expansive application. You can access the data [here](#). This data is created using a range of base years applicable to different analyses. The specifics of how these Bartik instruments are predicted are provided in section 3.3.4. The Gini's have been calculated and provided already; alternative income inequality measures can be calculated using the predicted percentiles income shares for specific base years. These instruments are a powerful means of addressing endogeneity in some applications.

The income inequality Bartik instruments have been created solely for research purposes using data from the World Income Inequality Database. The author takes no responsibility for any errors in their creation or the results achieved using these instruments.

Appendix K: Income Inequality Short- and Long-run Dynamics

The Bounds test for cointegration was inconclusive when considering the income Gini model. The model failed to reject the null hypothesis that no cointegration exists between the explanatory variables and income inequality. This test result is presented in Table 4.1. Because not enough evidence is prevalent that a cointegrating relationship exists, caution is advised when trying to isolate the short- and long-run dynamics of the house price and income inequality relationship. The estimates of each of these are still given, with the short-run dynamics presented in Table K-1, and the long-run coefficients are outlined in Table K-2. Because the house price variable only has a contemporaneous relationship with income inequality, it does not appear in the short-run model.

Table K-1: Estimated short-run coefficients using the ARDL approach (dependent variable = $\ln(\text{Income Gini})$)

Variable	Coefficient	t-statistic
Δ Unemployment rate	0.0308 *** (0.0086)	3.6024
Inflation rate	-1.2775 * (0.7132)	-1.7913
Structural break	-16.4914 (10.2775)	-1.6046
Multiplicative structural break	0.0082 (0.0051)	1.5996
ECT	-0.6259 *** (0.1142)	-5.4826
Constant	4.1247 *** (0.7469)	5.5223
Trend	-0.0348 *** (0.0063)	-5.5195

Notes: The standard error is reported in parenthesis underneath the coefficients. HAC standard errors & covariance have been used throughout. () is significant at 10%; (**) significant at 5%; and (***) significant at 1%.*

Table K-2: Estimated long-run coefficients using the ARDL approach (dependent variable = $\ln(\text{Income Gini})$)

Variable	Coefficient	t-statistic
$\ln(\text{House prices})$	0.2881 ** (0.1172)	2.4584
$\ln(\text{Real GDP per capita})$	2.6286 * (1.3071)	2.0111
Population PC	-0.1031 (0.1468)	-0.7021
Unemployment rate	0.0851 * (0.0427)	1.9939
Foreign investment	0.0064 (0.0037)	1.7422
$\ln(\text{Trade volume})$	0.4525 (0.2814)	1.6081

Note: See notes for Table K-1.

Appendix L: Income Inequality Robustness Check

The primary income inequality model in section 4.2 consists of six distinct control variables, resulting in 64 unique combinations of control variables that can be modelled.

These combinations labelled by number are as follows:

1. Population PC, the Unemployment rate, Foreign investment, $\ln(\text{Trade volume})$, and the inflation rate
2. $\ln(\text{Real GDP per capita})$, the Unemployment rate, Foreign investment, $\ln(\text{Trade volume})$, and the inflation rate
3. $\ln(\text{Real GDP per capita})$, Population PC, Foreign investment, $\ln(\text{Trade volume})$, and the Inflation rate
4. $\ln(\text{Real GDP per capita})$, Population PC, the Unemployment rate, $\ln(\text{Trade volume})$, and the Inflation rate
5. $\ln(\text{Real GDP per capita})$, Population PC, the Unemployment rate, Foreign investment, and the Inflation rate
6. $\ln(\text{Real GDP per capita})$, Population PC, the Unemployment rate, Foreign investment, and $\ln(\text{Trade volume})$
7. the Unemployment rate, Foreign investment, $\ln(\text{Trade volume})$, and the Inflation rate
8. Population PC, Foreign investment, $\ln(\text{Trade volume})$, and the Inflation rate
9. Population PC, the Unemployment rate, $\ln(\text{Trade volume})$, and the Inflation rate
10. Population PC, the Unemployment rate, Foreign investment, and the Inflation rate
11. Population PC, the Unemployment rate, Foreign investment, and $\ln(\text{Trade volume})$

12. $\ln(\text{Real GDP per capita})$, Foreign investment, and $\ln(\text{Trade volume})$, and the Inflation rate
13. $\ln(\text{Real GDP per capita})$, the Unemployment rate, $\ln(\text{Trade volume})$, and the Inflation rate
14. $\ln(\text{Real GDP per capita})$, the Unemployment rate, Foreign investment, and the Inflation rate
15. $\ln(\text{Real GDP per capita})$, the Unemployment rate, Foreign investment, and $\ln(\text{Trade volume})$
16. $\ln(\text{Real GDP per capita})$, Population PC, $\ln(\text{Trade volume})$, and the Inflation rate
17. $\ln(\text{Real GDP per capita})$, Population PC, Foreign investment, and the Inflation rate
18. $\ln(\text{Real GDP per capita})$, Population PC, Foreign investment, and $\ln(\text{Trade volume})$
19. $\ln(\text{Real GDP per capita})$, Population PC, the Unemployment rate, and the Inflation rate
20. $\ln(\text{Real GDP per capita})$, Population PC, the Unemployment rate, and $\ln(\text{Trade volume})$
21. $\ln(\text{Real GDP per capita})$, Population PC, the Unemployment rate, and Foreign investment
22. The Inflation rate, $\ln(\text{Trade volume})$, and Foreign investment
23. The Inflation rate, $\ln(\text{Trade volume})$, and the Unemployment rate
24. The Inflation rate, $\ln(\text{Trade volume})$, and Population PC
25. The Inflation rate, $\ln(\text{Trade volume})$, and $\ln(\text{Real GDP per capita})$
26. The Inflation rate, Foreign investment, and the Unemployment rate
27. The Inflation rate, Foreign investment, and Population PC

