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Evidence on the determinants and variation of idiosyncratic risk in housing markets

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EVIDENCE ON THE DETERMINANTS AND VARIATION OF IDIOSYNCRATIC RISK IN HOUSING MARKETS

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ABSTRACT

Using around 1 million repeat sales, we show idiosyncratic risk in real house price appreciation is time-varying, depends negatively on the initial house price, varies across locations, and decreases with the holding period. These systematic movements in idiosyncratic risk can be explained by time and regional variations in market thinness and differences in information quality across markets. We find borrowing costs and deposit requirements have offsetting effects on risk. Higher interest rates are associated with lower idiosyncratic pricing, while tighter deposit requirements are associated with shorter holding periods, which are subject to a higher risk. Finally, we find the systematic variations in idiosyncratic housing risk tend to be positively associated with excess capital returns. However, the risk–return trade-off emerges only through risk differences across house prices and holding periods, while idiosyncratic risk differences across time and regions are not rewarded in excess capital returns.

Keywords: idiosyncratic risk, house prices, housing markets

JEL codes: G10, R10

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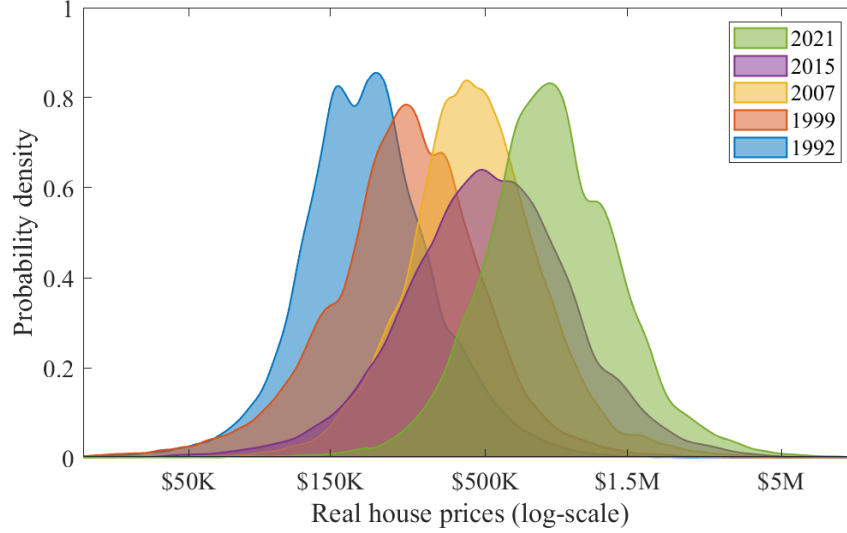
1 INTRODUCTION

House price appreciation is not homogeneous. In fact, long-established evidence conveys very heterogeneous appreciation rates across houses. For example, Case and Shiller (1989) report that annual house price appreciation has a standard deviation of close to 15% for individual houses, and go on to argue homeowners should not expect to realize capital gains measured by house price indices. Figure 1 depicts how the distribution of house prices has evolved since 1992 in New Zealand. It is clear house prices are widely dispersed at any point in time, and their distribution dynamics are nontrivial. Homeowners typically own only one house—the family home—and therefore carry a considerable idiosyncratic risk on housing. Although in many households' investment portfolios the family home has by far the largest weight (OECD, 2021), surprisingly little is known about how idiosyncratic risk in real house price appreciation varies across individual houses, whether the risk is priced, and what are its determinants. This is unfortunate because a better understanding of the nature of idiosyncratic risk in housing investment is definitely important, as it cannot be easily diversified away, unlike the case with, say, a stock portfolio that diversifies away the idiosyncratic risk of individual stocks.

Our paper provides answers to three important questions on the nature of idiosyncratic risk in housing markets. First, is there any systematic variation in idiosyncratic risk? If certain houses carry higher idiosyncratic risk, households clearly would want to know, since households *choose* which house to buy.¹ Households decide *when* to buy, *where* to buy, *what* house to buy, and *how long* to hold the house before resale. Does idiosyncratic risk vary along those choices? We find idiosyncratic risk varies systematically across the four dimensions of time of purchase, location, initial

¹ Others, such as mortgage lenders and investment funds, should also be interested: in case of default, the recovery amount would depend on the idiosyncratic risk, while portfolio optimization requires a proper quantification of risks.

Figure 1: Evolution of the Distribution of House Prices in New Zealand



Note: Real house prices are based on the New Zealand Consumer Price Index, taking 2021 as the base year.

Source: Real Estate Institute of New Zealand.

price of the house, and holding period. Second, why does idiosyncratic risk vary along these dimensions? We find the systematic variation in idiosyncratic risk identified in our model can be associated with credit conditions and valuation uncertainty, which are important factors determining search and matching frictions in the house trading process. Third, is systematically higher idiosyncratic risk rewarded with higher excess returns? The risk–return trade-off is a perennial question in finance. We find that some but not all systematic variation in idiosyncratic risk is rewarded with higher excess returns. Namely, only idiosyncratic risk variation across house prices and holding periods is positively associated with excess returns.²

To obtain answers to our three questions, we use a novel large dataset of around a million repeat sales observations in the entire New Zealand housing market over a long period (1992–2021). To answer our first question, we estimate how idiosyncratic risk varies

² Throughout this paper, we use the terms “idiosyncratic” and “excess returns” interchangeably to reflect individual house price appreciation that cannot be associated with regional/segmented market movements and housing improvements through the lens of our statistical model. Meanwhile, “returns” refer only to the house’s capital price appreciation.

across four dimensions in an extension of the repeat sales model of house price changes of Landvoigt et al. (2015). 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 $\epsilon_{i,t}$. Idiosyncratic risk is measured via the standard deviation of the shock. It measures how much individual house annual price appreciation deviates from the average annual appreciation, also accounting for a time-dependent house price effect intended to capture segmentation in housing markets. Landvoigt et al. (2015) allow this standard deviation—that is, 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 idiosyncratic risk in the San Diego housing market is indeed time-varying and quite large. It varies between 8% and 13.8% depending on the year.

We extend the model in several directions. First, in contrast to Landvoigt et al. (2015), we have information on house features (such as number of bedrooms, bathrooms, and garages, as well as floor area). This allows us to control for house remodeling changes in the regression. This is important as variation in house price appreciation owing 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 remodeling investments when estimating idiosyncratic risk in the California housing market. We find that remodeling does indeed increase the average rate of appreciation of house prices but that controlling for remodeling has only limited effects on our estimates of idiosyncratic risk. Second, we allow the average annual house price appreciation to vary across 16 different regional markets in New Zealand, as well as pinning down the house price segmentation effect to the median house in each regional market. Third, we allow idiosyncratic risk to vary in the four dimensions of time, location, initial house price, and holding period. The last three dimensions are an innovation to the previous model.

