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Abstract

Using around one million repeat sales observations of single-family homes across New Zealand, over the period 1992 to 2021, we provide evidence that idiosyncratic risk in real house price appreciation varies considerably across houses. We find that idiosyncratic risk is time varying, depends negatively on the initial house price, varies strongly across locations and reduces significantly as the holding period of the house increases. Location is the most important of these factors. By buying an above the median house in a low-risk region, and holding on to the property for a longer period, households can significantly reduce idiosyncratic risk.

Keywords: idiosyncratic risk, house prices, housing markets
JEL classifications: G1, R1

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1 Introduction

House price appreciation is not homogeneous. In fact, evidence suggests very heterogeneous appreciation rates across houses. Case and Shiller (1989) report that annual house price appreciation has a standard deviation of close to 15 percent for individual houses and go on to argue that home-owners should not expect to realize capital gains measured by house price indices. Home-owners typically own only one house, the family home, and therefore carry a considerable idiosyncratic risk on housing. Although the family home has by far the largest weight in many household's investment portfolio (OECD, 2021), surprisingly little is known about how idiosyncratic risk in real house price appreciation varies across individual houses. This is unfortunate, because knowledge of the level and variation of idiosyncratic risk of housing investment is definitely important as it cannot be easily diversified away, contrary to, say, a stock portfolio which diversifies away the idiosyncratic risk of individual stocks. If certain houses carry higher idiosyncratic risk, households clearly would want to know,[1] since households *choose* which house to buy. Households clearly decide *where* to buy, *what* house to buy, *when* to buy and *how long* to hold the house before resale. Does idiosyncratic risk vary along those dimensions?

In this paper, we provide empirical evidence on the variation of idiosyncratic risk of house price appreciation across time, location, initial price of the house and holding period. These are four dimensions on which households choose and so knowing whether idiosyncratic risk varies along those dimensions is important. We use around one million repeat sales observations in the New Zealand housing market over the period 1992-2021 to estimate idiosyncratic risk. To estimate how idiosyncratic risk varies across those four dimensions we extend the repeat sales model of house price changes of Landvoigt et al. (2015).

Landvoigt et al. (2015) consider a log-linear regression model of annual price changes of individual houses. In the model, annual house price appreciation is a function of annual time dummies (measuring the annual average increase in house prices), the current price of the house and an idiosyncratic shock $\varepsilon_{i,t}$. Idiosyncratic risk is measured by the standard deviation of the

[1] Others, such as mortgage lenders, should also be interested: in case of default, the recovery amount would depend on the idiosyncratic risk.

shock. It measures how much individual house annual price appreciation is expected to deviate from the average annual appreciation. Landvoigt et al. (2015) allow this standard deviation, i.e. idiosyncratic risk to vary across time. They estimate the model using repeat sales data from San Diego county and thus obtain a yearly estimate of idiosyncratic risk. They show that idiosyncratic risk in the San Diego housing market is indeed time varying and quite large. It varies between 8 percent and 13.8 percent depending on the year.

To investigate the variation of idiosyncratic risk, we extend the model in a number of directions. First, we have information on house features (such as bedrooms, bathrooms, garages and floor area). This allows us to control for house remodelling changes in the regression. This is important as variation in house price appreciation due to remodeling of the house could affect the estimated magnitude of idiosyncratic risk. This argument has been made recently by Giacoletti (2021) who controls for major remodelling investments when estimating idiosyncratic risk in the California housing market. We find that indeed remodelling increases the average rate of appreciation of house prices but that controlling for remodelling has only limited effects on our estimates of idiosyncratic risk. Second, we allow the house price appreciation to vary across 16 different regional markets in New Zealand. Average house price appreciation does vary across regions but is highly correlated. Third, we allow idiosyncratic risk to vary in the four dimensions of time, location, initial house price and holding period.

We find considerable variation in idiosyncratic risk across houses in New Zealand in all four dimensions. First, we find that idiosyncratic risk varies across time. For example, a median priced house in Auckland (held for a period of 5 years) has an idiosyncratic risk that varies between 9.47 percent (in 2006) to 12.66 percent (in 2002). Interestingly, Auckland and San Diego are 6500 miles apart but have similar levels of magnitude of idiosyncratic risk in their housing markets. Second, we show large regional differences in idiosyncratic risk across New Zealand. Moving away from the Auckland region (which includes the largest city) to Nelson (situated in the North of the South Island) households are able to reduce idiosyncratic risk by as much as 26 percent. Equally, moving from Auckland to the West Coast of the South Island increases idiosyncratic risk by 24 percent. These results show that location is an important factor driving differences in the level of idiosyncratic risk in housing. Third, we find that households can reduce idiosyncratic risk by buying a house higher up in the price distribution. Landvoigt et al. (2015) argue that the price of the house is a reasonable summary indicator of quality. Our results therefore indicate that cheaper houses or houses of lower quality are more risky. A house at the 10th percentile of the house price distribution has a 7 percent higher idiosyncratic risk than a house at the median. A house at the 90th percentile of the price distribution has a 7 percent lower risk than a house at the median. Fourth, we find that holding the house for a longer period reduces idiosyncratic risk. The housing market in New Zealand is very active and houses are typically held for only a short period. The median holding period is 5 years. Each additional year the house is kept reduces the idiosyncratic risk by around 2.3 percent. This is consistent with recent findings in Giacoletti (2021) for the Californian housing market.

Our study broadens our understanding of the nature and the importance of idiosyncratic risk and the potential of households to mitigate such risk. A large part of the literature on housing return and risk ignores the idiosyncratic risk of an individual home-owner. Indices of house prices, not individual house prices, are typically used to calculate historical risk and return in housing markets. For instance, Jorda et al. (2019) ignores idiosyncratic risk when arguing that over long periods of time residential real estate has been the best long-run investment with returns around the same level of equity, but with much lower volatility. It is well known that house price capital gains vary across location; however, idiosyncratic risk is often omitted from studies that investigate geographical variation in risk and return. Sinai (2009) documents widely varying volatility of housing markets across metropolitan areas in the US, using house price indices at the metropolitan level but stays silent on the idiosyncratic risk of an individual home-owner within a metropolitan area. Han (2013) uses metropolitan statistical level repeat sales house price indices to investigate the relationship between expected return and risk in housing markets in the US. Cannon et al. (2006) argue that broad metropolitan area indices may be misleading for investors as an indicator of capital appreciation or risk and investigate house price risk and return at the ZIP code level but falls short of using individual house price data.

Our paper uses individual house price data and builds on a growing literature that uses repeat sales data and considers idiosyncratic risk in house prices. The idea that house price indices are misleading indicators of the return and risk of individual houses goes back at least as far as the early work on repeat sales price indices by Case and Shiller (1987). Case and Shiller (1989) show that the magnitude of the idiosyncratic risk is high.[2] In another seminal paper, Goetzmann (1993) using results from Case and Shiller (1987) compares risk and return for an individual house versus a portfolio of houses. He finds that a one-year investment in a broad portfolio of houses, even within a single urban market, reduces risk by about half compared to owning a single home. Flavin and Yamashita (2002) consider the risk and return portfolio problem of jointly holding owner-occupied housing, bonds and stocks. Dröes and Hassink (2013) show that idiosyncratic risk is a sizable part of total house price risk. Using repeat sales data for San Diego, Landvoigt et al. (2015) show that idiosyncratic risk varies over time.[3] In a recent paper Giacoletti (2021) shows that in the Californian housing market, idiosyncratic risk decreases when the house is held over a longer period.[4] We add to the literature in a number of ways. First, our paper combines the ideas of time varying idiosyncratic risk in Landvoigt et al. (2015) and risk that varies with the holding period in Giacoletti (2021) with the idea of risk as a function of location and initial price of the house. This allows us to consider the four important ways in which idiosyncratic risk varies and enables us to determine the relative importance of these four factors (time, location, price and holding period). Particularly, comparing a house at the 10th percentile of idiosyncratic risk with a house at the 90th percentile,[5] we find that: 37 percent of the variation in idiosyncratic risk is due to the regional factor, 27 percent is due to the holding period factor, 21 percent is due to the time variation and 15 percent is due to the initial price variation. Location is the most important factor driving the variation in idiosyncratic risk. Second, we provide an analysis of idiosyncratic risk across an entire country, not just one sub-market. Third, we provide estimates of idiosyncratic risk over a long period.

The rest of the paper is structured as following. In section 2 we describe the data. In section

[2] Case and Shiller (1989) report that annual house price appreciation has a standard deviation of close to 15 percent for individual house prices.

[3] Landvoigt et al. (2015) estimate idiosyncratic volatility of individual house price changes in San Diego to be 8 percent in 2003 and rising to 13.8 percent in the housing bust of 2007.