28. The Inflation rate, Foreign investment, and $\ln(\text{Real GDP per capita})$
29. The Inflation rate, the Unemployment rate, and Population PC
30. The Inflation rate, the Unemployment rate, $\ln(\text{Real GDP per capita})$
31. The Inflation rate, Population PC, $\ln(\text{Real GDP per capita})$
32. $\ln(\text{Trade volume})$, Foreign investment, and the Unemployment rate
33. $\ln(\text{Trade volume})$, Foreign investment, and Population PC
34. $\ln(\text{Trade volume})$, Foreign investment, and $\ln(\text{Real GDP per capita})$
35. $\ln(\text{Trade volume})$, the Unemployment rate, and Population PC
36. $\ln(\text{Trade volume})$, the Unemployment rate, $\ln(\text{Real GDP per capita})$
37. $\ln(\text{Trade volume})$, Population PC, $\ln(\text{Real GDP per capita})$
38. Foreign investment, the Unemployment rate, and Population PC
39. Foreign investment, the Unemployment rate, $\ln(\text{Real GDP per capita})$
40. Foreign investment, Population PC, $\ln(\text{Real GDP per capita})$
41. the Unemployment rate, Population PC, and $\ln(\text{Real GDP per capita})$
42. $\ln(\text{Real GDP per capita})$, and Population PC
43. $\ln(\text{Real GDP per capita})$, and the Unemployment rate
44. $\ln(\text{Real GDP per capita})$, and Foreign investment
45. $\ln(\text{Real GDP per capita})$, and $\ln(\text{Trade volume})$
46. $\ln(\text{Real GDP per capita})$, and the Inflation rate
47. Population PC and the Unemployment rate
48. Population PC and Foreign investment
49. Population PC and $\ln(\text{Trade volume})$
50. Population PC and the Inflation rate
51. the Unemployment rate and Foreign investment
52. the Unemployment rate and $\ln(\text{Trade volume})$

53. the Unemployment rate and the Inflation rate
54. Foreign investment and ln(Trade volume)
55. Foreign investment and the Inflation rate
56. ln(Trade volume) and the Inflation rate
57. ln(Real GDP per capita)
58. Population PC
59. the Unemployment rate
60. Foreign investment
61. ln(Trade volume)
62. The Inflation rate
63. No control variables
64. All control variables (the results are provided in section 4.2)

Each of these 64 models is estimated using an ARDL approach, the results of which are presented in Table L-1. Results are given by the model number referring to the combinations labelled above.

Table L-1: ARDL house price coefficient estimates for 63 different income inequality control variable specifications (dependent variable = ln(Income Gini))

Model	Coefficient	t-statistic
<i>1</i>	0.183 (0.1065)	1.7178
<i>2</i>	0.1658 *** (0.0526)	3.1499
<i>3</i>	0.1334 (0.077)	1.7333
<i>4</i>	0.2385 *** (0.0771)	3.0941
<i>5</i>	0.2667 ** (0.1249)	2.1353
<i>6</i>	0.199 ** (0.0723)	2.7528
<i>7</i>	0.1817 * (0.0923)	1.9682
<i>8</i>	0.1368 * (0.067)	2.0436
<i>9</i>	0.2141 ** (0.1017)	2.1057
<i>10</i>	0.1583 (0.0941)	1.6826
<i>11</i>	0.1969 (0.1154)	1.7056
<i>12</i>	0.1551 ** (0.0737)	2.1044
<i>13</i>	0.2384 *** (0.0661)	3.6043
<i>14</i>	0.1302 * (0.0669)	1.9467
<i>15</i>	0.174 ** (0.0644)	2.7029

Model	Coefficient	t-statistic
16	0.1698 ** (0.0795)	2.1358
17	0.124 * (0.0701)	1.7697
18	0.165 * (0.0909)	1.8148
19	0.1925 * (0.0932)	2.0651
20	0.2333 ** (0.087)	2.6824
21	0.1614 ** (0.0682)	2.3647
22	0.1456 * (0.0709)	2.0527
23	0.2232 *** (0.0773)	2.8883
24	0.1674 ** (0.0727)	2.3034
25	0.2143 ** (0.0766)	2.7974
26	0.1557 * (0.0806)	1.9325
27	0.1201 * (0.0587)	2.0472
28	0.153 ** (0.0674)	2.2687
29	0.19 * (0.0929)	2.0454
30	0.1951 ** (0.0757)	2.5762
31	0.141 * (0.0731)	1.9292
32	0.1854 *	1.8347

Model	Coefficient	t-statistic
	(0.101)	
33	0.1408	1.7127
	(0.0822)	
34	0.1768 **	2.1308
	(0.0829)	
35	0.2113 *	1.9342
	(0.1092)	
36	0.1998 ***	3.3228
	(0.0601)	
37	0.1547	1.5276
	(0.1013)	
38	0.1736 *	1.8228
	(0.0952)	
39	0.1425 **	2.2703
	(0.0628)	
40	0.1404 *	1.8183
	(0.0772)	
41	0.1941 *	2.0665
	(0.0939)	
42	0.1279	1.4674
	(0.0872)	
43	0.1756 **	2.7668
	(0.0635)	
44	0.1561 **	2.3483
	(0.0665)	
45	0.1807 **	2.353
	(0.0768)	
46	0.1865 **	2.5731
	(0.0725)	
47	0.1915 *	2.0009
	(0.0957)	
48	0.0762	1.3702
	(0.0556)	