We find considerable variation in idiosyncratic risk across houses in New Zealand in all four dimensions. First, we find 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 7.90% (in 2018) and 10.55% (in 2002). 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%. Equally, moving from Auckland to the West Coast of the South Island increases idiosyncratic risk by 25%. These results show that location is an important factor driving differences in the level of idiosyncratic risk in housing. Third, we find households can reduce idiosyncratic risk by buying a house higher up in the price distribution. Landvoigt et al. (2015) argue 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 (90th) percentile of the house price distribution has an 8% higher (lower) idiosyncratic risk than a house at the median. These estimates supplement previous findings in the literature. For example, Guerrieri et al. (2013) document a higher variance in appreciation rates for initially low-priced neighborhoods during city-wide housing booms in the United States (US) cities.³ Fourth, we find 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 7.8%. This is consistent with recent

³ Guerrieri et al. (2013) find that the standard deviation of housing price growth between 2000 and 2006 is 61% (or 10.17% in annual terms) for neighborhoods in the lowest initial house price quartile and 46% (or 7.67% in annual terms) for neighborhoods in the top initial house price quartile. Covering a longer sample period, from 1996 to 2012, Peng and Thibodeau (2017) find a U-shaped relationship between risk and zip code-level median household income in the US and note that neighborhood income levels may be associated with neighborhood house price levels and varying degrees of liquidity.

findings in Giacoletti (2021) for the Californian residential housing market and Sagi (2021) for US commercial real estate.⁴

We believe our paper to be the first that considers simultaneously the four important ways in which idiosyncratic risk varies systematically. This 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: 58% of the systematic variation in idiosyncratic risk owes to the holding period factor, 21% owes to the regional factor, 11% owes to the time variation, and 10% owes to the initial price variation. The holding period is the most important factor driving the systematic variation in idiosyncratic risk, followed by location. The answer to our first question broadens our understanding of the nature and importance of idiosyncratic risk and the potential of households to mitigate such risk.

With respect to our second question, we provide an empirical analysis of why idiosyncratic risk varies systematically along the dimensions we investigate. We approach this question by separately regressing the different dimensions of variation in idiosyncratic risk, while keeping the other dimensions constant, on explanatory variables that cover different channels. Particularly, and guided by the previous literature, we consider how credit conditions and informational asymmetries can be associated with the systematic variation in risk elicited by our estimates. For credit conditions, we find borrowing costs and deposit requirements have offsetting effects on risk. Although higher interest rates are associated with lower idiosyncratic risk, both across time and through higher holding periods, higher deposit requirements are associated with shorter holding periods, which increases risk. These effects can be interpreted through the lens of a “market thinness” mechanism. Namely, the sizes of the pools of buyers and sellers in the market impact idiosyncratic pricing through their effect on matching frictions. While

⁴ Giacoletti (2021) finds idiosyncratic risk declines nonlinearly with the holding period, following a quadratic function: from 12% for a 2-year hold, to 8.6% for a 5-year hold, to 7% for a 15-year hold.

⁵ In absolute terms, this corresponds to an increase in idiosyncratic risk from 2.8% to 13.8%.

tighter access to credit increases risk by decreasing the pool of potential buyers in the market, higher borrowing costs decrease risk by constraining mortgage rollover and leading to forced sales, which increases the pool of houses available in the market. Moreover, the impact of borrowing costs is also consistent with a risk-taking behavioral channel, where higher interest rates may restrain high-risk speculative investments that would otherwise increase volatility in housing prices. While the negative correlation between credit supply and idiosyncratic risk has been previously documented in the literature (e.g., Giacoletti, 2021; Jiang and Zhang, 2023), we believe we are the first to document such a relationship between borrowing costs and idiosyncratic risk, the identification of which benefited from the risk decomposition provided by our model.⁶

We also find informational asymmetries are relevant in determining idiosyncratic risk through a “valuation uncertainty” channel in the house search process. Poorer information and difficulties in valuing houses lead to more heterogeneous house valuations and increase the potential variation of transaction prices. To assess this channel, we consider two variables, related to benchmarking difficulties and information access. First, for the benchmarking issues, we construct regional measures of house atypicality, which compare how the characteristics of individual houses deviate from typical characteristics of houses in their corresponding suburbs. We find more atypical houses tend to be located in regions with higher risk and also tend to be held for a shorter period. Hence, part of the regional and holding period differences in risk can be attributed to the varying degrees of relative heterogeneity of housing characteristics and the underlying valuation uncertainty. This valuation uncertainty channel, as captured through housing atypicality measures, is consistent with the findings of Bourassa et al. (2009) for the New Zealand market and Giacoletti (2021) for the US market. Second, we

⁶ There is substantial research on the relationship between interest rates and *average* house prices. While the workhorse present value user cost model predicts a negative relationship between interest rates and house prices, empirical evidence suggests a limited role for borrowing costs in explaining fluctuations in average house price (see, e.g., Glaeser et al., 2012). For New Zealand, Shi et al. (2014) find real interest rates are positively related to real housing prices.

consider how access to information impacts risk by looking at (sub)regional differences in internet access. We find regions with lower internet access have higher risk estimates. In addition, we also find cheaper houses tend to be located in suburbs with lower internet access. Considering the relative house prices as a proxy for house quality, this evidence suggests lower-quality houses are subject to higher valuation uncertainty owing to limited access to information about the house. We believe we are the first to document evidence of the effects of this channel of valuation uncertainty on idiosyncratic risk through differences in access to information. All in all, our empirical analysis indicates credit conditions and informational asymmetries are key drivers of systematic variation in idiosyncratic risk.

Our last question asks whether idiosyncratic risk is rewarded—that is, do houses with higher idiosyncratic risk have higher returns? A large part of the literature on housing return and risk ignores the idiosyncratic risk of an individual homeowner. Indices of house prices, not individual house prices, are typically used to calculate historical risk and return in housing markets.⁷ However, households buy a house, not a house price index. Moreover, although it is well known that house price capital gains vary across locations, idiosyncratic risk is often omitted from studies that investigate geographical variation in risk and return.⁸ In contrast to this literature, our paper uses individual house price data to investigate the risk–return relationship in idiosyncratic house price changes.

⁷ 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.

⁸ Sinai (2009) documents widely varying volatility of housing markets across metropolitan areas in the US, using house price indices at the metropolitan level but staying silent on the idiosyncratic risk of an individual homeowner within a metropolitan area. Peng and Thibodeau (2017) analyze idiosyncratic risk only at the zip code level in the US and find evidence that risk follows a U-shaped relationship with the neighborhood median household income, being higher for low-income and to a lesser degree for high-income markets. 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 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 fall short of using individual house price data. Guerrieri et al. (2013) document empirical facts on the variation in house prices within the US cities, including a relationship between initial house prices and the variance of appreciation rates during city-wide housing booms, but only at the zip code and census tract levels.

Taking advantage of our model’s decomposition of systematic variation in idiosyncratic risk, we also shed light on potential channels through which a tradeoff between excess returns and idiosyncratic risk emerges.

We find excess returns are positively associated with idiosyncratic risk, though not across all four identified dimensions of systematic variation in idiosyncratic risk. Namely, only the idiosyncratic risk variations across house prices and holding periods are positively and statistically significantly associated with excess returns. The idiosyncratic risk–return relationship across holding periods is consistent with the findings and model of Sagi (2021), who attributes higher idiosyncratic risk and returns for shorter holding periods to atemporal transaction frictions and selection. In contrast, the idiosyncratic risk–return tradeoff across house prices likely owes to differences in liquidity and information uncertainty across housing market segments (proxied by house price), which appears to lead to risk compensation as the players in these markets internalize such systematic factors. Finally, we find no evidence of idiosyncratic risk–return relationships across time and regions. Although timing and location choices are important determinants of idiosyncratic risk exposure, these risks do not seem to be compensated in excess returns. We attribute this finding to difficulties in arbitraging along these dimensions, as individual house price fluctuations are hard to predict and the decision of where to buy a house is likely determined by exogenous factors such as family origin, employment, and education opportunities.⁹

The rest of the paper is structured as follows. In section 2, we describe the data. In section 3, we present our model; this is followed by estimation results in section 4. In section 5, we discuss the determinants for the variation in idiosyncratic risk. In section 6,

⁹ Two important caveats to our results are in order. First, the estimates of risk and return examined in this paper are based on *ex-post* realized capital gains. This is important because investment decisions are based on expected returns. Second, we do not account for rents, which are important for both non-owner occupier investment returns and the shadow cost of housing for owner occupiers. Nevertheless, the historical analysis of realized capital gains offers lessons about the sources of risk that need to be priced in housing investment decisions.

we investigate whether higher idiosyncratic risk is rewarded with higher returns. In section 7, we conclude. Supplementary derivations and results are provided in an online Appendix, available at <http://dx.doi.org/10.22617/WPS250202-2>.