[4] Giacoletti (2021) finds levels of individual house price volatility of around 8.6 percent annually for houses held over a five-year holding period, dropping to below 7 percent when a house is held longer than 15 years.

[5] In absolute terms this corresponds to an increase in idiosyncratic risk from 5.5 percent to 15.2 percent.

3 we present our model followed by results in section 4. Section 5 concludes.

2 Data

2.1 Data source

We obtained individual house sale transactions data from the Real Estate Institute of New Zealand (REINZ). REINZ is a membership organisation representing more than 14,000 real estate professionals in New Zealand. According to REINZ, more than 90 percent of New Zealand's real estate agents are a member. It collects transactions data from its real estate agent members and it is one of the leading sources of real estate transaction data in New Zealand. Our original dataset contains over 2.4 million home sales transactions and covers the years from 1992 to 2021. Geographically, our dataset covers the entire New Zealand. Individual house sales transactions variables include the basic characteristics of the property, such as the address, number of bedrooms, bathrooms, garages, floor area as well as the sale price and sale date. Each individual property has a unique ID, which we use to identify repeat sales.

New Zealand has a surface area of 268,021 km^2 (about the size of the state of Colorado in the US or a bit larger than the United Kingdom) with a small population of around 5.1 million (estimate 2022) and most people live close to regional city centres. The New Zealand housing market can really be considered as a set of geographically separated markets each centred around a major city. Major cities in New Zealand are quite small in population in international comparison. Geographically, the New Zealand housing market can be divided up into 16 regional markets. The largest housing market in terms of population is the Auckland region (with Auckland city as the main centre) with around 1.4 million inhabitants for the entire region (according to 2013 census). The second largest region is Canterbury with less than 600,000 inhabitants (and Christchurch as the main centre). The third largest region is Wellington, centred around New Zealand's capital (with the same name as the region) with less then 500,000 inhabitants. Six regions in New Zealand have each less than 100,000 inhabitants. For comparison, when estimating idiosyncratic risk, Landvoigt et al. (2015) consider San Diego county as one market. San Diego county has around 3.3 million inhabitants which is twice the population size of the Auckland region in New Zealand.

2.2 Sample

The raw dataset contains 2,445,989 individual house sales observations. We exclude some clear outlying observations. This guards against potential input error in the information about house features. We remove a house sale observation if the house has either nine or more bedrooms, six or more bathrooms, seven or more garages, or a floor area larger than 885 m^2.[6] A total of 8,266 sales observations are removed by this filter.

From this dataset we compile the repeat sales, i.e., observations of the same house sold at least twice over different years. Repeated sales that occur within the same year are averaged into a single observation. This leaves us with a total of 1,065,782 repeated sales transactions on 585,242 houses. We then calculate the house price real appreciation between repeat sales. All house prices used in our calculations are in real terms. We convert nominal prices to real prices using the New Zealand consumer price index, taking 2021 as the base year. Finally, we exclude observations with absolute annualized capital gain greater than 50 percent. This leaves us with a final sample of 1,058,391 repeat sales observations on 583,561 houses.[7] The average annualized capital gain is 5.52 percent. The standard deviation is 8.20 percent, showing indeed a large heterogeneity in the capital gains among home-owners.

We use five variables to control for remodelling changes: number of bedrooms, number of bathrooms, number of garages, floor area, and whether there was a construction of a new dwelling on the property. Unfortunately, for a substantial number of sale observations, there is some missing information on the house features.[8] As we do not want to throw away data, we construct four different samples for our analysis. In our first sample we keep all 1,058,391 repeat sales observations on 583,561 houses. This sample provides our baseline estimates. In these baseline estimates, we treat missing values in the house features as no remodelling change for those features. The effect of this assumption is that some actual remodelling changes are not captured in our baseline estimates. This does have some small upward effect on the id-

[6]These cut-off values are obtained as the top 0.1 percent available values for each variable.
[7]Table A.1 in the Appendix presents the number of observations by region.
[8]Table A.2 in the Appendix presents the summary statistics of these variables.

iosyncratic risk estimates. In a second sample we exclude all house sale observations where the record shows that a new dwelling was built on the property. We do this to avoid comparing an older building with an entire new building. This sample has 1,026,613 repeat sales, somewhat reduced from our first sample, where we simply control for new dwellings in the regression with a dummy variable. In our third sample we exclude all observations where some features of the house is missing. This greatly reduces our sample size, which still remains at a substantial 522,616 observations. In our fourth sample, we exclude all repeat sales that are less than 2 years apart. This sample therefore excludes houses that are bought for quick 'flipping' purposes.

3 Model and Estimation

To analyse idiosyncratic risk, we estimate the model of annual house price changes of Landvoigt et al. (2015). In this model, idiosyncratic risk is time-varying. We extend the model in three dimensions. First, we account for regional differences in annual average price changes. This extension accounts for the fact that location factors determine average price appreciation. Second, we account for the effect of remodelling on house price appreciation. This extension allows us to control for changes in house features that will affect realized capital gains. Third, we allow the variance of the idiosyncratic shocks to depend on location, the initial house price (measured as a deviation from the regional median price) and the holding period. This extension allows us to analyze three other dimensions (beside time) in which idiosyncratic risk might vary.

The model is estimated in two stages. The first stage focuses on house price changes. The residuals from the first stage are then used in a second stage to obtain estimates of the variance of idiosyncratic shocks.

3.1 Model of Price Changes

Letting $p_{i,t}$ denote the (log) price of a house i in year t, and $X_{i,t} = [x_{1,i,t}, ..., x_{F,i,t}]'$ denote the change in a set of F house features for house i between periods t and $t+1$, the price change of house i between year t and $t+1$ is given by

$$p_{i,t+1} - p_{i,t} = \alpha_{r,t} + \beta_t(p_{i,t} - \widetilde{p}_{r,t}) + \Psi X_{i,t} + \varepsilon_{i,t}, \qquad (1)$$

where $\varepsilon_{i,t}$ represents idiosyncratic shocks with mean zero, $\alpha_{r,t}$ captures the expected price change that is common for all houses in region r, β_t captures the effect of the house price deviation from the regional median, $\widetilde{p}_{r,t}$, on its expected price change, and $\Psi = [\psi_1, ..., \psi_F]$ is a set of coefficients that capture the (average) effect of changes in the corresponding house features on the expected price appreciation of the house.[9] The coefficients β_t affect the evolution of the distribution of price changes across house quality. Namely, $\beta_t < 0$ implies that prices of initially cheaper houses will, on average, have higher price appreciation than more expensive houses, i.e., there is convergence of house prices towards the regional median between periods t and $t+1$. In contrast, if $\beta_t > 0$ the distribution of house prices is diverging as initially cheaper houses are expected to appreciate less than more expensive houses.

In order to capture the dynamics of the distribution of house prices the relevant coefficients of model (1) are time dependent. Therefore, the model identification comes from the cross section variation of house prices and capital gains observed from the repeat sales data. To avoid selection bias, estimates of these coefficients are obtained from all repeat sales simultaneously. Namely, the estimated coefficients $\alpha_{r,t}$ and β_t reflect any repeat sale that brackets the year t. In contrast, the effect of changes in house features, captured by Ψ, is assumed constant over time. In spite of having assumed a time independent effect on price appreciation, the effect of changes in house features for repeat sales extending over multiple periods need to be compounded with the differential effects of initial house price. Given that the state of house features is only observed when the house is sold, an assumption regarding the evolution of changes between repeat sales is required. Here we assume that such changing house features evolved according to a simple average in the (unobserved) periods between repeat sales.

Under these assumptions, estimation of model (1) with repeat sales data is achieved by extending the model to a system of non-linear equations covering all possible pairs of repeat

[9] Landvoigt et al. (2015) do not subtract the regional median $\widetilde{p}_{r,t}$ from the price of the house as they only estimate their model on one region. We introduce this useful re-scaling to aid in interpreting the regional coefficients $\alpha_{r,t}$. These represent the average price change in region r of the median priced house with no remodelling changes.

sales observed in the sample. Specifically, compounding of (1) provides a model for the capital gain over k periods given by

$$p_{i,t+k} - p_{i,t} = a_{r,t,k} + b_{t,k} p_{i,t} - c_{t,k} + d_{t,k} \Psi X_{i,t} + e_{i,t,k}, \tag{2}$$

where $a_{r,t,k}$, $b_{t,k}$ and $d_{t,k}$ are functions of the parameters of equation (1), $c_{t,k}$ is a composite of median regional prices, $\widetilde{p}_{r,t}$, and $e_{i,t,k}$ is also a composite of the original idiosyncratic shocks, $\varepsilon_{i,t}$. Specifically, it can be shown that the parameters and error term of equation (2) evolve with the repeat sale interval ($k > 1$) according to

$$a_{r,t,k} = a_{r,t,k-1} \left(1 + \beta_{t+k-1}\right) + \alpha_{r,t+k-1}, \tag{3}$$

$$b_{t,k} = b_{t,k-1} \left(1 + \beta_{t+k-1}\right) + \beta_{t+k-1}, \tag{4}$$

$$c_{t,k} = c_{t,k-1} \left(1 + \beta_{t+k-1}\right) + \beta_{t+k-1} \widetilde{p}_{r,t+k-1}, \tag{5}$$

$$d_{t,k} = d_{t,k-1} \left(1 + \beta_{t+k-1}\right) + 1, \tag{6}$$

$$e_{i,t,k} = e_{i,t,k-1} \left(1 + \beta_{t+k-1}\right) + \varepsilon_{i,t+k-1}, \tag{7}$$

where the recursions depart from $a_{r,t,1} = \alpha_{r,t}$, $b_{t,1} = \beta_t$, $c_{t,1} = \beta_t \widetilde{p}_{r,t}$, $d_{t,1} = 1$, and $e_{i,t,1} = \varepsilon_{i,t}$.