Model	Coefficient	t-statistic
49	0.1276 (0.0848)	1.5046
50	0.1353 ** (0.0653)	2.0727
51	0.1634 * (0.0805)	2.0303
52	0.1954 *** (0.0679)	2.8795
53	0.1985 ** (0.0729)	2.7224
54	0.15 * (0.0864)	1.7372
55	0.1355 * (0.0696)	1.9469
56	0.2106 ** (0.08)	2.6322
57	0.1553 ** (0.0608)	2.5535
58	0.0717 (0.0624)	1.1495
59	0.1809 *** (0.0611)	2.9595
60	0.0949 * (0.0533)	1.7813
61	0.1664 ** (0.08)	2.0797
62	0.18 ** (0.0777)	2.3167
63	0.1102 * (0.0564)	1.9539

Notes: The standard error is reported in parenthesis underneath the coefficients. HAC standard errors & covariance have been used throughout. () is significant at 10%; (**) significant at 5%; and (***) significant at 1%.*

Appendix M: Income Inequality Heterogeneity

In section 4.2.3, the heterogeneity in the house price and income inequality relationship was estimated using a double-log model; hence, the coefficients indicated the percentage change in the income share of that decile following a one per cent increase in house prices. Because the variables in that model are in elasticity form, the coefficient represents the percentage change in the percentage share of NZ income. A percentage change to a percentage can be a confusing interpretation, and percentage variables are not regularly logged in economic literature. Therefore, in addition to the double-log model, a semi-log model was used where the income share is left in levels, and the house price variable is in logarithmic form. The coefficients in a semi-log model offer an alternate interpretation and instead estimate the amount that the income share of each decile will increase or decrease following a change in house prices. The results of the semi-log model are presented in Table M-1, and the sum of ARDL coefficients is displayed visually across the income distribution in Figure M-1. Figure M-1 does not consider that some coefficients are not statistically different from zero; hence, it purely compares the magnitudes of each decile's house price coefficient.

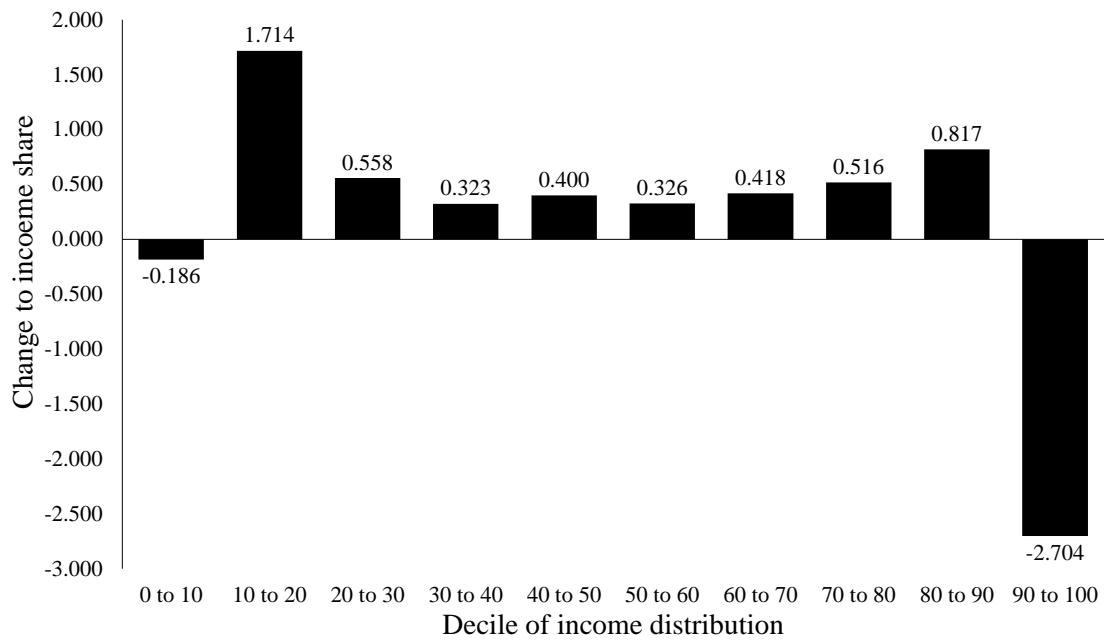
Table M-1: Change to income share for each decile of the income distribution following an increase in house prices, using the nonlogarithmic form for the dependent variables (semi-log model)

Income decile	Σ ARDL coefficients	F-Bounds test	t-Bounds test	Long-run coefficient	Cointegration relationship
0 to 10	-0.1855 ** (0.0845)	-2.1949	-6.2010 ***	-0.1326 ** (-0.0546)	Cointegration
10 to 20	1.7139 ** (0.7532)	-2.2754	-5.5495 ***	0.1816 *** (0.0393)	Cointegration
20 to 30	0.5578 *** (0.1381)	4.0391	-4.1321	0.6218 *** (0.1921)	Nonsensical cointegration
30 to 40	0.3227 ** (0.1469)	2.1977	-3.7664	0.8306 ** (0.3041)	Inconclusive
40 to 50	0.3999 * (0.2177)	1.8367	-4.0133	0.5486 (0.3211)	Inconclusive
50 to 60	0.3256 (0.2825)	1.1529	-2.5206	0.5545 (0.3324)	No cointegration