2 DATA

2.1 Data Source

We use individual house sales transaction data from the Real Estate Institute of New Zealand (REINZ). REINZ is a membership organization representing more than 14,000 real estate professionals in New Zealand. According to REINZ, more than 90% of New Zealand's real estate agents are a member. REINZ collects transaction data from its real estate agent members and 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 all of New Zealand. Individual house sales transaction variables include the basic characteristics of the property, such as the address; number of bedrooms, bathrooms, and garages; floor area; and 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 km² (about the size of the state of Colorado in the US or a bit larger than the UK), with a small population of around 5.1 million (estimate 2022). Most people live close to regional city centers. The New Zealand housing market can best be described as a set of geographically separated markets, each centered around a major city. Major cities in New Zealand are quite small in population in international terms. 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 center), with around 1.4 million inhabitants for the entire region (according to the 2013 census). The second largest region is Canterbury, with fewer than

600,000 inhabitants (and Christchurch as the main center). The third largest region is Wellington, centered around New Zealand's capital (with the same name as the region), with fewer than 500,000 inhabitants. Six regions in New Zealand have each fewer 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 m².¹⁰ This filter removes a total of 8,266 sales observations.

From this dataset, we compile the repeat sales—that is, 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 repeat 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%. This leaves us with a final sample of 1,058,391 repeat sales observations on 583,561 houses. Table 1 presents the summary statistics for this sample.¹¹ The average annualized capital gain is 5.52%. The standard deviation is 8.20%, showing indeed a large heterogeneity in the capital gains among homeowners.

¹⁰These cutoff values are obtained as the top 0.1% available values for each variable.

¹¹Table B.1 in the Appendix presents the number of observations by region.

Table 1: Full Sample Summary Statistics

Variable	Mean	Std Dev.	1st	Percentile				N. Obs.
				25th	50th	75th	99th	
House characteristics:								
Bedrooms	3.06	0.82	1	3	3	3	5	1,054,105
Bathrooms	1.43	0.69	0	1	1	2	4	541,315
Garages	1.46	0.87	0	1	1	2	4	1,026,847
Floor area (m ²)	143.11	65.16	50	100	126	174	351	1,029,021
Repeat sales:								
Initial price deviation* (%)	12.67	66.63	-71.43	-25.64	-1.27	32.90	253.69	1,058,391
Price change (% annual)	5.52	8.20	-12.27	1.20	4.28	8.30	34.96	1,058,391
Holding years	6.70	5.23	1	3	5	9	24	1,058,391

Note: *Price of purchase relative to regional median.

Source: Authors' calculations.

We use five variables to control for remodeling 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 sales observations, there is some missing information on the house features. 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 remodeling change for those features. The effect of this assumption is that our baseline estimates do not capture some actual remodeling changes. This does have some small upward effect on the idiosyncratic risk estimates. In a second sample, we exclude all house sale observations where the record shows 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 are 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 analyze 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 remodeling on house price appreciation. This extension allows us to control for changes in house features that will affect realized capital gains. Third, inspired by findings in the literature, we allow the variance of the idiosyncratic shocks to depend on location, initial house price (measured as a deviation from the regional median price), and holding period.¹²

The model is estimated in two stages. The first focuses on house price changes. The residuals from this first stage are then used in the 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 $X_{i,t} = [x_{1,i,t}, \dots, x_{F,i,t}]'$ 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 years t and $t+1$ is given by

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

¹²Sinai (2009), Peng and Thibodeau (2017), and Han (2013) provide evidence on varying returns and risk across location. Guerrieri et al. (2013) provide evidence on the variation of the variance of appreciation rates according to initial house price and Giacoletti (2021) shows idiosyncratic risk varies as a function of the holding period. None of these papers combines all these factors, however.

where $\varepsilon_{i,t}$ represents idiosyncratic shocks with mean 0, $\alpha_{r,t}$ 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, $\tilde{p}_{r,t}$, on its expected price change, and $\Psi = [\psi_1, \dots, \psi_F]$ 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.¹³ The coefficients β_t affect the evolution of the distribution of price changes across house quality. Namely, $\beta_t < 0$ implies prices of initially cheaper houses will, on average, have higher price appreciation than more expensive houses—that is, there is convergence of house prices toward 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 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-sectional 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 . This is important as ignoring the impacts of unobserved price changes of unsold houses can bias risk estimates.¹⁴ 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 needs to be compounded with the differential effects of the initial house price. Given that the state of

¹³Landvoigt et al. (2015) do not subtract the regional median $\tilde{p}_{r,t}$ from the price of the house as they estimate their model on only one region. We introduce this useful rescaling 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 remodeling changes.

¹⁴Our estimates (available upon request) indicate that using raw repeat sales data leads to a downward bias in risk estimates of about 2 to 3 percentage points relative to model-based estimates. This difference can be traced to (i) the time variation in β_t , which weights the averaging of idiosyncratic shocks between initial purchase and resale, (ii) the time variation in σ_t that is identified through the overlapping repeat sales, and (iii) the controlled effects of regional and relative price differences in risk.

house features is observed only when the house is sold, an assumption regarding the evolution of changes between repeat sales is required. Here, we assume 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 nonlinear equations covering all possible pairs of repeat sales observed in the sample. Details about this system of equations and the mappings to the structural parameters $\alpha_{r,t}$, β_t , and Ψ are provided in Appendix A. The parameters of the model of price changes are estimated using nonlinear 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 systematic variation of the idiosyncratic risk that is associated with housing investment. In our repeat sales model, idiosyncratic risk is captured by the standard deviation of the idiosyncratic shocks $\varepsilon_{i,t}$. We assume the idiosyncratic shocks $\varepsilon_{i,t}$ are independently normally distributed with variance $\sigma_{\varepsilon,i,t}^2$. As in Landvoigt et al. (2015), we allow this variance to change over time. However, we also allow the variance 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 assumed to behave as a zero mean normal random variable with variance given by

$$\sigma_{\varepsilon,i,t}^2 = \exp(\phi_{r_i} + \delta \ddot{p}_i + \rho(k_i - 1)) \sigma_t^2, \quad (2)$$

where \tilde{p}_i stands for the initial house price deviation from the regional median (in logs), ϕ_{r_i} 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_i as the number of years between repeat sales of the same house. The set of parameters $\phi_r, \delta, \rho, \sigma_t^2$ determines the “expected” idiosyncratic risk of an individual house, at a particular location, initial price, and holding period, in a particular year.¹⁵ In econometric terms, this is equivalent to heteroskedastic errors in the determination of housing returns.

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. Derivations of the likelihood function are provided in Appendix A.

4 ESTIMATION 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 three other samples to check for robustness. We first discuss the resulting estimates for the model of price changes. We then focus on the estimates of systematic variation in idiosyncratic risk.

4.1 Price Changes Model Estimates

Table 2 shows the estimates of Ψ , which determine the effect of remodeling 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

¹⁵This quantity is “expected” in the statistical sense of the expected value of the second moment of a random variable. As discussed in the text, our estimates are based on a full sample of realized housing returns, hence not a direct estimate of *ex-ante* returns.

adding floor space or a new dwelling. For instance, adding one bedroom increases the value of the house by around 6.5%, while adding a bathroom adds around 1.5% to the value of the house. The results are quite robust across the different samples.