The coefficients $\alpha_{r,t}$, β_t and Ψ can be estimated from repeat sales data using non-linear estimation methods on the system of equations characterized by one equation (2) for each possible pair of repeat sale periods, and the restrictions imposed by equations (3)-(6). Note the number of equations in this system grows with the number of periods in the sample (T) according to the binomial coefficient formula, $T!/(T-2)!2$. The parameters of the model of price changes are estimated using non-linear least squares in two steps. In the first step, every equation in the system is weighted equally. In the second step, each equation is weighted by the inverse of the variance of their residuals from the first step of estimation.

3.2 Variances of Idiosyncratic Shocks

We are interested in estimates of the idiosyncratic risk that is associated with housing investment. In our repeat sales model, such measure is captured by the variance of the idiosyncratic shocks, $\varepsilon_{i,t}$. As in Landvoigt et al. (2015), we allow this variance to change over time and assume they are independently distributed as a normal distribution across houses each period. However, we also extend our model to allow the idiosyncratic risk to depend on three additional factors: (i) the region where the house is located; (ii) the initial price of the house; and, (iii) the holding period between the house's repeat sales.

To be precise, the idiosyncratic shocks are estimated as a zero mean normal random variable with variance given by

$$\sigma_{\varepsilon,t}^2(\ddot{p},k,r) = \exp(\phi_r + \delta\ddot{p} + \rho(k-1))\,\sigma_t^2, \tag{8}$$

where $\ddot{p}$ stands for the initial house price deviation from the regional median (in logs), ϕ_r captures regional differences in idiosyncratic risk, δ regulates the sensitivity of idiosyncratic risk to the initial house price deviation from the regional median, and ρ captures the effect of the holding period, given by k as the number of years between repeat sales of the same house. The set of parameters $\phi_r, \delta, \rho, \sigma_t^2$ determine the (expected) idiosyncratic risk of an individual house, at a particular location, initial price and holding period, in a particular year.

Under these assumptions, the parameters underlying the variances of the idiosyncratic shocks are estimated using maximum likelihood on the residuals from the system of multi-period repeat sales equations defined above. Specifically, assuming $\varepsilon_{i,t} \sim N\left(0, \sigma_{\varepsilon,t}^2\right)$, it follows from (7) that $e_{i,t,k} \sim N\left(0, \sigma_{e,t,k}^2\right)$, where $\sigma_{e,t,k}^2 = \sigma_{\varepsilon,t}^2$, for $k=1$, and

$$\sigma_{e,t,k}^2 = \sum_{h=0}^{k-1} \sigma_{\varepsilon,t+h}^2 \prod_{l=h+1}^{k} (1+\beta_{t+l})^2, \tag{9}$$

for $k>1$. Under normality, the corresponding log likelihood function for the sample of N estimated residuals is given by[10]

$$\ln LF\left(\left\{\sigma_{e,t,k}^2\right\}\right) = -\frac{N}{2}\ln 2\pi - \frac{1}{2}\sum_{i=1}^{N}\ln\sigma_{e,t_i,k_i}^2 - \frac{1}{2}\sum_{i=1}^{N}\frac{e_{i,t,k}^2}{\sigma_{e,t_i,k_i}^2}. \tag{10}$$

Estimates of $\sigma_{\varepsilon,t}^2$ can be obtained by maximizing (10), using (9) to expand $\sigma_{e,t,k}^2$ in terms of

[10] A slight abuse of notation here, where we let i index for the repeat sale observation, and t_i and k_i stand for observation i's period t and repeat sale interval k, respectively.

$\sigma^2_{\varepsilon,t}$. To account for potential heteroskedasticity coming from regional variation, the initial house price, and holding period, the variance of the idiosyncratic shocks can be estimated by setting $\sigma^2_{\varepsilon,t}$ according to (8). This only adds two plus the number of regions in terms of parameters (δ, ρ, and ϕ_r) to the estimation of $\sigma^2_{\varepsilon,t}$, and a re-scaling of $\sigma^2_{e,t,k}$ in equation (9) by $\exp(\phi_r + \delta \ddot{p} + \rho(k-1))$.

4 Results

In this section, we present the estimation results of our extended model. We estimate the model on our main sample of 1.06 million observations and re-estimate it on the three other samples to check for robustness. Our main interest is in the idiosyncratic risk $\sigma_{\varepsilon,t}(\ddot{p},k,r)$.[11]

We first discuss the estimates of Ψ, which determine the effects of our controls for remodelling. Table 1 shows the effect of remodelling on annual price appreciation. The positive and significant coefficient estimates show, unsurprisingly, that adding bedrooms, bathrooms, or garages increases the value of the house. So does adding a new dwelling. Similarly does adding floor space. For instance, adding one bedroom increases the value of the house by around 6.5 percent, while adding a bathroom adds around 1.5 percent to the value of the house. The results are quite robust across the different samples.

Figure 1 shows how idiosyncratic risk varies over time and across region, i.e. it shows $\sigma_{\varepsilon,t}(\ddot{p},k,r)$ for each region r, for a median priced house that is held for five years (so $\ddot{p}=0$ and $k=5$) for each of the years 1992 to 2020.[12] We use a holding period of five years as this is the median holding period for houses in New Zealand. Estimates of σ_t and ϕ_r which determine the regional shifts in idiosyncratic risk are in the Appendix (see Table B.2 and Table B.3). Figure 1 shows that idiosyncratic risk varies over time. It was relatively high in 1992 at the start of our sample, then gradually dropped until 1998. It rose again to reach a high in 2002, after which it dropped again until 2006. It rose in 2007, however between 2008 and 2018 it was relatively stable. Interestingly, during the Covid years of 2019 and 2020 idiosyncratic risk

[11] Figure C.1 in the Appendix shows the coefficient estimates of the regional time dummies $\alpha_{r,t}$ which determine the time varying annual average price appreciation. Figure C.2 in the Appendix shows the coefficient estimates of β_t in Equation 1.

[12] Estimates shown are those obtained using the full sample.

Table 1: Model estimates.

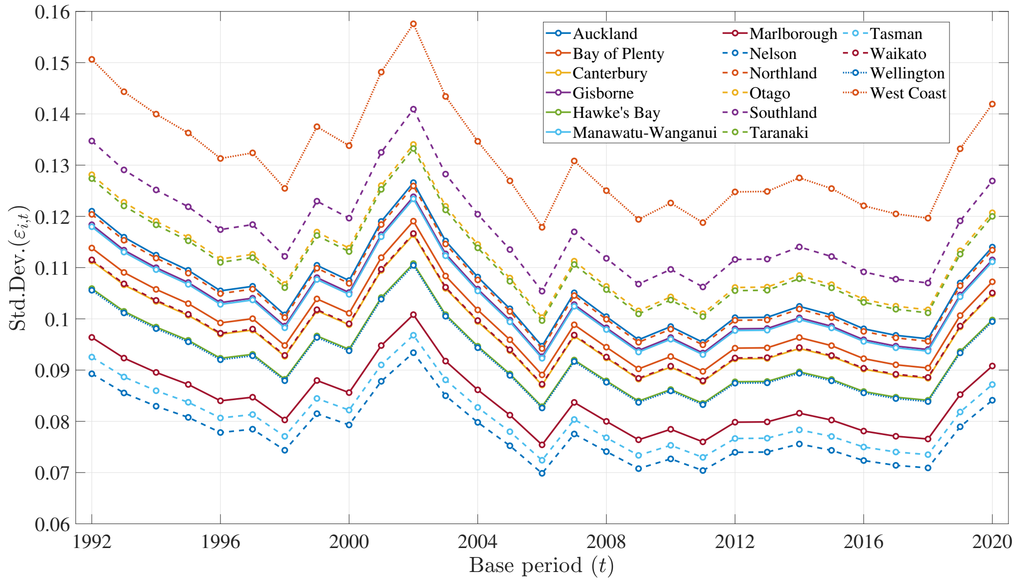
	(1)	(2)	(3)	(4)
Elasticity estimates:				
Bedrooms	6.515	6.446	6.092	7.331
	(0.061)	(0.062)	(0.081)	(0.069)
Bathrooms	1.467	1.477	1.284	1.574
	(0.082)	(0.082)	(0.085)	(0.097)
Garages	0.637	0.645	0.331	0.666
	(0.050)	(0.049)	(0.058)	(0.053)
Floor area	0.539	0.531	0.545	0.587
($25m^2$)	(0.029)	(0.030)	(0.035)	(0.032)
New dwelling	2.402		2.834	1.925
	(0.125)		(0.172)	(0.157)
Variance parameter estimates:				
Initial price deviation, $\hat{\delta}$	-0.252	-0.259	-0.300	-0.248
	(0.007)	(0.007)	(0.010)	(0.007)
Holding period, $\hat{\rho}$	-0.046	-0.045	-0.050	-0.038
	(0.001)	(0.001)	(0.001)	(0.001)
Sample	All	Excluding new dwelling	Excluding missing	Excluding hold < 2 years
R-squared (equation 1)	0.760	0.761	0.776	0.773
Avg. log likelihood (equation 8)	0.189	0.193	0.257	0.142
N. Obs.	1,058,391	1,026,613	522,616	947,089