Income decile	Σ ARDL coefficients	F-Bounds test	t-Bounds test	Long-run coefficient	Cointegration relationship
60 to 70	0.4184 ** (0.1676)	2.4968	-1.4678	1.0422 * (0.5578)	Inconclusive
70 to 80	0.5163 ** (0.1805)	2.8611	-3.0126	0.4001 *** (0.1147)	Nonsensical cointegration
80 to 90	0.8172 ** (0.3286)	2.4869	-3.612	0.5259 *** (0.1787)	Nonsensical cointegration
90 to 100	-2.7035 * (1.3752)	-1.9659	-1.326	-5.3258 * (2.5439)	No cointegration

Notes: (i) Each row represents a separate ARDL equation estimation where the dependent variable is the income share in levels for the decile specified in the first column; (ii) the coefficient is for the explanatory variable of house prices; (iii) the change to the dependent variable from a percentage change ($p\%$) in house prices is calculated as $\hat{\beta} \cdot \log([100 + p]/100)$; (iv) null hypothesis for Bounds test is there is no cointegration relationship in levels ($H_0: \pi_y \cap \{\pi_j\}_{j=1}^k = 0$); (v) The standard error is reported in parenthesis underneath the coefficients. HAC standard errors & covariance have been used throughout. (*) is significant at 10%; (**) significant at 5%; and (***) significant at 1%.

Figure M-1: Change in the income share for each decile of the income distribution following a house price increase using a semi-log model



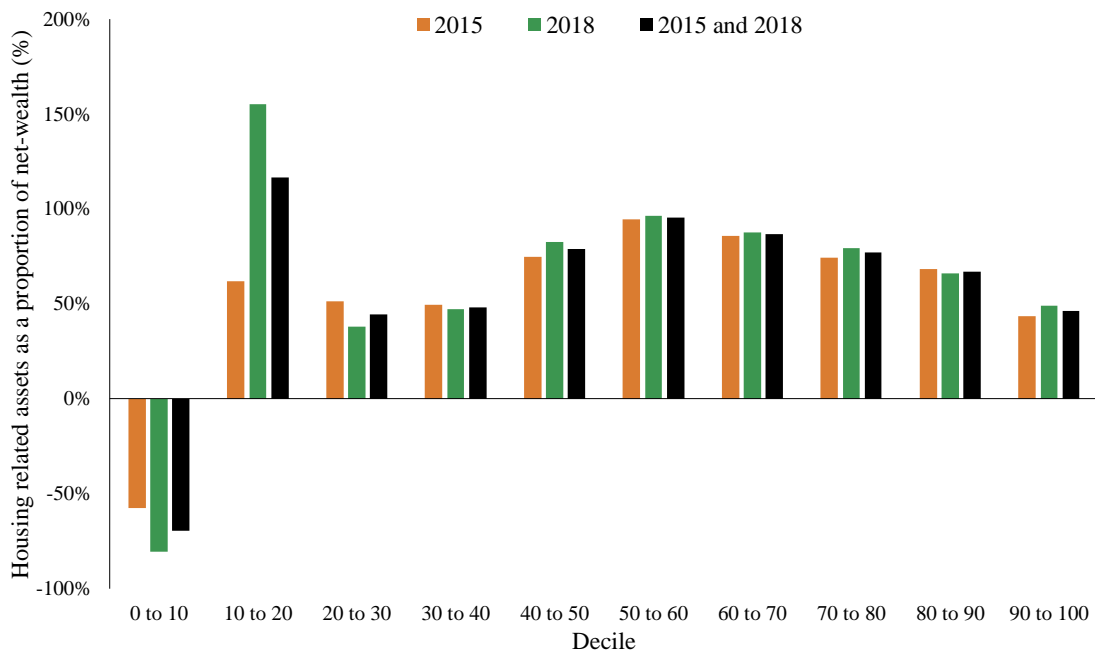
Note: Values are sourced from the \sum ARDL coefficients in Table M-1 and still include the statistically insignificant coefficients.

Appendix N: The Inverted U-Curve for the Wealth Distribution

When creating the inverted U-curve of housing-related assets across the wealth distribution, data from Rashbrooke et al. (2021) is utilised. For the graph used in the primary discussion, Figure 5.14, trusts are not accounted for in the calculations. As Rashbrooke et al. (2021) explains, the questioning used regarding assets in trusts changed for different Household Economic Surveys, reducing the comparability over time. Additionally, the makeup of assets within trusts is complicated. However, one method to account for housing assets in a trust is to approximate it based on the average proportion. Rashbrooke et al. (2021) argue that around 60 per cent of assets in a trust will be housing, on average. Using this proportion alongside each decile's average trust asset value, Figure 5.14 can be recreated to account for the housing assets contained within trusts – the result of this is provided in Figure N-1. For comparison, Figure 5.14 has been reproduced in this appendix as Figure N-2. It can be seen that considering housing assets in trusts primarily only changes the proportions for the top decile. The percentage of housing-related assets for the other deciles remains comparable mainly. Considering trust would make the top decile marginally more sensitive to house price shocks than what is suggested in Figure 5.14.