Table 2: Model Estimates

	(1)	(2)	(3)	(4)
Elasticity estimates:				
Bedrooms	6.515 (0.061)	6.446 (0.062)	6.092 (0.081)	7.331 (0.069)
Bathrooms	1.467 (0.082)	1.477 (0.082)	1.284 (0.085)	1.574 (0.097)
Garages	0.637 (0.050)	0.645 (0.049)	0.331 (0.058)	0.666 (0.053)
Floor area (25m ²)	0.539 (0.029)	0.531 (0.030)	0.545 (0.035)	0.587 (0.032)
New dwelling	2.402 (0.125)		2.834 (0.172)	1.925 (0.157)
Variance parameter estimates:				
Initial price deviation, $\hat{\delta}$	-0.278 (0.008)	-0.286 (0.008)	-0.332 (0.011)	-0.275 (0.008)
Holding period, $\hat{\rho}$	-0.156 (0.003)	-0.152 (0.003)	-0.192 (0.005)	-0.117 (0.003)
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 2)	0.192	0.195	0.261	0.143
N. obs.	1,058,391	1,026,613	522,616	947,089

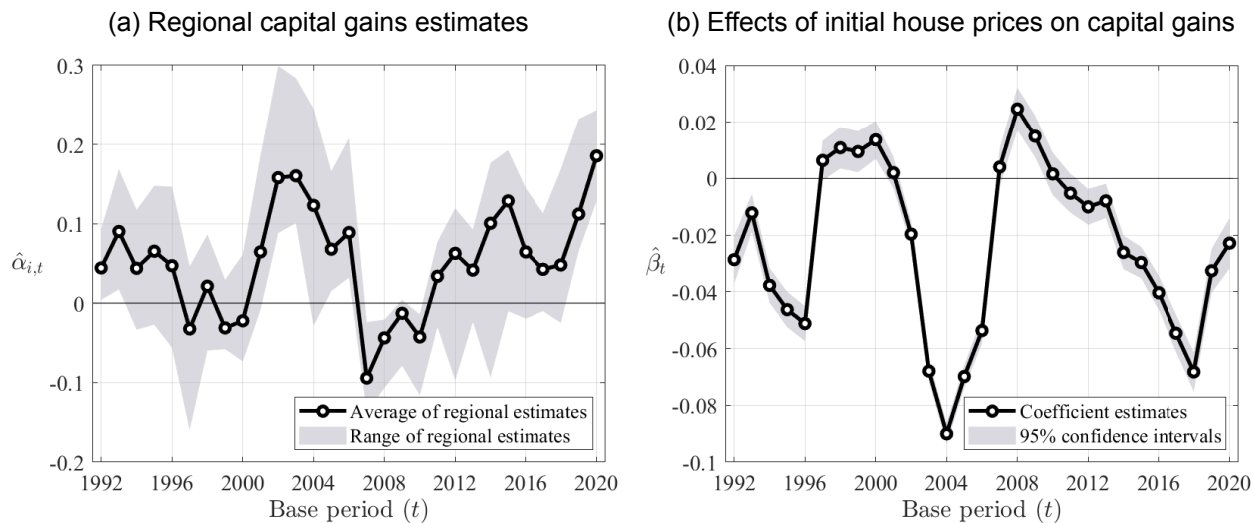
Notes: Elasticity estimates are estimates of Ψ from Equation 1. These can be interpreted in terms of annualized (log) capital returns. Variance parameter estimates are estimates of δ and ρ from Equation 2. The complete set of estimates of $\alpha_{r,t}$ and β_t , and estimates of ϕ_r and σ_t^2 , are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

Source: Authors' calculations.

Figure 2 shows the time-varying parameter estimates in this model. Panel (a) shows the coefficient estimates of the regional time dummies $\alpha_{r,t}$, which determine the time-varying annual average price appreciation. These estimates are consistent with the price trends observed over the period—namely, a sharp and broad-based increase in house

prices prior to the global financial crisis, followed by another period with a positive trend over the past decade. Panel (b) shows the coefficient estimates of β_t in Equation 1.

Figure 2: Time-Varying Model Parameter Estimates



Notes: Panel (a) shows estimates of $\alpha_{r,t}$ from Equation 1. These represent estimates of the average (log) annual capital gains for a median house in each region. The regional average is weighted by the number of sales in the region/year. The shaded areas indicate the minimum and maximum $\hat{\alpha}_{r,t}$ values across the regions for each year. Panel (b) shows estimates of β_t from Equation 1. These capture the effect 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.

Source: Authors' calculations.

Recall that these estimates give us an indication of what is happening with the distribution of house prices. Namely, a negative β indicates cheaper houses have been appreciating faster than more expensive ones, hence house prices are converging (and vice versa if β is positive). As depicted in Figure 2 these estimates are significantly cyclical, and mostly negative, suggesting the distribution of house prices has tended to shrink over time. But there have been some periods of divergence too, particularly between 1997 and 2000 and between 2007 and 2009, the bust phases of the housing cycles. One potential interpretation for this effect is that owners of cheaper houses are more likely to be forced to sell during busts, which makes cheaper homes depreciate faster. This evidence is consistent with Landvoigt et al. (2015) findings for San Diego

county, who argue that cheaper credit for poor households is a major driver of house prices at the low end of the market.¹⁶ Of course, these predictions do not account for idiosyncratic variation in house prices, which we now focus on.

4.2 Idiosyncratic Risk Estimates

Idiosyncratic risk is measured by the standard deviation of the shocks to house prices not captured by the model of price changes. Table 2 shows the estimates of the parameters determining how the variance of idiosyncratic shocks is affected by the initial price of the house relative to the regional median (δ) and by the holding period between purchase and resale of the house (ρ).

The estimates of δ in Table 2 are consistently negative, indicating that a house purchased at a price below the regional median is subject to a higher risk of idiosyncratic price changes. In terms of magnitude, the baseline estimate, $\hat{\delta} = -0.278$, indicates a house purchased at a price 25% below the regional median has an idiosyncratic risk about 4.1% higher than the median house.¹⁷ Cheap houses are therefore more risky.

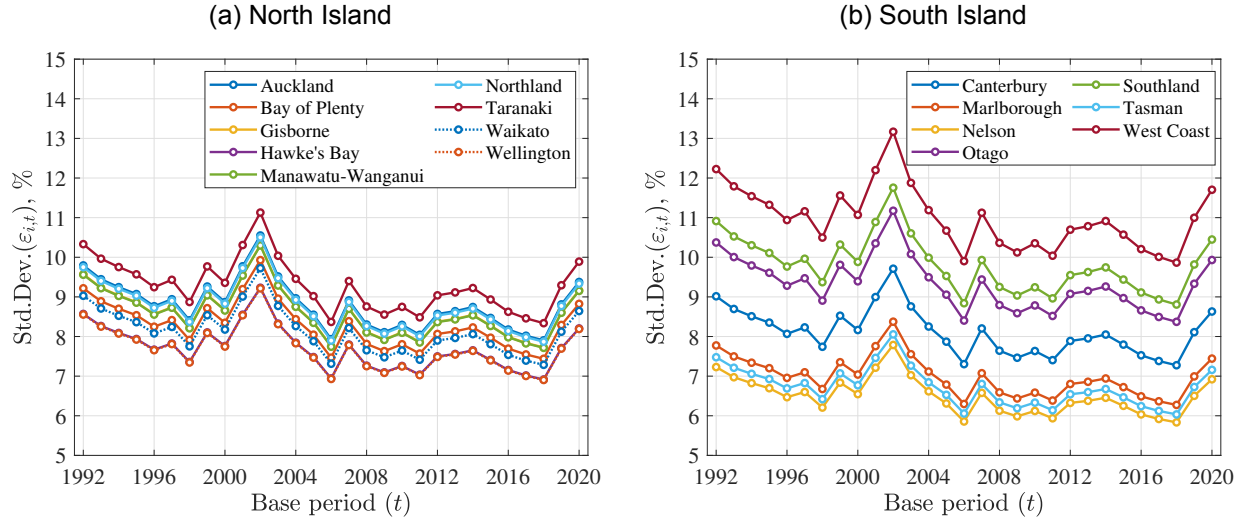
The estimates of ρ in Table 2 are also negative, indicating that holding the house for longer reduces the risk of idiosyncratic price changes. The baseline estimate, $\hat{\rho} = -0.156$, indicates that, for every additional year the house is held, idiosyncratic risk declines by about 7.8%. Giacoletti (2021) shows idiosyncratic risk varies across holding periods. Houses that are held over longer periods have less idiosyncratic risk. We find this to be also true in New Zealand.