Notes: Elasticity estimates are estimates of Ψ from equation 1. These can be interpreted in terms of annualized (log) capital returns. Variance parameter estimates are estimates of δ and ρ from equation 8. The complete set of estimates of $\alpha_{r,t}$ and β_t, and estimates of ϕ_r and σ_t^2, are reported in the Appendix. Robust standard errors are presented between brackets. All estimates are statistically significant at the 1% significance level.

rose significantly (by more than 1 percentage point in 2019 and around 0.8 percentage point in 2020). All in all however, the time-variation of idiosyncratic risk is within limits. For instance, for a median priced house in Auckland and a holding period of five year, idiosyncratic risk varied from a low of 9.47 percent (2006) to a high of 12.66 percent (2002). This represents a 33.7 percent increase in risk.

Figure 1 also shows the wide regional variation in risk. Our specification assumes that regions vary simultaneously in risk across time. Essentially we have only allowed regions to differ in risk with a shift factor, $exp(\phi_r)$, which is constant over time. Otherwise said, we estimate 29 parameters σ_t^2 (one for each t) and 15 parameters ϕ_r (one for each r). (Shift factors are relative to Auckland, which is the base region with $\phi_r = 0$.) In the Appendix we show results where we estimate regional time varying risk, i.e. 464 estimates $\sigma_{r,t}^2$ (see Figure C.5

Figure 1: Idiosyncratic risk estimates by region.



Notes: These are obtained by maximum likelihood from the residuals of the repeat sales model, assuming the idiosyncratic shocks are distributed as a Normal and iid with variance given by equation 8. The estimates are for a median priced house in the corresponding regions and holding period of five years between repeat sales.

and Figure C.6). The shift factor however explains most of the variation across regions in idiosyncratic risk.

To have a better understanding of how idiosyncratic risk varies in the dimensions of location, initial price deviation from the regional median and holding period, we use the coefficient estimates of our model to calculate and present relative risk factors. The exponential specification of total idiosyncratic risk (see equation 8) allows us to disentangle risk into its different components. The relative risk factors tell us by how much we have to multiply the time varying risk parameter σ_t to obtain the idiosyncratic risk of a particular house at a particular location, initial price deviation from the regional median and holding period. We calculate relative risk factors for location, for initial price deviation from the regional median and for holding period. The total relative risk of a particular house is simply the product of those three relative risk factors.

We first calculate relative risk factors for location using our estimates $\hat{\phi}_r$. We calculate a relative risk factor for each region as $\sqrt{exp(\hat{\phi}_r)}$. Calculated this way, the risk factor tells us the risk relative to the risk in Auckland (which we used as our base). We also calculate and present the absolute idiosyncratic risk, i.e. the standard deviation of the idiosyncratic shocks.

Table 2: Relative and absolute idiosyncratic risk across region

Region	Relative risk*	Absolute risk** pct
Auckland	1.00	11.40
Bay of Plenty	0.94	10.72
Canterbury	0.92	10.49
Gisborne	0.98	11.15
Hawke's Bay	0.88	9.98
Manuwatu-Wanganui	0.97	11.11
Marlborough	0.80	9.08
Nelson	0.74	8.41
Northland	0.99	11.34
Otago	1.06	12.07
Southland	1.11	12.69
Taranaki	1.05	12.00
Tasman	0.76	8.72
Waikato	0.92	10.51
Wellington	0.87	9.95
West Coast	1.24	14.19

Notes: *Relative risk factor $\sqrt{exp(\hat{\phi}_r)}$ (relative to Auckland). **Absolute risk in 2020 of house purchased at regional median price held for 5 years, $\sqrt{exp(\hat{\phi}_r)exp(\hat{\rho}(5-1))\hat{\sigma}_t}$.

Table 2 shows how relative risk and absolute risk differ across regions. The absolute risk is calculated for 2020 for a median priced house (at time of purchase) that is held for 5 years (i.e. the median of holding period in our sample). Table 2 shows that location matters. A household can reduce idiosyncratic risk by 26 percent when deciding to live in Nelson versus Auckland. On the other hand, by moving from Auckland to the West Coast the household will incur an increased risk of 24 percent. Absolute risk (in 2020) varied between 8.41 percent (Nelson) and 14.19 percent (West Coast). Moving from the least risky region to the most risky region increases risk by 68.7 percent. The variation in idiosyncratic risk across regions is therefore much larger than the variation across time discussed earlier. It is interesting to speculate about the driving factors of these regional differences. West Coast, which has the largest idiosyncratic risk, is the region with the lowest population (below 50,000) and the lowest population density (below 2 persons per square km). At the same time, Nelson, the lowest risk region, has the second highest population density (below that of Auckland). A potential driver is therefore market liquidity as suggested in Giacoletti (2021). Given the very low population and low population density in West Coast, market thinness is a potential explanation of why idiosyncratic risk is higher.[13]

We next present results in Table 3 on how idiosyncratic risk is different across the initial price of the house. The relative risk factors of initial price deviation from the median are constructed as $\sqrt{exp(\hat{\delta}\ddot{p})}$, which indicates the risk relative to a house that was bought at the median price. Buying a house at the 10th percentile of the house price distribution increases the risk by 7 percent relative to a median priced house. Similarly, buying a house at the 90th percentile decreases risk by 7 percent.[14] Cheap houses are therefore more risky. This indicates that houses might be more risky for the poor who naturally would buy cheaper houses.

Table 3: Relative risk across initial house price deviation from median price

Percentile*	Deviation from median**	Relative risk***
1	-1.29	1.17
		(0.005)
10	-0.57	1.07
		(0.002)
25	-0.29	1.04
		(0.001)
50	0	1.00
		-
75	0.30	0.96
		(0.001)
90	0.61	0.93
		(0.002)
99	1.34	0.85
		(0.004)

Notes: *Percentiles of the house price distribution. ** Log price deviation from the median, $\ddot{p}$, at given percentiles (average over the period 1992-2021).*** Defined as $\sqrt{exp(\hat{\delta}\ddot{p})}$. Standard errors in parenthesis, constructed using the delta method: S.E. $\left[\sqrt{exp(\hat{\delta}\ddot{p})}\right] = \frac{1}{2}\ddot{p}.exp(0.5\hat{\delta}\ddot{p})\ S.E.\left[\hat{\delta}\right]$

[13]With only 16 regions it is difficult to do any formal econometric analysis due to lack of degrees of freedom. A simple correlation between the absolute risk of each region with the population density is -0.09. Excluding Auckland (which is an outlier with respect to population density) the correlation coefficient becomes -0.50. This is highly suggestive that thinness of markets has a considerable role to play in explaining regional risk differences in the New Zealand context.

[14]Figure C.4 in the Appendix depicts the effect of different initial house prices across time.