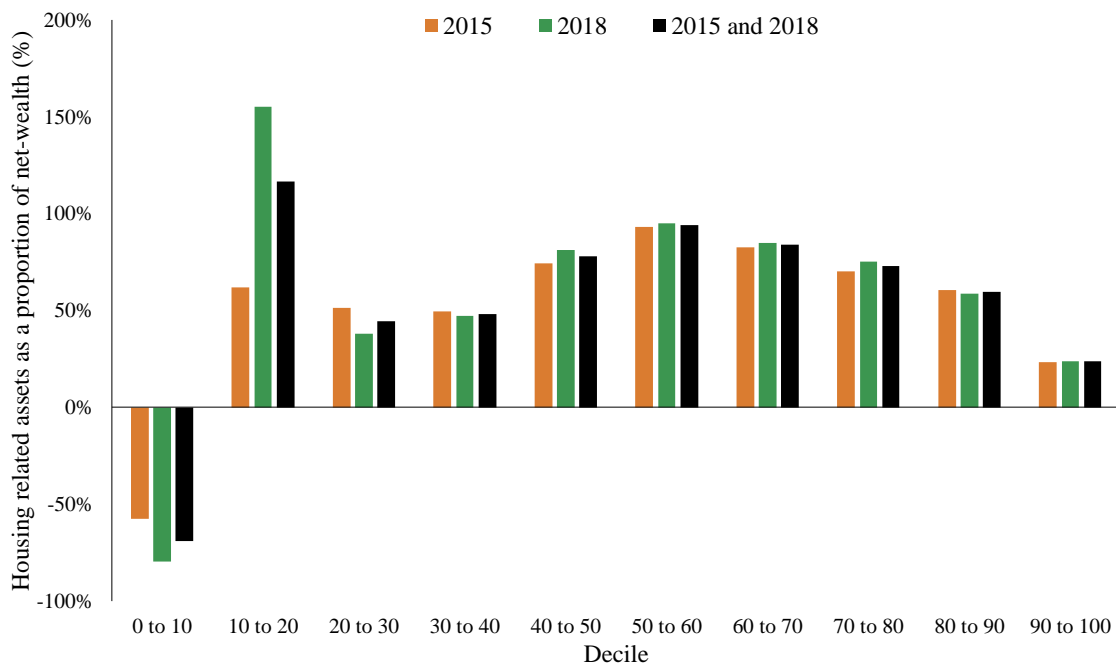
Anyone wanting to consider other asset classes within a NZ context should explore the work of Rashbrooke et al. (2021). The authors provide a comprehensive and relatively granular breakdown of wealth in NZ which can be accessed [here](#).

Figure N-1: The inverted U-curve of housing related assets across the wealth distribution in NZ from 2015 to 2018 while taking into account trusts



Notes: The calculations for this figure are done using data from Rashbrooke et al. (2021). Housing assets in trusts are taken into account unlike Figure 5.14. For the 10 to 20 per cent decile in 2018, housing makes up over 100 per cent of their total net worth.

Figure N-2: The inverted U-curve of housing related assets across the wealth distribution in NZ from 2015 to 2018 without taking into account trusts



Note: This is the replicated graph from Figure 5.14 used solely as a comparison to Figure N-1.

Appendix O: Wealth Inequality Robustness Check

Four different control variables are included in the wealth inequality model. That leads to 24 various combinations of control variables that could be modelled. Those combinations labelled by number are as follows:

1. ln(Real GDP per capita), ln(Share prices), and Population PC
2. ln(Real GDP per capita), ln(Share prices), and Development PC
3. ln(Real GDP per capita), Population PC, and Development PC
4. ln(Share prices), Population PC, and Development PC
5. ln(Real GDP per capita), ln(Share prices), and Development PC
6. ln(Real GDP per capita), ln(Share prices), and Population PC
7. ln(Share prices), Population PC, and Development PC
8. ln(Real GDP per capita), Population PC, and Development PC
9. ln(Real GDP per capita), ln(Share prices), and Population PC
10. ln(Share prices), Population PC, and Development PC
11. ln(Real GDP per capita) Population PC, and Development PC
12. ln(Real GDP per capita) ln(Share prices), and Development PC
13. ln(Real GDP per capita) and ln(Share prices)
14. ln(Real GDP per capita) and Development PC
15. ln(Real GDP per capita) and Population PC
16. ln(Share prices) and Population PC
17. ln(Share prices) and Development PC
18. Population PC and Development PC
19. ln(Real GDP per capita)
20. ln(Share prices)

21. Population PC
22. Development PC
23. No control variables
24. All control variables (the results are provided in section 5.2)

Each of these 24 models is estimated, and the ARDL, long-run coefficients and Bounds testing, and short-run coefficients are presented in Table O-1, Table O-2, and Table O-3, respectively. Results are given by the model number referring to the combinations labelled above.

Table O-1: ARDL house prices coefficient estimates for 23 different wealth inequality control variable specifications (dependent variable = $\ln(\text{Wealth Gini})$)

Model	Variable	Coefficient	t-statistic
<i>1</i>	$\ln(\text{House prices})$	-0.0142 ** (0.0057)	-2.505
	$\ln(\text{House prices } (-1))$	0.0015 (0.0073)	0.2084
	$\ln(\text{House prices } (-2))$	-0.0036 (0.0072)	-0.4921
	$\ln(\text{House prices } (-3))$	-0.0187 *** (0.0042)	-4.431
<i>2</i>	$\ln(\text{House prices})$	-0.0284 *** (0.0038)	-7.4927
	$\ln(\text{House prices } (-1))$	0.0076 (0.0068)	1.1131
	$\ln(\text{House prices } (-2))$	0.0004 (0.0051)	0.0812
	$\ln(\text{House prices } (-3))$	-0.0218 *** (0.0043)	-5.0678
<i>3</i>	$\ln(\text{House prices})$	-0.0056	-0.9465