The absolute level of idiosyncratic risk is determined by considering these factors jointly with the regional and time factors in the model, Equation 2. Figure 3 shows how idiosyncratic risk varies over time and across regions for a median-priced house that is

¹⁶The impact of the initial house price on the house price appreciation in our sample is nevertheless limited, as indicated by the magnitudes of $\hat{\beta}_t$. Figure D.2 in the Appendix shows the time variation in returns fitted by the model is mostly determined by shifts in $\hat{\alpha}_t$.

¹⁷Noting that the price deviation in Equation 2 is transformed to logarithms, the relative effect can be calculated as $\sqrt{(1 - 0.25)^{-0.278}} - 1$.

Figure 3: 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 2. The estimates are for a median-priced house in the corresponding regions and a holding period of 5 years between repeat sales. Estimates shown are those obtained using the baseline sample from Table 2.

Source: Authors' calculations.

held for 5 years (so $\bar{p} = 0$ and $k = 5$). We use a holding period of 5 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 C.2 and Table C.3).

Figure 3 shows 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.¹⁸ Interestingly, during the coronavirus disease years,

¹⁸This evolution of risk in housing parallels with the developments of the banking sector and financial regulation in New Zealand over the period (see, e.g., Murphy, 2011). Following a period of financial liberalization in the 1990s, whereby private banks replaced the state as the primary suppliers of mortgage finance, the early 2000s were characterized by increased price competition and financial product innovations in the banking sector. At the same time a substantial portion of the New Zealand mortgage market at the time was funded by overseas carry-trades, which tied the domestic credit conditions to a roughly unregulated and less conservative global market. Prompted by the global financial crisis turmoil, the Reserve Bank of New Zealand (RBNZ) introduced a series of new prudential liquidity policies that sought to reduce the retail banks' reliance on external sources of funding (see, e.g., Nield, 2008; Hoskin et al., 2009). Moreover, in October 2013, the RBNZ introduced loan-to-value ratio (LVR) restrictions to curb risky mortgage lending,

idiosyncratic risk rose significantly (by about 0.9 and 0.6 percentage points in 2019-2020 and 2020-2021, respectively). 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 5 years, idiosyncratic risk varied from a low of 7.90% (2018) to a high of 10.55% (2002).

Figure 3 also shows the wide regional variation in risk. Our specification assumes 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—that is, 464 estimates $\sigma_{r,t}^2$ (see Figure D.5 and Figure D.6). However, the shift factor explains most of the variation across regions in idiosyncratic risk.

To determine the relative importance of each of the factors in the systematic variation of idiosyncratic risk, we perform 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. Given the multiplicative nature of the relative risk factors, we can calculate the relative contribution of each factor in the increase of risk of buying a house at the 90th percentile versus the 10th percentile.¹⁹ A house at the 10th percentile has an absolute idiosyncratic risk of 2.8%. A house at the 90th percentile has an absolute idiosyncratic risk of 13.8%.²⁰ Calculating the relative contributions as explained above, this almost five-fold increase of risk owes 58% to the holding period factor, 21% to the regional factor, 11% to the time

while the LVR values have been revised over time (see Lu, 2019 for an early review, and McDonald and Markham, 2023 for a recent account of LVR's evolution).

¹⁹This calculation boils down to calculating the ratio of each of the bracketed terms in $0.5 [\hat{\phi}_{r90} - \hat{\phi}_{r10}] + 0.5 [\hat{\delta}\ddot{p}_{90} - \hat{\delta}\ddot{p}_{10}] + 0.5 [\hat{\rho}(k_{90} - 1) - \hat{\rho}(k_{10} - 1)] + [ln(\sigma_{t90}) - ln(\sigma_{t10})]$ to the total sum of bracketed terms, where the subscripts 90 and 10 indicate the 90th and 10th percentiles.

²⁰A house at the 10th percentile of risk is located in Tasman, was bought in 2017 at a price 80% above the median, and is held for 14 years. A house at the 90th percentile of risk is located in Otago, was bought in 2003 at a price 43% below the median, and was held for 2 years.

variation, and 10% to the initial price variation. The holding period is the most important factor driving the systematic variation in idiosyncratic risk, followed by location.

5 WHY DOES IDIOSYNCRATIC RISK VARY?

We find idiosyncratic risk varies systematically in the dimensions of region, time, holding period, and initial price. What can explain this variation? In this section, we investigate potential determinants by regressing the idiosyncratic risk estimates on explanatory variables that cover different channels.

5.1 Potential Channels

Before describing the empirical framework of this section, we discuss the potential mechanisms through which variation in idiosyncratic risk may be determined. Generally, idiosyncratic pricing is associated with “matching uncertainty” in the house trading process, which, in turn, can emerge through two main channels: (i) market thinness and (ii) informational asymmetries.

Market thinness is a leading potential driver of idiosyncratic pricing, as smaller pools of potential buyers and sellers decrease the probability of matching. Given that housing investments are highly dependent on mortgage financing, credit conditions are a key determinant of market thinness. Tighter credit conditions reduce the availability of funds for borrowers, thereby reducing the pool of potential house buyers. However, in markets where mortgage rates are re-negotiated throughout the loan tenure, credit conditions can also affect the supply side of the housing market. Higher borrowing costs can constrain mortgage rollover and lead to forced sales, increasing the pool of houses available in the market as some of the distressed households switch to renting. Credit conditions can also have a behavioral impact on risk-taking. Particularly, lower borrowing costs may lead to increased speculative and risk-taking behavior, consequently increasing idiosyncratic volatility in housing prices. Hence, in theory, the impact of credit conditions

on idiosyncratic risk is ambiguous. In our empirical analysis, we investigate how credit conditions are related to the estimated variation in risk across time, initial house prices, and holding period. In addition, housing market thinness is likely to depend on regional market sizes, hence we also control for variation in market size and liquidity across time and regions.²¹

Another key potential driver of idiosyncratic risk relates to informational asymmetries. According to the theory of search and matching, the poorer the information on house valuations, the larger the heterogeneity of buyers' valuations, which increases the potential variation of transaction prices. Giacoletti (2021) provides empirical evidence that houses with higher valuation uncertainty have both a larger idiosyncratic risk and a more steeply declining term structure of risk over an increasing holding period.²² This uncertainty can further interact with the supply of credit at the individual level, as poorer information about the house may lead to collateral value uncertainty and reduced mortgage credit.²³ Information quality may also be associated with the quality of the house, which may be proxied by the house price. Hence, the effect of initial house price on risk may also be associated with the varying degree of information uncertainty across house prices. Finally, heterogeneity of information access may be another dimension through which this channel operates, especially across regions. As housing markets rely heavily on internet advertising, regions with less internet access will tend to face higher valuation uncertainty. The remoteness of certain areas in New Zealand indeed implies some areas have no internet access. Although the data does not allow a proper disentangling of these channels, we test their general implications for estimated risk

²¹In New Zealand, cities are relatively small, with significant variation in population density across regions. For example, West Coast, which has the largest estimated idiosyncratic risk, is the region with the lowest population (below 50,000) and the lowest population density (below 2 persons per square kilometer), while Nelson, the lowest risk region, has the second highest population density (below that of Auckland).