Table 4: Relative risk across holding period (from median holding period)

Percentile*	Holding Period**	Relative risk***
1	1	1.10 (0.002)
11	2	1.07 (0.002)
25	3	1.05 (0.001)
50	5	1.00 –
75	9	0.91 (0.002)
90	14	0.81 (0.004)
99	24	0.65 (0.006)

Notes: *Percentiles of the holding period distribution. ** Holding period (in years). *** Defined as $\sqrt{exp(\hat{\rho}(k-5))}$ with k the holding period. Standard errors in parenthesis, constructed using the delta method: S.E. $\left[\sqrt{exp(\hat{\rho}(k-5))}\right] = 0.5 * abs(k-5).exp(0.5\hat{\rho}(k-5))\ S.E.\left[\hat{\rho}\right]$

The relative risk factor of holding period is calculated as $\sqrt{\exp(\hat{\rho}(k-1)/\exp(\hat{\rho}(5-1))}$, which is $\sqrt{\exp(\hat{\rho}(k-5))}$. It represents the risk relative to a house that was sold after a holding period of 5 years, which is the median holding period in our sample. We estimate ρ to be -0.045. This implies that relative risk drops by about 2.3 percent for every additional year the house is held. Giacoletti (2021) shows that idiosyncratic risk varies across holding period. Houses that are held over longer periods have less idiosyncratic risk. We find this to be also true in New Zealand. A house that is sold after two years of holding has a 7 percent higher risk than a house sold after 5 years. A house sold after 14 years (at the 90th percentile of holding period) has 19 percent less idiosyncratic risk. Figure C.3 in the Appendix depicts the effect of different holding periods across time.

The relative risk factors of location, price and holding period are multiplicative. Therefore judiciously choosing *where* the house is located, at what *price* the house is bought and how long it is *held* can significantly alter the idiosyncratic risk of the house. For instance, relative to purchasing a median-priced house in Auckland (and holding it for 5 years), buying a house in

Nelson, at the 90th percentile of the price distribution and keeping it in ownership for 14 years would have reduced the idiosyncratic risk by 44 percent.[15]

To determine the relative importance of each of the factors in the variation of idiosyncratic risk, we do the following calculation. We calculate the idiosyncratic risk of a house that is at the 10th percentile in all dimensions (of time, region, holding period and initial price) and compare it with a house at the 90th percentile in all dimensions. Due to the multiplicative nature of the relative risk factors of location, initial price and holding period with the time varying average risk, we can calculate the relative contribution of each factor in the increase of risk by buying a house at the 90th percentile versus the 10th percentile. This calculation boils down to calculating the ratio of each of the bracketed terms in $0.5\left[\hat{\phi}_{r90} - \hat{\phi}_{r10}\right] + 0.5\left[\hat{\delta}\ddot{p}_{90} - \hat{\delta}\ddot{p}_{10}\right] + 0.5\left[\hat{\rho}(k_{90}-1) - \hat{\rho}(k_{10}-1)\right] + \left[ln(\sigma_{t90}) - ln(\sigma_{t10})\right]$ to the total sum of bracketed terms, where the subscripts 90 and 10 indicate the 90th and 10th percentile. A house at the 10th percentile has an absolute idiosyncratic risk of 5.5 percent. A house at the 90th percentile has an absolute idiosyncratic risk of 15.2 percent.[16] Calculating the ratio as explained above, this almost tripling of risk is for 37 percent due to the regional factor, for 27 percent due to the holding period factor, for 21 percent due to the time variation and for 15 percent due to the initial price variation. Location is the most important factor driving the variation in idiosyncratic risk, followed by holding period.

5 Conclusion

We estimate idiosyncratic risk of annual house price appreciation using around 1.06 million repeat sales observations in New Zealand from 1992 to 2021. Our estimates show that idiosyncratic risk varies considerably along a number of dimensions. Time, location, initial house price and holding period are all important factors determining the idiosyncratic risk of the house, and location is the most important.

As households choose which house to buy, our results seem to suggest that households

[15] The total relative risk of this house is calculated as 0.74*0.93*0.81.

[16] A house at the 10th percentile of risk is located in Tasman, was bought at a price 84 percent above the median and was held for 14 years and is observed in 2009. A house at the 90th percentile of risk was located in Southland, was bought at a price 44 percent below the median and was held for 2 years and is observed in 2001.

should be able to choose (to some extent) the risk they are facing. An obvious caveat is at its place. Our estimates are ex post. It is unclear to what extent households can know risk ex ante. For example, we don't know if in the next thirty years idiosyncratic risk will still remain shaped as it has in the past. However certain facts seem robust. First, the considerable persistence of our estimates of σ_t^2 suggest that households should expect considerable idiosyncratic risk at all times. Second, certain regions are less risky. Third, holding the house for longer reduces the risk, a result that coincides with findings for the Californian market in Giacoletti (2021). Fourth, buying a higher priced house (i.e. a better quality house) reduces risk. Interestingly this suggests that the households who need to be least shielded from idiosyncratic risk, i.e. the "rich", are likely most protected from it. Poorer households will naturally (have to) buy cheaper houses, with bigger risk.

A number of important questions remain. In particular, why does idiosyncratic risk vary by location so much? And why do cheaper houses have higher risk? We have not delved deeper into more fundamental causes of why idiosyncratic risk varies along those dimensions we observe. We can only tentatively speculate at possible causes but prefer to refrain from it at this stage. Now we have established that idiosyncratic risk varies substantially, a natural follow up is to investigate why it does so. We leave that for future research.

A Supplementary Sample Statistics

Table A.1: Number of observations by region.

Region	N
Auckland	325,677
Bay of Plenty	70,002
Canterbury	140,602
Gisborne	8,897
Hawke's Bay	36,375
Manawatu-Wanganui	60,777
Marlborough	13,655
Nelson	14,361
Northland	25,746
Otago	59,688
Southland	33,020
Taranaki	29,525
Tasman	8,802
Waikato	101,635
Wellington	124,574
West Coast	5,055
Total	1,058,391

Table A.2: Summary statistics of property characteristics.

	Mean	Std. dev.	Min.	Max.	N
Bedrooms	3.064	0.819	1	9	1,054,103
Bathrooms	1.432	0.693	0	6	541,315
Garages	1.464	0.871	0	7	1,026,847
Floor area (m^2)	143.106	65.163	1	885	1,029,021

B Supplementary Results

Table B.1: Model estimates of β_t.

t	(1)	(2)	(3)	(4)
1992	-2.868	-2.896	-2.161	-1.979
	(0.427)	(0.431)	(0.738)	(0.608)
1993	-1.220	-1.182	-0.560	-0.896
	(0.339)	(0.344)	(0.610)	(0.519)
1994	-3.772	-3.713	-3.593	-3.938
	(0.310)	(0.314)	(0.552)	(0.460)
1995	-4.628	-4.619	-4.468	-4.090
	(0.318)	(0.321)	(0.569)	(0.456)
1996	-5.118	-5.045	-4.241	-5.085
	(0.315)	(0.318)	(0.557)	(0.433)
1997	0.631	0.730	0.805	0.705
	(0.358)	(0.363)	(0.619)	(0.462)
1998	1.083	1.083	0.998	1.053
	(0.375)	(0.377)	(0.647)	(0.475)
1999	0.944	0.893	1.281	0.946
	(0.371)	(0.371)	(0.654)	(0.464)
2000	1.363	1.370	0.949	1.216
	(0.346)	(0.346)	(0.607)	(0.445)
2001	0.198	0.101	1.119	-0.047
	(0.285)	(0.285)	(0.491)	(0.382)
2002	-1.969	-1.945	-1.450	-1.449
	(0.222)	(0.223)	(0.383)	(0.333)
2003	-6.793	-6.794	-7.331	-6.929
	(0.190)	(0.191)	(0.306)	(0.303)
2004	-9.002	-9.058	-9.223	-9.304
	(0.188)	(0.190)	(0.295)	(0.296)
2005	-6.984	-7.230	-7.450	-6.375
	(0.206)	(0.210)	(0.313)	(0.316)
2006	-5.366	-5.560	-6.136	-5.043
	(0.235)	(0.241)	(0.333)	(0.331)
2007	0.400	0.461	0.678	0.176
	(0.345)	(0.355)	(0.461)	(0.423)
2008	2.462	2.378	2.878	2.405
	(0.384)	(0.396)	(0.506)	(0.456)
2009	1.493	1.565	1.785	1.420
	(0.377)	(0.390)	(0.518)	(0.440)
2010	0.155	0.132	-0.004	0.047
	(0.382)	(0.395)	(0.507)	(0.450)
2011	-0.525	-0.472	-0.332	-0.566
	(0.350)	(0.364)	(0.438)	(0.423)
2012	-1.007	-0.960	-1.545	-0.947
	(0.322)	(0.338)	(0.392)	(0.397)
2013	-0.796	-0.819	-0.883	-0.694
	(0.308)	(0.326)	(0.369)	(0.397)
2014	-2.612	-2.462	-3.208	-2.630
	(0.302)	(0.318)	(0.359)	(0.395)
2015	-2.969	-2.838	-2.875	-2.844
	(0.283)	(0.294)	(0.344)	(0.372)
2016	-4.034	-4.206	-5.133	-4.064
	(0.308)	(0.311)	(0.374)	(0.394)
2017	-5.459	-5.420	-6.217	-5.536
	(0.336)	(0.336)	(0.387)	(0.424)
2018	-6.822	-6.832	-7.693	-6.675
	(0.352)	(0.352)	(0.393)	(0.442)
2019	-3.261	-3.223	-4.178	-3.227
	(0.395)	(0.395)	(0.422)	(0.509)
2020	-2.288	-2.244	-3.866	-1.761
	(0.453)	(0.453)	(0.477)	(0.591)
Sample	All	Excluding new dwelling	Excluding missing	Excluding hold < 2 years
R-squared	0.760	0.761	0.776	0.773
N. Obs.	1,058,391	1,026,613	522,616	947,089

Notes: These are estimates of β_t from equation 1. Robust standard errors are presented between brackets.