Model	Variable	Coefficient	t-statistic
		(0.0059)	
	ln(House prices (-1))	-0.001	-0.1069
		(0.0091)	
	ln(House prices (-2))	-0.0014	-0.1362
		(0.0104)	
	ln(House prices (-3))	-0.0208 **	-2.9647
		(0.007)	
4	ln(House prices)	-0.0248 *	-2.1551
		(0.0115)	
	ln(House prices (-1))	0.0021	0.2342
		(0.0091)	
	ln(House prices (-2))	0.0014	0.1381
		(0.0098)	
	ln(House prices (-3))	-0.0233 ***	-3.6001
		(0.0065)	
5	ln(House prices)	-0.0284 ***	-7.4927
		(0.0038)	
	ln(House prices (-1))	0.0076	1.1131
		(0.0068)	
	ln(House prices (-2))	0.0004	0.0812
		(0.0051)	
	ln(House prices (-3))	-0.0218 ***	-5.0678
		(0.0043)	
6	ln(House prices)	-0.0142 **	-2.505
		(0.0057)	
	ln(House prices (-1))	0.0015	0.2084
		(0.0073)	
	ln(House prices (-2))	-0.0036	-0.4921
		(0.0072)	
	ln(House prices (-3))	-0.0187 ***	-4.431
		(0.0042)	
7	ln(House prices)	-0.0248 *	-2.1551

Model	Variable	Coefficient	t-statistic
		(0.0115)	
	ln(House prices (-1))	0.0021	0.2342
		(0.0091)	
	ln(House prices (-2))	0.0014	0.1381
		(0.0098)	
	ln(House prices (-3))	-0.0233 ***	-3.6001
		(0.0065)	
8	ln(House prices)	-0.0056	-0.9465
		(0.0059)	
	ln(House prices (-1))	-0.001	-0.1069
		(0.0091)	
	ln(House prices (-2))	-0.0014	-0.1362
		(0.0104)	
	ln(House prices (-3))	-0.0208 **	-2.9647
		(0.007)	
9	ln(House prices)	-0.0142 **	-2.505
		(0.0057)	
	ln(House prices (-1))	0.0015	0.2084
		(0.0073)	
	ln(House prices (-2))	-0.0036	-0.4921
		(0.0072)	
	ln(House prices (-3))	-0.0187 ***	-4.431
		(0.0042)	
10	ln(House prices)	-0.0248 *	-2.1551
		(0.0115)	
	ln(House prices (-1))	0.0021	0.2342
		(0.0091)	
	ln(House prices (-2))	0.0014	0.1381
		(0.0098)	
	ln(House prices (-3))	-0.0233 ***	-3.6001
		(0.0065)	
11	ln(House prices)	-0.0056	-0.9465

Model	Variable	Coefficient	t-statistic
		(0.0059)	
	ln(House prices (-1))	-0.001	-0.1069
		(0.0091)	
	ln(House prices (-2))	-0.0014	-0.1362
		(0.0104)	
	ln(House prices (-3))	-0.0208 **	-2.9647
		(0.007)	
12	ln(House prices)	-0.0284 ***	-7.4927
		(0.0038)	
	ln(House prices (-1))	0.0076	1.1131
		(0.0068)	
	ln(House prices (-2))	0.0004	0.0812
		(0.0051)	
	ln(House prices (-3))	-0.0218 ***	-5.0678
		(0.0043)	
13	ln(House prices)	-0.0153 ***	-3.0495
		(0.005)	
	ln(House prices (-1))	0.0049	0.946
		(0.0052)	
	ln(House prices (-2))	-0.0132 ***	-4.4423
		(0.003)	
14	ln(House prices)	-0.0068	-0.893
		(0.0076)	
	ln(House prices (-1))	0.0021	0.2416
		(0.0086)	
	ln(House prices (-2))	0.0022	0.185
		(0.0118)	
	ln(House prices (-3))	-0.0197 *	-1.929
		(0.0102)	
15	ln(House prices)	-0.0068 *	-1.8226
		(0.0037)	
	ln(House prices (-1))	-0.0008	-0.0961

Model	Variable	Coefficient	t-statistic
		(0.0079)	
	ln(House prices (-2))	-0.0007	-0.0749
		(0.0091)	
	ln(House prices (-3))	-0.0212 ***	-3.1821
		(0.0067)	
16	ln(House prices)	-0.014 **	-2.4709
		(0.0057)	
	ln(House prices (-1))	-0.0003	-0.0398
		(0.007)	
	ln(House prices (-2))	-0.0025	-0.322
		(0.0077)	
	ln(House prices (-3))	-0.0196 ***	-3.7063
		(0.0053)	
17	ln(House prices)	-0.0299 **	-2.8302
		(0.0106)	
	ln(House prices (-1))	0.0038	0.3828
		(0.0098)	
	ln(House prices (-2))	0.0032	0.3136
		(0.0101)	
	ln(House prices (-3))	-0.0246 ***	-3.2573
		(0.0076)	
18	ln(House prices)	-0.0069	-1.4128
		(0.0049)	
	ln(House prices (-1))	-0.0013	-0.1419
		(0.0089)	
	ln(House prices (-2))	-0.0011	-0.1018
		(0.0103)	
	ln(House prices (-3))	-0.0212 **	-2.9539
		(0.0072)	
19	ln(House prices)	-0.0057	-1.1932
		(0.0047)	
20	ln(House prices)	-0.017 ***	-2.9741