²²Similarly, investigating house price changes in New Zealand, Bourassa et al. (2009) find atypical houses tend to have more volatile prices than those of standard properties.

²³For example, Jiang and Zhang (2023) estimate a hedonic price model and find less standardized houses tend to have greater value uncertainty, which ends up affecting the amount of credit offered in mortgages.

variation across regions, initial prices, and holding periods, by looking at a measure of house atypicality and data on internet access across different levels of geographical granularity.²⁴

5.2 Regression Framework

In order to identify the determinants of risk variation across each dimension, we first calculate risk estimates, controlling for the variation in the remaining dimensions. For example, when looking at risk variation across time, we subtract from the risk estimate the variation that is determined by the other three dimensions. The general regression specification is given by

$$\ln \hat{\sigma}_{\varepsilon,i,t} - \ln \tilde{\sigma}_{\varepsilon,i,t} = \alpha + \mathbf{\Lambda} \mathbf{X}_{i,t} + u_{i,t}, \quad (3)$$

where $\hat{\sigma}_{\varepsilon,i,t}$ is calculated according to Equation 2 for each repeat sales i and sequence of years t between the repeat sale initial and end transactions, $\tilde{\sigma}_{\varepsilon,i,t}$ is calculated similarly but keeping one (or all) of the dimensions of risk variation constant, and $\mathbf{X}_{i,t}$ is a set of explanatory variables.²⁵ Note that a logarithmic transformation is adopted, owing to the multiplicative formulation of risk estimates. Also note that our dataset is expanded to cover all periods between repeat sales in order to allow identification of time-specific effects from time-varying explanatory variables, such as interest rates. Finally, there is only time and (sub)regional variation in the explanatory variables.²⁶

²⁴Bargaining power asymmetry is another potential channel through which market thinness and informational quality can lead to higher price variability (see, e.g., Harding et al., 2003).

²⁵For example, when we look at year effects, $\tilde{\sigma}_{\varepsilon,i,t} = \exp\left(\frac{1}{2}\hat{\phi}_{r_i} + \frac{\hat{\delta}}{2}\hat{p}_{i,t} + \frac{\hat{\rho}}{2}(k_{i,t} - 1)\right) \hat{\sigma}_{1992}$, where 1992 is taken as baseline; when we look at regional effects, we set $\hat{\phi}_{r_i} = 0$ (i.e., Auckland is the baseline) and calculate $\tilde{\sigma}_{\varepsilon,i,t} = \exp\left(\frac{\hat{\delta}}{2}\hat{p}_{i,t} + \frac{\hat{\rho}}{2}(k_{i,t} - 1)\right) \hat{\sigma}_t$; and so on for the initial price and holding period dimensions.

²⁶Because relative prices and holding periods vary both across time and across houses, we consider variables that vary across time and across statistical areas (level 2) or SA2, which is the lowest level of geographical aggregation we managed to match with the house sales data. There are a total of 2,104 SA2s with over 2 million matched house sales in our data. The median area and population of SA2s are 1.93 km² and 1,942 people, respectively.

As explanatory variables we use measures associated with the two broad channels discussed above: (i) for credit conditions we use the central bank's policy rate to capture borrowing costs and loan-to-value ratios (LVR) to capture borrowing constraints; and (ii) for informational asymmetries and uncertainty we construct a measure of house atypicality based on a hedonic regression and use census data on the share of households with internet access.²⁷ As control variables for market activity and size, we use number of house sales, total population, and new building consented area.²⁸

5.3 Regression Estimates

Table 3 presents the results of five regressions. Columns (1) to (4) show how the explanatory variables correlate with the estimated idiosyncratic risk variation across time, region, initial house price, and holding period, respectively, each at a time while controlling for the variation in the other dimensions. In each of these regressions, as much as possible we focus on variables presenting variation along the risk dimension of interest. Column (5) shows how the same variables correlate with the total variation in the estimated idiosyncratic risk—that is, without controlling for any dimension.

Credit conditions are found to be particularly relevant for risk across time and holding periods. Across time, higher interest rates and lower LVR are associated with lower risk, though the latter effect is statistically insignificant (panel (i), column 1). Hence, tighter credit conditions are associated with periods of lower idiosyncratic risk, which is consistent with the costly refinancing and risk-taking behavioral channels. Interest rates have a similar effect on risk across holding periods, but the impact of macro-prudential

²⁷Our measure of house atypicality is similar to that adopted in the literature (e.g., Bourassa et al., 2009). First, we estimate a hedonic regression of house (log) prices on house characteristics, which include number of bedrooms, bathrooms, and garages; floor area; decade built; and fixed effects for region, year, and type of property. Second, we calculate the deviations of each house's characteristics from its corresponding neighborhood (SA2) mode values (except for floor area, where we take the median). Third, we use the estimated hedonic regression to calculate the total implicit price of each house's characteristics deviations from its neighborhood's typical values. Fourth, we average the absolute standardized valuation differences by region.

²⁸Descriptive statistics and sources for these variables are provided in Table B.3 in the Appendix.

Table 3: Regression Results on Idiosyncratic Risk Estimates

Explanatory Variables	(1)	(2)	(3)	(4)	(5)
(i) Credit conditions:					
• Interest rate (%, national)	-2.080** (0.773)		0.017 (0.026)	-2.372*** (0.532)	-2.262*** (0.616)
• Loan-to-value ratio (%, national)	0.156 (0.105)		-0.012* (0.006)	-0.536** (0.198)	-0.443** (0.153)
(ii) Informational asymmetries/uncertainty:					
• Average house atypicality (regional)		0.276** (0.116)	0.009 (0.036)	1.425*** (0.466)	0.982** (0.399)
• Internet access, 2006 (%, regional/SA2)		-1.363** (0.511)	-0.266*** (0.071)	0.013** (0.005)	-0.328*** (0.045)
Variation in risk	Year	Region	Price	Hold	All
Explan. vars. aggregation	Country	Region	SA2	SA2	SA2
N. obs.	7,088,089	6,834,835	6,535,077	6,535,077	6,535,077
R-squared	0.575	0.275	0.282	0.137	0.101

Notes: Each column represents a regression with dependent variable equal to the repeat sales (log) estimate of idiosyncratic risk excluding the controlled variation, $\ln \hat{\sigma}_{\varepsilon,i,t} - \ln \tilde{\sigma}_{\varepsilon,i,t}$, where applicable. All regressions include additional controls for market activity/size given by year/region/SA2 number of sales, total population, and new building consents area. Cluster robust standard errors are presented in brackets, where the clusters are defined according to the variation in risk for regressions (1) to (4) and two-way clusters by region and year for regression (5). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels of significance, respectively. SA2 stands for statistical area (level 2) definition from the New Zealand's 2018 Census of Population and Dwellings.