Table B.2: Estimates of variances of idiosyncratic shocks.

t	(1)	(2)	(3)	(4)
1992	1.758 (0.061)	1.704 (0.061)	1.601 (0.091)	1.654 (0.180)
1993	1.614 (0.045)	1.584 (0.045)	1.491 (0.067)	1.525 (0.151)
1994	1.518 (0.039)	1.466 (0.038)	1.414 (0.057)	1.322 (0.121)
1995	1.439 (0.037)	1.396 (0.036)	1.285 (0.055)	1.507 (0.108)
1996	1.336 (0.033)	1.305 (0.032)	1.212 (0.052)	1.123 (0.091)
1997	1.358 (0.036)	1.333 (0.036)	1.247 (0.055)	1.309 (0.091)
1998	1.220 (0.035)	1.193 (0.034)	1.094 (0.052)	1.022 (0.093)
1999	1.465 (0.040)	1.423 (0.040)	1.400 (0.064)	1.401 (0.096)
2000	1.387 (0.038)	1.374 (0.038)	1.323 (0.061)	1.108 (0.101)
2001	1.701 (0.043)	1.676 (0.042)	1.565 (0.064)	1.763 (0.105)
2002	1.924 (0.039)	1.907 (0.039)	1.811 (0.060)	1.858 (0.095)
2003	1.593 (0.029)	1.584 (0.029)	1.485 (0.041)	1.499 (0.083)
2004	1.405 (0.027)	1.378 (0.027)	1.270 (0.037)	1.376 (0.071)
2005	1.248 (0.024)	1.225 (0.024)	1.163 (0.034)	1.183 (0.067)
2006	1.076 (0.022)	1.053 (0.022)	0.969 (0.028)	0.952 (0.063)
2007	1.326 (0.028)	1.292 (0.028)	1.219 (0.035)	1.042 (0.065)
2008	1.211 (0.030)	1.187 (0.030)	1.112 (0.036)	1.175 (0.077)
2009	1.105 (0.032)	1.078 (0.033)	0.969 (0.037)	0.888 (0.084)
2010	1.165 (0.036)	1.155 (0.037)	1.128 (0.042)	1.212 (0.090)
2011	1.093 (0.032)	1.082 (0.033)	1.043 (0.037)	0.858 (0.091)
2012	1.206 (0.033)	1.187 (0.034)	1.156 (0.036)	1.181 (0.085)
2013	1.208 (0.032)	1.183 (0.033)	1.186 (0.035)	1.035 (0.084)
2014	1.260 (0.030)	1.235 (0.030)	1.237 (0.034)	1.203 (0.079)
2015	1.219 (0.027)	1.202 (0.027)	1.227 (0.031)	1.009 (0.071)
2016	1.155 (0.029)	1.136 (0.029)	1.101 (0.034)	1.049 (0.073)
2017	1.125 (0.032)	1.110 (0.031)	1.083 (0.034)	1.086 (0.074)
2018	1.109 (0.031)	1.091 (0.030)	1.096 (0.032)	0.903 (0.073)
2019	1.375 (0.038)	1.359 (0.038)	1.291 (0.036)	1.331 (0.080)
2020	1.561 (0.057)	1.531 (0.056)	1.405 (0.047)	1.542 (0.114)
$\hat{\delta}$	-0.252 (0.007)	-0.259 (0.007)	-0.300 (0.010)	-0.248 (0.007)
$\hat{\rho}$	-0.046 (0.001)	-0.045 (0.001)	-0.050 (0.001)	-0.038 (0.001)
Sample	All	Excluding new dwelling	Excluding missing	Excluding hold < 2 years
Log likelihood (avg.)	0.189	0.193	0.257	0.142
N. Obs.	1,058,391	1,026,613	522,616	947,089

Notes: These are estimates of $\exp(\phi_{Akl})\sigma_t^2$ (scaled by 100x), δ and ρ from equation 8. Note the estimates are scaled to Auckland region; see Table B.3 for the other regions' estimates of ϕ_r. Robust standard errors are presented between brackets.

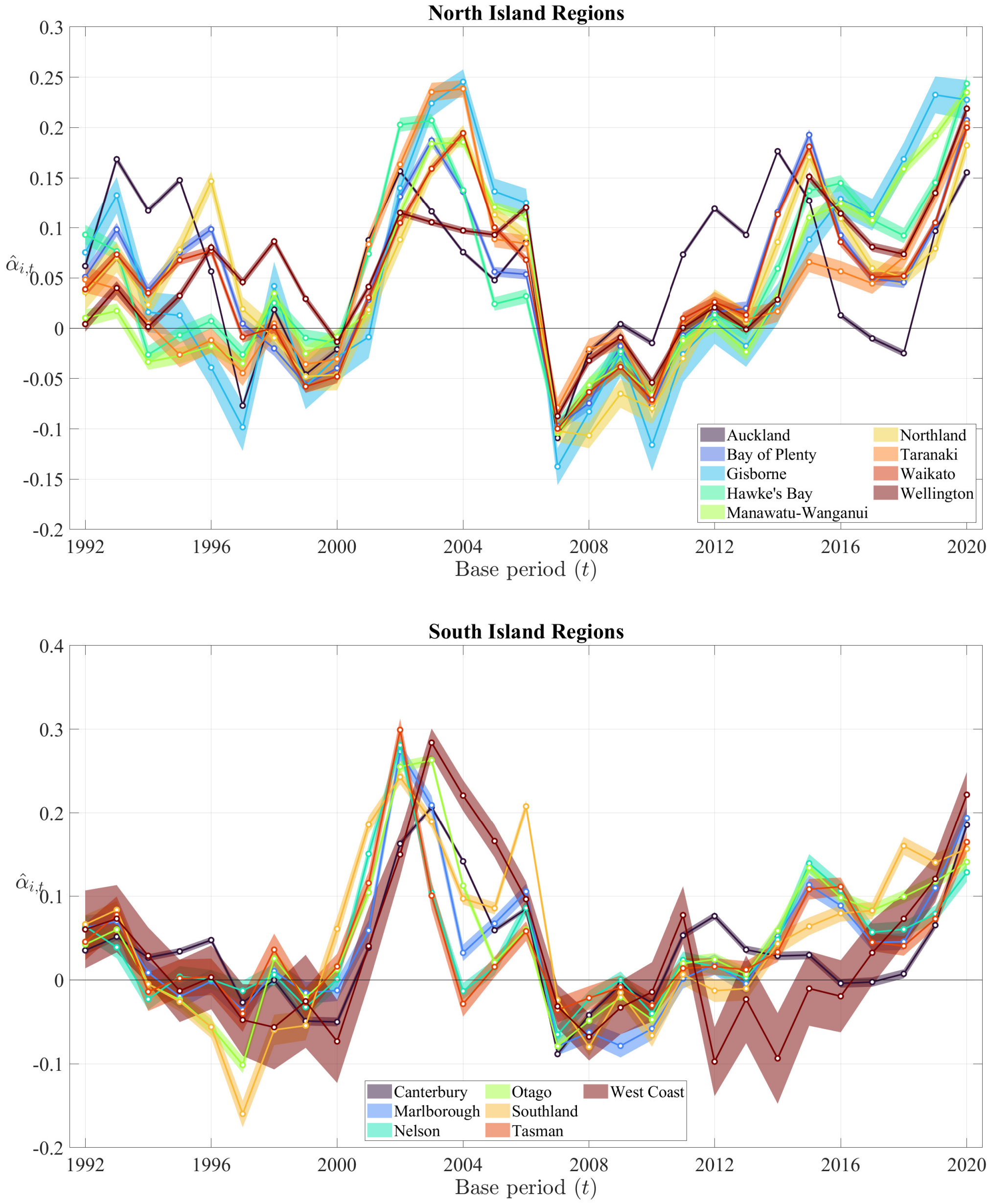
Table B.3: Estimates of regional shifts on variances of idiosyncratic shocks.