Model	Variable	Coefficient	t-statistic
		(0.0057)	
21	ln(House prices)	-0.0075 **	-2.2417
		(0.0033)	
	ln(House prices (-1))	-0.0011	-0.1377
		(0.0077)	
	ln(House prices (-2))	-0.0007	-0.0744
		(0.0088)	
	ln(House prices (-3))	-0.0212 ***	-3.1899
		(0.0067)	
22	ln(House prices)	-0.0093	-1.5526
		(0.006)	
	ln(House prices (-1))	0.0015	0.1822
		(0.0085)	
	ln(House prices (-2))	0.0026	0.2219
		(0.0119)	
	ln(House prices (-3))	-0.0199 *	-1.9163
		(0.0104)	
23	ln(House prices)	-0.0076 *	-2.0484
		(0.0037)	

Notes: The standard error is reported in parenthesis underneath the coefficients. HAC standard errors & covariance have been used throughout. () is significant at 10%; (**) significant at 5%; and (***) significant at 1%.*

Table O-2: Long-run house price coefficients and cointegration testing for 23 different wealth inequality control variable specifications

Model	Long-run coefficient	t-statistic	F-Bounds test	t-Bounds test
<i>1</i>	-0.0163 *** (0.0013)	-12.6072	10.4751 ***	-6.890144
<i>2</i>	-0.0179 *** (0.0014)	-12.7968	15.4239 ***	-8.410578
<i>3</i>	-0.0153 *** (0.0018)	-8.3493	5.3 **	-4.877702
<i>4</i>	-0.0199 *** (0.0027)	-7.4949	8.2503 ***	-6.19414
<i>5</i>	-0.0179 *** (0.0014)	-12.7968	15.4239 ***	-8.410578
<i>6</i>	-0.0163 *** (0.0013)	-12.6072	10.4751 ***	-6.890144
<i>7</i>	-0.0199 *** (0.0027)	-7.4949	8.2503 ***	-6.19414
<i>8</i>	-0.0153 *** (0.0018)	-8.3493	5.3 **	-4.877702
<i>9</i>	-0.0163 *** (0.0013)	-12.6072	10.4751 ***	-6.890144
<i>10</i>	-0.0199 *** (0.0027)	-7.4949	8.2503 ***	-6.19414
<i>11</i>	-0.0153 *** (0.0018)	-8.3493	5.3 **	-4.877702
<i>12</i>	-0.0179 *** (0.0014)	-12.7968	15.4239 ***	-8.410578
<i>13</i>	-0.0162 *** (0.0019)	-8.5301	8.7569 ***	-5.690439
<i>14</i>	-0.0185 *** (0.0054)	-3.424	4.7113 *	-4.154448
<i>15</i>	-0.0295 ***	-4.2482	8.5849 ***	-5.544238

Model	Long-run coefficient	t-statistic	F-Bounds test	t-Bounds test
	(0.0069)			
16	-0.017 ***	-11.8481	11.2439 ***	-6.54159
	(0.0014)			
17	-0.0214 ***	-8.5002	10.247 ***	-6.202052
	(0.0025)			
18	-0.016 ***	-12.7537	7.2176 **	-5.21979
	(0.0013)			
19	-0.0115	-1.09	3.552972	-2.917577
	(0.0105)			
20	-0.0158 ***	-3.8249	7.2357 **	-4.445376
	(0.0041)			
21	-0.016 ***	-14.4739	12.1879 ***	-5.972036
	(0.0011)			
22	-0.0205 ***	-5.772	6.6251 **	-4.370515
	(0.0036)			
23	-0.0151	-1.6141	5.2381 *	-3.040424
	(0.0093)			

Notes: Null hypothesis for Bounds test is there is no cointegration relationship in levels ($H_0: \pi_y \cap \{\pi_j\}_{j=1}^k = 0$), and see notes for Table O-1.

Table O-3: Short-run house price coefficients for 23 different wealth inequality control variable specifications

Model	Variable	Coefficient	t-statistic
<i>1</i>	$\Delta \ln(\text{House prices})$	-0.0142 *** (0.0035)	-4.0401
	$\Delta \ln(\text{House prices } (-1))$	0.0222 *** (0.0051)	4.392
	$\Delta \ln(\text{House prices } (-2))$	0.0187 *** (0.0047)	3.9706
<i>2</i>	$\Delta \ln(\text{House prices})$	-0.0284 *** (0.0038)	-7.5343
	$\Delta \ln(\text{House prices } (-1))$	0.0214 *** (0.0042)	5.1561
	$\Delta \ln(\text{House prices } (-2))$	0.0218 *** (0.0042)	5.2506
<i>3</i>	$\Delta \ln(\text{House prices})$	-0.0056 (0.0047)	-1.1816
	$\Delta \ln(\text{House prices } (-1))$	0.0222 *** (0.0067)	3.2995
	$\Delta \ln(\text{House prices } (-2))$	0.0208 ** (0.0066)	3.1598
<i>4</i>	$\Delta \ln(\text{House prices})$	-0.0248 *** (0.0047)	-5.2413
	$\Delta \ln(\text{House prices } (-1))$	0.0219 *** (0.0055)	3.9541
	$\Delta \ln(\text{House prices } (-2))$	0.0233 *** (0.0056)	4.1222
<i>5</i>	$\Delta \ln(\text{House prices})$	-0.0284 *** (0.0038)	-7.5343
	$\Delta \ln(\text{House prices } (-1))$	0.0214 *** (0.0042)	5.1561
	$\Delta \ln(\text{House prices } (-2))$	0.0218 ***	5.2506