Source: Authors' calculations.

policy inverts (panel (i), column 4). Namely, a more restrictive LVR (equivalent to a lower LVR) is associated with higher risk across holding periods. As the risk estimates decrease with the holding period, these estimates indicate that, while higher borrowing costs incentivize holding onto a property for longer, which is consistent with the costly refinancing and risk-taking behavioral channels, periods of higher deposit requirements are associated with shorter holding periods, leading to higher risk. Hence, the impact of LVR on idiosyncratic housing risk is consistent with the market thinness channel.²⁹ The effects of credit conditions on risk variation across holding periods dominate the impact on total risk variation (panel (i), column 5). Quantitatively, an interest rate decrease of 1

²⁹This result is consistent with one of Giacomelli (2021)'s findings that contractions in local credit supply are associated with a higher level of idiosyncratic risk.

percentage point is associated with an increase in idiosyncratic risk of 2.26%, while an LVR tightening of 10 percentage points increases risk by 4.43%.

Information uncertainty effects are found to be mostly consistent in determining idiosyncratic risk across regions, relative house prices, and holding periods. First, regions with more atypical houses tend to have higher risk estimates (panel (ii), column 2) and shorter holding periods (panel (ii), column 4). Second, regions with lower internet access also tend to have higher risk estimates. Third, differences in internet access are also associated with the variation in risk across initial house prices (panel (ii), column 3). Recall risk is found to decrease with relative house price. Hence, the effects here may be interpreted in relation to how the variables impact relative house prices. Lower internet access is associated with higher risk, hence cheaper houses. Although it is not possible to determine the direction of causality, the fact that internet access is a significant determinant of regional risk, where price effects are held constant, suggests access to information is an important factor in the determination of idiosyncratic risk. The small (though positive and statistically significant) coefficient on internet access for risk variation across holding periods (panel (ii), column 4) suggests this specific channel is not a major determinant of housing turnover. Finally, the impact of information uncertainty on total risk variation is consistent with the expected signs of this channel (panel (ii), column 5). Thus, by affecting the house valuation process, informational asymmetries also have a bearing on idiosyncratic housing risk, with effects operating mainly through differences in access to information across regions and house prices, and varying degrees of heterogeneity of housing characteristics across regions and its impacts on holding periods.

6 RISK–RETURN RELATIONSHIPS

Is the systematic variation in idiosyncratic risk related to idiosyncratic housing returns? In this section, we analyze the risk–return relationship in housing investments implied by

our model estimates. Importantly, the analysis is based on *ex-post* realized excess capital gains, as identified by our model of price changes. Realized returns carry stronger variability than *ex-ante* excess returns, which are equal to zero under the martingale hypothesis that is common in frictionless asset pricing models. The fact that realized idiosyncratic risk shows systematic variation, whether that comes from informational asymmetries or changes in credit conditions, challenges this hypothesis. Likewise, systematic variation in realized excess returns may emerge as the result of similar mechanisms or risk compensation, which could generate risk–return relationships in the idiosyncratic component of house prices. By decomposing the systematic variation in idiosyncratic risk, our model sheds light on potential channels through which idiosyncratic risk and returns are determined.

6.1 Idiosyncratic Risk–Return Calculations

Our model of price changes, Equation 1, contains four components in the determination of returns. First, returns can vary across regions and time as captured by the $\alpha_{r,t}$ term. This variation can be interpreted as a regional market factor. Second, returns can vary across segments of the regional housing markets, captured by the $\beta_t(p_{i,t} - \tilde{p}_{r,t})$ term. This variation can be interpreted as a second layer of the market factor, as it accounts for within-region segmentation by house quality. Third, house remodeling is accounted for by the $\Psi X_{i,t}$ term. Finally, the remaining change in the house price is captured by the idiosyncratic return, $\varepsilon_{i,t}$, which can be interpreted as an excess return to the housing investment. This last component is the return of interest here. Namely, after accounting for market-wide return fluctuations, how much is idiosyncratic risk compensated in idiosyncratic returns?

Since the individual $\varepsilon_{i,t}$ shocks are not identified, we rely on the compounded repeat sales estimates of idiosyncratic returns, annualized by dividing it by the repeat sales

holding period.³⁰ Similarly, the idiosyncratic risk estimate for each repeat sale is calculated by compounding the variance estimates over the repeat sales period and dividing it by the holding period. Finally, the risk estimates are recalculated as standard deviations by taking the square root of the annualized variance estimates.

6.2 Regression Estimates

Table 4 presents estimates of the relationship between idiosyncratic risk and returns. The excess returns are found to be positively associated with the systematic variation in total idiosyncratic risk. A 1 percentage point increase in total risk is associated with an average 0.37 percentage point increase in excess returns (column 1). However, the explanatory power of idiosyncratic risk is relatively low (R-squared $\approx 1\%$), indicating risk compensation is not a major determinant of housing excess returns—the potential underlying mechanisms will be discussed in the next subsection.³¹

Columns (2) to (5) in Table 4 look at the risk–return relationships across the different dimensions of systematic variation in idiosyncratic risk identified by our model. This is done by controlling for the other dimensions using fixed effects. For example, in column (2), the variation in risk and returns across regions, initial house prices, and holding periods is controlled through corresponding fixed effects, leaving only the variation in returns across the years to be explained by the time variation in risk.

Across the identified dimensions of systematic variation in idiosyncratic risk, only risk across house segments (price) and holding period is compensated in excess returns. For every 1 percentage point increase in risk driven by the house price and the holding

³⁰This is equivalent to the term $e_{i,t,k}$ from Equation A.1 divided by k . For example, a repeat sale between periods t and $t+2$ has an annualized idiosyncratic return given by

$$\frac{e_{i,t,2}}{2} = \frac{(p_{i,t+2} - p_{i,t}) - \hat{\alpha}_{r,t} (1 + \hat{\beta}_{t+1}) - \hat{\alpha}_{r,t+1} - \hat{\beta}_t (1 + \hat{\beta}_{t+1}) (p_{i,t} - \tilde{p}_{r,t}) - \hat{\beta}_{t+1} (p_{i,t} - \tilde{p}_{r,t+1}) - (2 + \hat{\beta}_{t+1}) \hat{\Psi} X_{i,t}}{2}.$$

³¹The low explanatory power may also owe to the use of realized excess returns, which vary significantly more than the risk estimates across repeat sales.

Table 4: Idiosyncratic Risk–Return Regression Estimates

Explanatory Variables	(1) $\hat{r}_{i,t}^e/k$	(2) $\hat{r}_{i,t}^e/k$	(3) $\hat{r}_{i,t}^e/k$	(4) $\hat{r}_{i,t}^e/k$	(5) $\hat{r}_{i,t}^e/k$
(i) Risk estimate:					
• $\hat{\sigma}_{e,i,t,k}/\sqrt{k}$	0.368*** (0.059)	0.046 (0.084)	-0.007 (0.061)	0.575*** (0.151)	0.842*** (0.185)
(ii) Fixed effects:					
• Years	No	No	Yes	Yes	Yes
• Region	No	Yes	No	Yes	Yes
• Initial price	No	Yes	Yes	No	Yes
• Holding period	No	Yes	Yes	Yes	No
Risk–return variation	Total	Year	Region	Price	Hold
N. obs.	1,058,391	1,058,391	1,058,391	1,058,391	1,058,391
R-squared	0.015	0.040	0.040	0.035	0.028

Notes: Each column represents a regression with dependent variable equal to the repeat sales estimate of idiosyncratic/excess (log) annualized return, $\hat{r}_{i,t}^e/k$, which excludes from the total repeat sales return the regional/time variation in returns, the relative initial price effects representing within-region market segmentation, and house remodeling effects. The idiosyncratic risk estimates are repeat sales annualized compounded standard deviations, $\hat{\sigma}_{e,i,t,k}/\sqrt{k}$. Year fixed effects are introduced as dummy variables for each year and set equal to 1 for years covered by the repeat sales, and 0 otherwise. Initial price fixed effects are defined by the percentile of the repeat sales initial house price, hence a total of 100 initial price categories. Cluster robust standard errors are presented in brackets, where the clusters are defined according to the variation in risk/return for regressions (2) to (5) and two-way clusters by region and year for regression (1). *** denotes statistical significance at the 1% level of significance.