Region	(1)	(2)	(3)	(4)
Auckland	0	0	0	0
	–	–	–	–
Bay of Plenty	-0.122	-0.114	-0.101	-0.135
	(0.014)	(0.014)	(0.019)	(0.015)
Canterbury	-0.167	-0.168	-0.084	-0.180
	(0.011)	(0.011)	(0.015)	(0.012)
Gisborne	-0.044	-0.034	-0.057	-0.075
	(0.030)	(0.031)	(0.035)	(0.034)
Hawke's Bay	-0.267	-0.258	-0.220	-0.283
	(0.018)	(0.019)	(0.026)	(0.021)
Manawatu-Wanganui	-0.051	-0.047	-0.032	-0.045
	(0.015)	(0.015)	(0.020)	(0.017)
Marlborough	-0.455	-0.453	-0.454	-0.476
	(0.034)	(0.035)	(0.049)	(0.040)
Nelson	-0.608	-0.599	-0.601	-0.648
	(0.030)	(0.031)	(0.043)	(0.035)
Northland	-0.010	-0.006	-0.175	-0.020
	(0.021)	(0.021)	(0.026)	(0.023)
Otago	0.114	0.120	0.099	0.113
	(0.014)	(0.014)	(0.019)	(0.015)
Southland	0.215	0.216	0.242	0.228
	(0.018)	(0.018)	(0.026)	(0.020)
Taranaki	0.103	0.097	0.014	0.119
	(0.018)	(0.018)	(0.024)	(0.020)
Tasman	-0.536	-0.540	-0.580	-0.539
	(0.042)	(0.042)	(0.055)	(0.046)
Waikato	-0.163	-0.156	-0.211	-0.164
	(0.012)	(0.012)	(0.017)	(0.013)
Wellington	-0.273	-0.268	-0.301	-0.296
	(0.012)	(0.012)	(0.018)	(0.014)
West Coast	0.438	0.440	0.404	0.470
	(0.048)	(0.049)	(0.041)	(0.050)
Sample	All	Excluding new dwelling	Excluding missing	Excluding hold < 2 years
N. Obs.	1,058,391	1,026,613	522,616	947,089

Notes: These are estimates of ϕ_r from equation 8 and taking Auckland as the base of reference. Robust standard errors are presented between brackets.

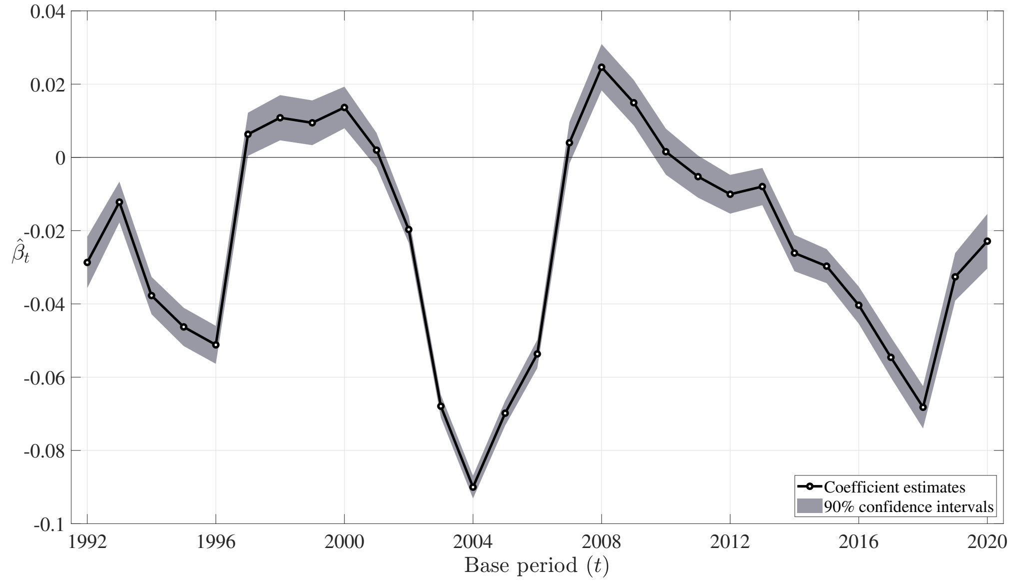
C Additional Figures

Figure C.1: Regional capital gains estimates.



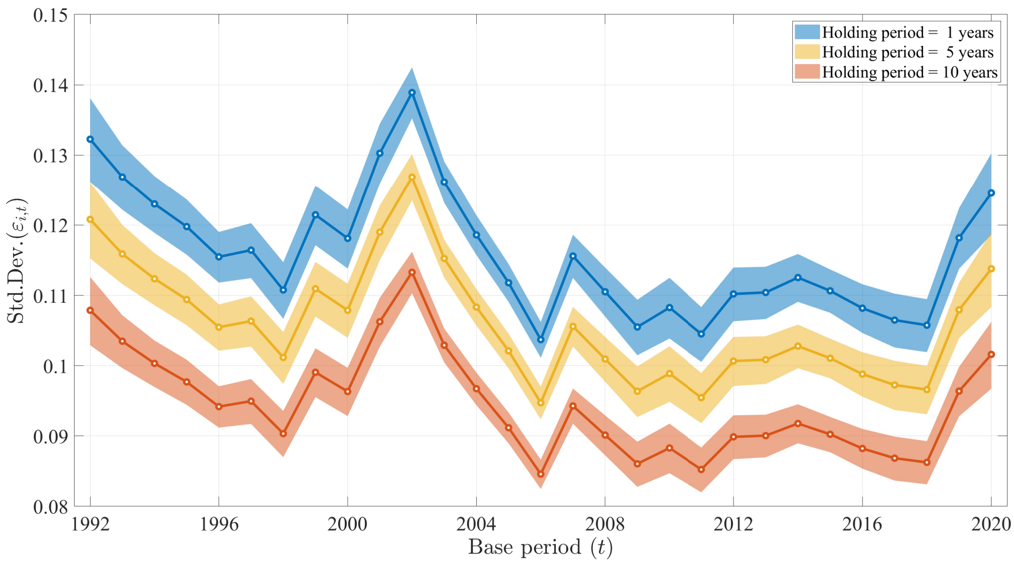
Notes: The lines depict estimates of the average (log) annual capital gains for a median house in the corresponding region. The shaded areas indicate the corresponding 90% confidence intervals.

Figure C.2: Effects of initial house prices on capital gains.



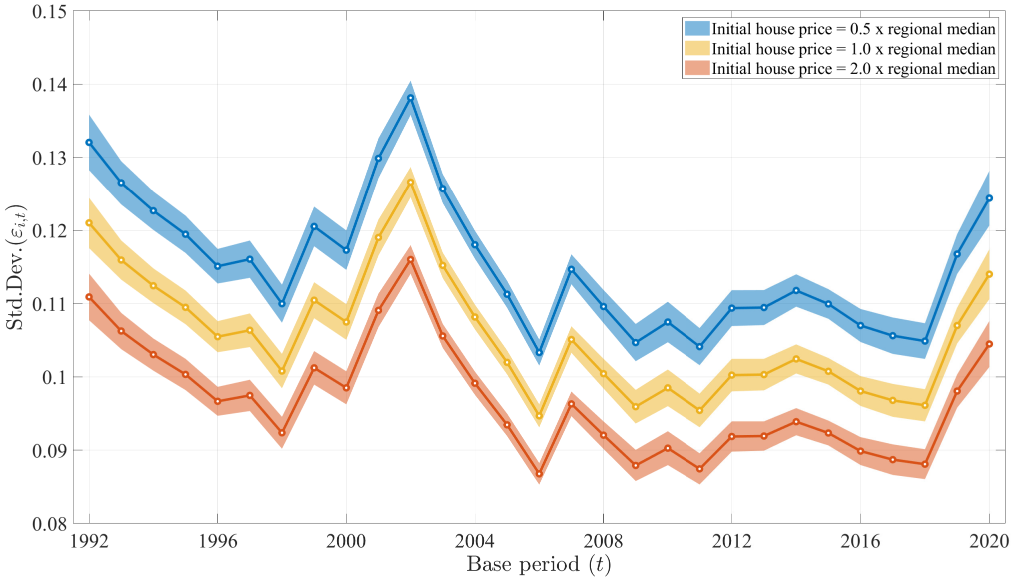
Notes: These capture the effect that the initial price of the house, relative to the regional median house price, has on the average (log) annual capital gains. Negative β means a house cheaper than the median regional house gained more value than the houses that are more expensive than the median. The confidence band is based on robust standard errors.

Figure C.3: Idiosyncratic risk estimates by holding period.