Model	Variable	Coefficient	t-statistic
		(0.0042)	
6	$\Delta \ln(\text{House prices})$	-0.0142 ***	-4.0401
		(0.0035)	
	$\Delta \ln(\text{House prices } (-1))$	0.0222 ***	4.392
		(0.0051)	
	$\Delta \ln(\text{House prices } (-2))$	0.0187 ***	3.9706
		(0.0047)	
7	$\Delta \ln(\text{House prices})$	-0.0248 ***	-5.2413
		(0.0047)	
	$\Delta \ln(\text{House prices } (-1))$	0.0219 ***	3.9541
		(0.0055)	
	$\Delta \ln(\text{House prices } (-2))$	0.0233 ***	4.1222
		(0.0056)	
8	$\Delta \ln(\text{House prices})$	-0.0056	-1.1816
		(0.0047)	
	$\Delta \ln(\text{House prices } (-1))$	0.0222 ***	3.2995
		(0.0067)	
	$\Delta \ln(\text{House prices } (-2))$	0.0208 **	3.1598
		(0.0066)	
9	$\Delta \ln(\text{House prices})$	-0.0142 ***	-4.0401
		(0.0035)	
	$\Delta \ln(\text{House prices } (-1))$	0.0222 ***	4.392
		(0.0051)	
	$\Delta \ln(\text{House prices } (-2))$	0.0187 ***	3.9706
		(0.0047)	
10	$\Delta \ln(\text{House prices})$	-0.0248 ***	-5.2413
		(0.0047)	
	$\Delta \ln(\text{House prices } (-1))$	0.0219 ***	3.9541
		(0.0055)	
	$\Delta \ln(\text{House prices } (-2))$	0.0233 ***	4.1222
		(0.0056)	
11	$\Delta \ln(\text{House prices})$	-0.0056	-1.1816

Model	Variable	Coefficient	t-statistic
		(0.0047)	
	$\Delta \ln(\text{House prices } (-1))$	0.0222 ***	3.2995
		(0.0067)	
	$\Delta \ln(\text{House prices } (-2))$	0.0208 **	3.1598
		(0.0066)	
12	$\Delta \ln(\text{House prices})$	-0.0284 ***	-7.5343
		(0.0038)	
	$\Delta \ln(\text{House prices } (-1))$	0.0214 ***	5.1561
		(0.0042)	
	$\Delta \ln(\text{House prices } (-2))$	0.0218 ***	5.2506
		(0.0042)	
13	$\Delta \ln(\text{House prices})$	-0.0153 ***	-3.2894
		(0.0046)	
	$\Delta \ln(\text{House prices } (-1))$	0.0132 **	2.3739
		(0.0056)	
	$\Delta \ln(\text{House prices } (-2))$		
14	$\Delta \ln(\text{House prices})$	-0.0068	-1.1518
		(0.0059)	
	$\Delta \ln(\text{House prices } (-1))$	0.0175 **	2.223
		(0.0079)	
	$\Delta \ln(\text{House prices } (-2))$	0.0197 **	2.6356
		(0.0075)	
15	$\Delta \ln(\text{House prices})$	-0.0068	-1.6629
		(0.0041)	
	$\Delta \ln(\text{House prices } (-1))$	0.0219 ***	3.503
		(0.0063)	
	$\Delta \ln(\text{House prices } (-2))$	0.0212 ***	3.4897
		(0.0061)	
16	$\Delta \ln(\text{House prices})$	-0.014 ***	-3.6318
		(0.0039)	
	$\Delta \ln(\text{House prices } (-1))$	0.022 ***	3.9429

Model	Variable	Coefficient	t-statistic
		(0.0056)	
	$\Delta \ln(\text{House prices } (-2))$	0.0196 ***	3.7058
		(0.0053)	
17	$\Delta \ln(\text{House prices})$	-0.0299 ***	-5.5835
		(0.0054)	
	$\Delta \ln(\text{House prices } (-1))$	0.0214 ***	3.7239
		(0.0058)	
	$\Delta \ln(\text{House prices } (-2))$	0.0246 ***	4.08
		(0.006)	
18	$\Delta \ln(\text{House prices})$	-0.0069	-1.4643
		(0.0047)	
	$\Delta \ln(\text{House prices } (-1))$	0.0222 ***	3.2886
		(0.0068)	
	$\Delta \ln(\text{House prices } (-2))$	0.0212 ***	3.1864
		(0.0066)	
21	$\Delta \ln(\text{House prices})$	-0.0075 *	-1.8146
		(0.0041)	
	$\Delta \ln(\text{House prices } (-1))$	0.0219 ***	3.4836
		(0.0063)	
	$\Delta \ln(\text{House prices } (-2))$	0.0212 ***	3.4734
		(0.0061)	
22	$\Delta \ln(\text{House prices})$	-0.0093	-1.5518
		(0.006)	
	$\Delta \ln(\text{House prices } (-1))$	0.0172 **	2.1836
		(0.0079)	
	$\Delta \ln(\text{House prices } (-2))$	0.0199 **	2.6346
		(0.0075)	

Note: See notes for Table O-1. Additionally, models where house prices only have a contemporaneous relationship with wealth inequality (model 19, 20 and 23) are omitted as they do not appear in the ECM.