Source: Authors' calculations.

period, the average excess return increases by about 0.6 and 0.8 percentage points, respectively. These can easily be translated into the impact of initial price deviations and holding periods on average excess returns using our model estimates from section 4. For example, a house located in Auckland, purchased in 2010 at a price 25% below the regional median and held for 5 years, has an annualized idiosyncratic risk estimated to be about 0.4 percentage points higher than the median house; according to Table 4 estimates, such a house yielded an excess return about 0.2 percentage points higher than the median house, on average. If that same house were resold after only one year, the implied increase in risk from the shorter holding period raised the average excess return by about 1.3 percentage points.

6.3 Discussion

Our estimates indicate that idiosyncratic risk in housing investments tends to be rewarded in excess capital returns, though only partially. One advantage of our modeling approach is that it allows a decomposition of systematic variations in idiosyncratic risk across time, region, price, and holding period. Comparing this decomposition with excess returns indicates that only idiosyncratic risk variations across house prices and holding periods are positively and statistically significantly associated with excess returns. However, most of the variation in excess returns is not explained by systematic variation in idiosyncratic risk. Hence, the extent to which idiosyncratic risk is compensated in excess returns is limited.

Holding onto the house for longer before reselling it leads to lower idiosyncratic risk and excess return. This finding is consistent with Sagi (2021), who finds both idiosyncratic risk and returns decline with the holding period for real estate investments in the US. Sagi (2021) then proposes an equilibrium search-based asset pricing model to explain this behavior. Idiosyncratic risk is higher on an annualized basis for shorter holding periods because atemporal transaction frictions at purchase and resale are averaged over a shorter time period. Returns are also higher at shorter holding periods owing to selection, as these occur only if the seller is offered a higher price than expected if holding for longer. Hence, the positive relationship we observe between idiosyncratic risk and return across holding periods may be driven by such frictions and selection mechanisms rather than risk compensation.

The risk–return tradeoff also depends on the initial price of the house. Our estimates indicate that, at the same time that cheaper houses tend to be subject to higher idiosyncratic returns, they also yield higher average excess returns. The price of a house can be taken as an indicator of its quality and attraction of different segments of the population of home buyers, which can reflect into different sizes of the pool of buyers across house prices. Hence, differences in liquidity across housing market segments

may be an explanation for the emergence of a risk–return tradeoff across prices. Moreover, our previous section’s analysis of determinants of idiosyncratic risk indicated that price effects are associated with location differences in access to information. If these liquidity and information uncertainties are internalized by the players in the segmented markets, the risk–return tradeoff across this dimension can be interpreted as emerging from risk compensation.

Finally, we find no evidence of risk–return relationships across time and regions. Hence, while timing when and selecting where to buy a house is important for idiosyncratic risk exposure, this risk does not seem to be compensated in, or corresponding frictions lead to the emergence of, excess returns. The insignificance of a risk–return relationship across time likely owes to the difficulty in predicting individual house price fluctuations. While idiosyncratic risk appears to be relatively cyclical, realized excess returns show no systematic behavior across time, which prevents home buyers from exerting arbitrage for risk compensation across time. Excess returns across regions are also unrelated to idiosyncratic risk differences. That is, moving to regions with higher idiosyncratic risk does not offer higher excess returns. Again, this implies home buyers have little scope to arbitrage for risk compensation across regions. We believe this is reasonable as the decision of location is likely determined by factors such as family origin, and employment and education opportunities, which are, arguably, mostly exogenous to the decision of where to buy.

7 CONCLUSIONS

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 idiosyncratic risk varies considerably and systematically along four dimensions. Time, location, initial house price, and holding period are all important factors

determining the idiosyncratic risk of the house, and the holding period is the most important, followed by location.

Our results have important implications for housing demand and housing portfolio choice. As households choose which house to buy, and therefore have a choice on the determinants of idiosyncratic risk, our results suggest they are able to affect the risk they are facing. First, we show location matters. The region where the house is located affects the magnitude of idiosyncratic risk. This owes to varying degrees of market thinness and information quality across regional housing markets. By buying in regions that have thicker markets and better information, households can reduce idiosyncratic risk. However, since we find higher risk regions are not rewarded with higher excess returns, this implies households' location choice is not perfectly priced. Likely, other determinants, such as good schools or high-paying jobs, attract people to live in locations where risk is high but average returns are not. Second, holding the house for longer reduces the risk, a result that coincides with findings for the Californian market in Giacoletti (2021). Households can affect this risk by waiting to buy when family size is stable and when job certainty is higher (so family growth and labor market shocks do not necessitate a move). Nevertheless, we find holding houses for longer also reduces their excess return. Third, buying a higher-priced house (i.e., a better-quality house) reduces risk. Interestingly, this suggests the households that need to be least shielded from idiosyncratic risk—that is, the “rich”—are likely most protected from it. Poorer households will naturally (have to) buy cheaper houses, with bigger risks.

Our analysis of the determinants of these systematic variations in idiosyncratic risk in housing also provides some useful lessons for policymaking. First, credit conditions are important drivers of time and holding period variation in risk. Interestingly, we find borrowing costs and deposit requirements have offsetting effects on risk. Higher interest rates are associated with lower risk, consistent with a decrease in risk-taking behavior as well as the potential impact that constrained mortgage rollover can have on market

thinness. At the same time, tighter deposit requirements increase risk, as the reduced availability of credit decreases the pool of potential buyers in the market. Hence, the New Zealand experience shows macro-prudential regulation can complement, if not substitute, interest rate policy in the control of housing risk. Second, information uncertainty is another important determinant of risk through its effects on the housing search and valuation process. We find these valuation uncertainty effects operate mainly through differences in access to information across regions and relative house prices, as well as varying degrees of benchmarking difficulties across regions. Hence, houses of lower quality may be harder to value and also lead to lower mortgage credit provisions owing to collateral uncertainty. Moreover, housing atypicality is also associated with shorter holding periods and the implied higher risk of idiosyncratic pricing. These findings provide useful directions for the design of regulatory policies in housing markets. Namely, improving access to information and public transparency in the valuation of houses can help mitigate the large and arguably undiversifiable idiosyncratic risks faced by homeowners.

Data availability

Owing to license restrictions, the repeat sales data used in this project are not publicly available. We obtained these data through a data supply agreement with the REINZ. The data can be acquired upon application directly to REINZ.

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Evidence on the Determinants and Variation of Idiosyncratic Risk in Housing Markets

This paper shows that housing idiosyncratic risk is time-varying, depends negatively on the house price, varies across locations, and decreases with the holding period. These systematic movements can be associated with information quality and offsetting factors in credit supply. While higher interest rates are associated with reduced idiosyncratic pricing, tighter deposit requirements are associated with higher risk. Idiosyncratic risk is positively associated with excess returns only through risk differences across house prices and holding periods, and not across time and regions.

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