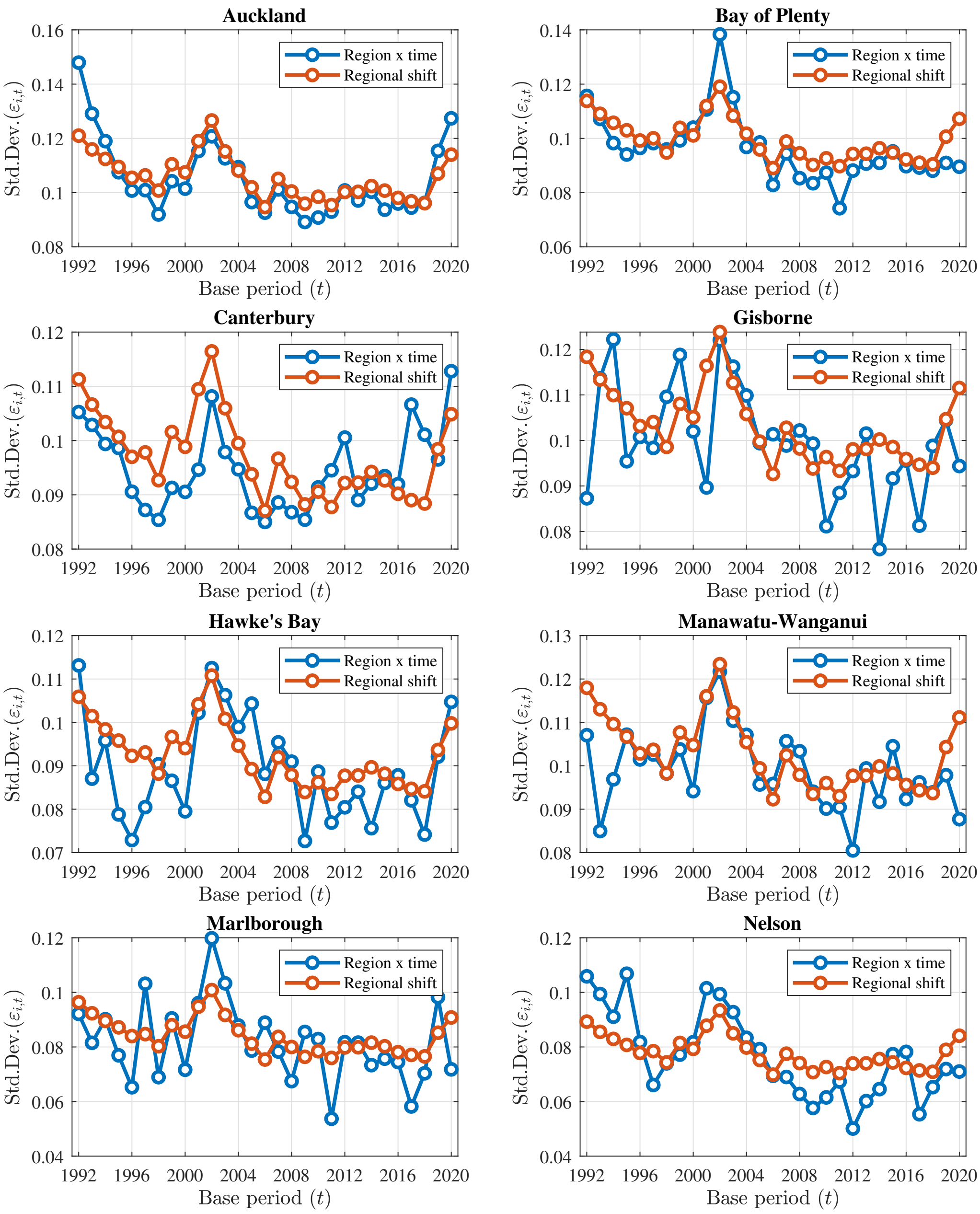
Notes: These are obtained by maximum likelihood from the residuals of the repeat sales model, assuming the idiosyncratic shocks are distributed as a Normal and iid with variance given by equation 8. The estimates are for a median priced house in Auckland Region and a holding period of five years. The confidence bands are based on robust standard errors and calculated at a 90% confidence level.

Figure C.4: Idiosyncratic risk estimates by initial house price.



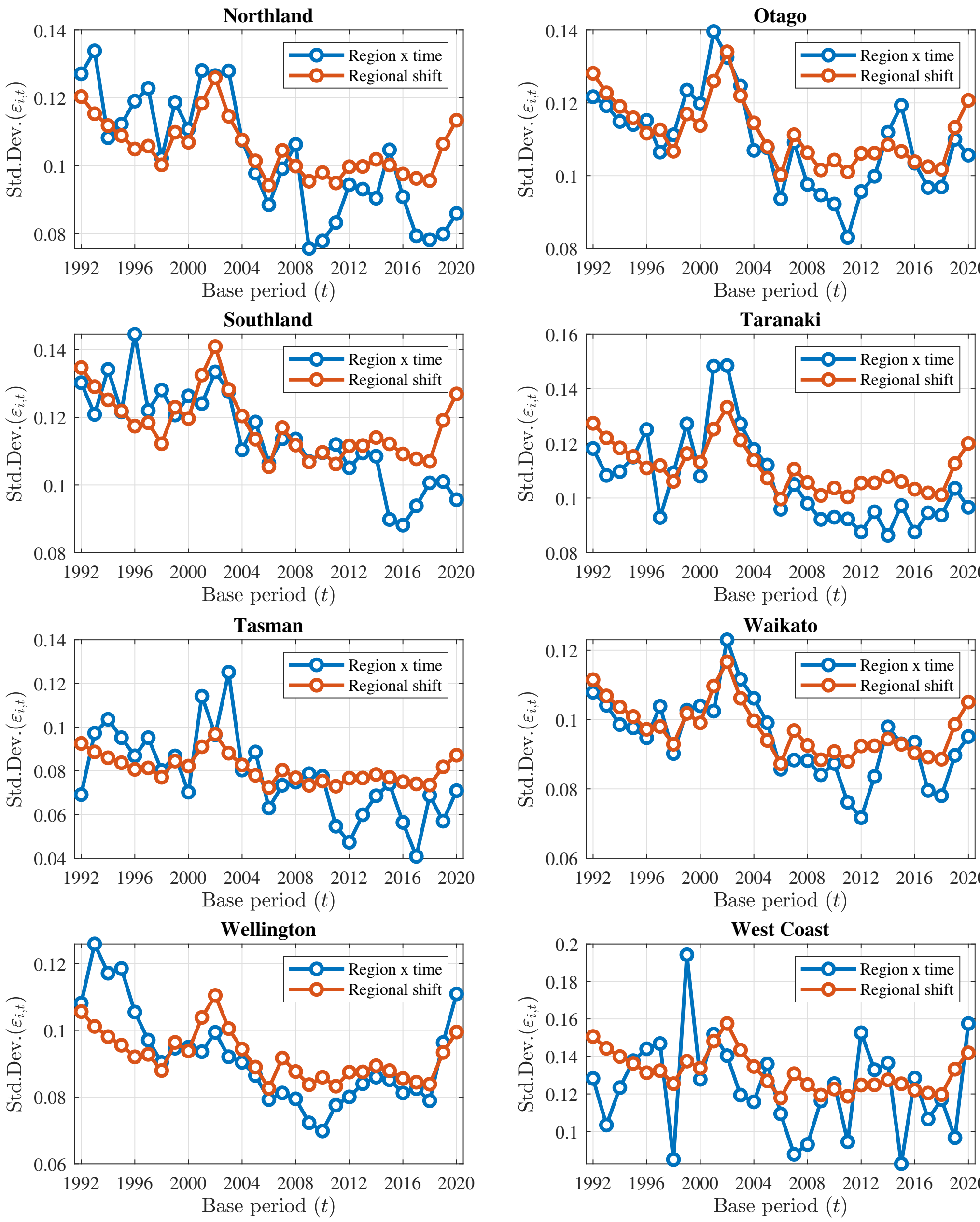
Notes: These are obtained by maximum likelihood from the residuals of the repeat sales model, assuming the idiosyncratic shocks are distributed as a Normal and iid with variance given by equation 8. The estimates account for the effect of the initial house price, relative to the regional median. The estimates are for Auckland Region and holding period of five years between repeat sales. The confidence bands are based on robust standard errors and calculated at a 90% confidence level.

Figure C.5: Comparative of regional risk estimates (1/2).



Notes: The plots compare implied risk estimates for each region allowing for these to vary by region and time (blue lines) versus only by a regional shift (orange).

Figure C.6: Comparative of regional risk estimates (2/2).



Notes: The plots compare implied risk estimates for each region allowing for these to vary by region and time (blue lines) versus only by a regional shift (orange).

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