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Research article

Evidence of anti-herding in Canadian regional housing markets

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Abstract: The lack of transparency in real estate markets, combined with issues of asset heterogeneity and illiquidity, makes participants particularly susceptible to the influence of behavioral biases. In this paper, I investigated the phenomena of herding and anti-herding in Canada's regional housing markets, using data from February 1986 to November 2023. A comprehensive set of econometric techniques, including sub-sample analysis, rolling window regressions, quantile regressions, and probit regressions, was employed to examine these behaviors. My findings were consistent with the presence of anti-herding in most regions studied, with significant temporal dynamics. Anti-herding behavior was more prevalent during periods of lower economic policy risk. Additionally, substantial cross-regional effects in herding and anti-herding behaviors were observed throughout the study period. These results suggested that strong private information, due to the regional segmentation of the Canadian housing market, plays a critical role in driving these behaviors. Robustness tests confirmed the reliability of my findings. This study contributes to the literature by highlighting the nuanced dynamics of behavioral biases in regional housing markets and offers insights into how economic policy uncertainty influences market behavior.

Keywords: herding; anti-herding; housing market; Canada; direct housing prices; regional analysis

JEL Codes: C32, G11, G14

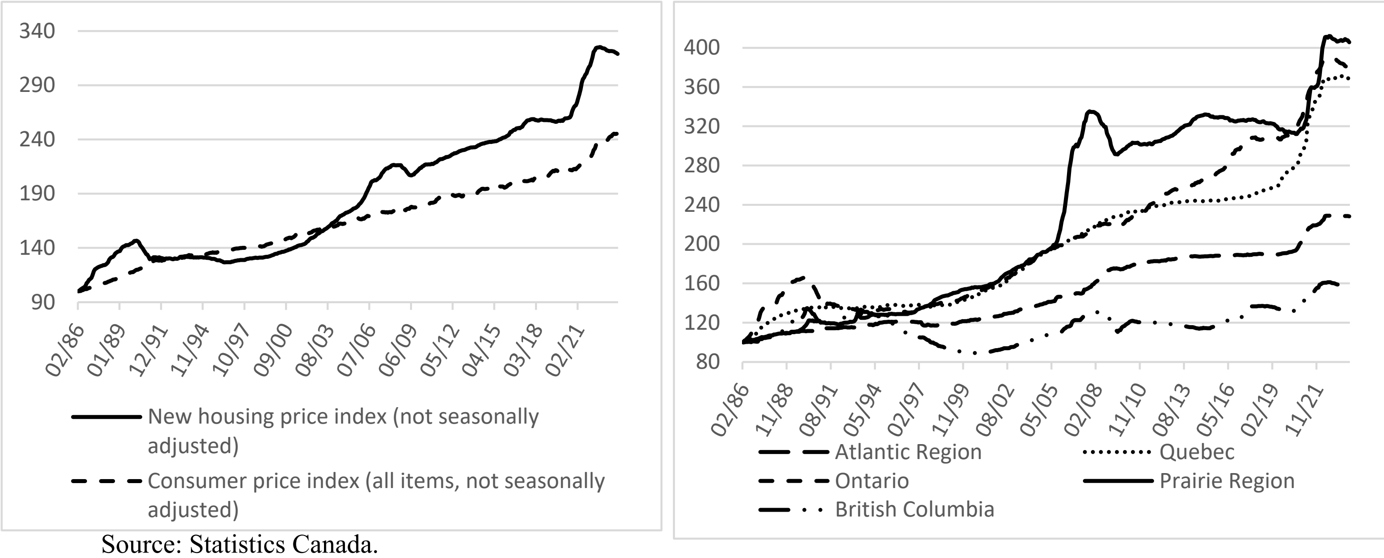
1. Introduction

Over the past decades, participants in the real estate market have been found to exhibit many behaviors typical of investors with bounded rationality. These behaviors include being influenced by sentiment and various psychological biases rooted in national culture, such as overconfidence and overoptimism (Breuer et al., 2014; Zheng and Osmer, 2021; Ding et al., 2022; McGough and Berry, 2022). As a result, prices in these markets tend to display signs of inefficiency, such as price predictability, excessive volatility, overreaction to information, and a tendency to form speculative bubbles and crashes (Beracha et al., 2012; Nneji et al., 2013; Fabozzi et al., 2020; Trojanek et al., 2023).

However, despite a considerable amount of research on behavioral tendencies in real estate markets, a notable gap persists in understanding the prevalence and factors driving herding and anti-herding behavior within these markets. In this study, I seek to address this gap by examining the dynamics of herding and anti-herding behavior among market participants in Canada's regional housing markets from February 1986 to November 2023. Herding behavior is characterized by investors disregarding their private information and instead following the market consensus, resulting in greater homogeneity of perspectives on asset values and excessive proximity of asset returns to the market return. On the other hand, anti-herding behavior manifests as a greater deviation of asset returns from the market consensus than warranted by rationality. Thus, according to Bekiros et al. (2017), anti-herding "(…) implies price increases (decreases) in an "excessive way", hence a systematic increase of market return dispersion above the level of rational pricing" (p. 109). Herding and anti-herding can be viewed as two contrasting behavioral phenomena that merit equal consideration in academic research (Hwang and Salmon, 2004).

Studying herding/anti-herding behavior holds significance for practitioners, academia, and market regulators alike. For practitioners, understanding these behaviors is crucial as they can lead to property prices deviating from their intrinsic values, presenting potential profit opportunities, and hindering portfolio diversification efficiency (Gebka and Wohar, 2013; Yao et al., 2014). Academia finds importance in herding/anti-herding as it challenges the rational asset pricing theory, which emphasizes the role of fundamentals in asset valuation, thus carrying significant theoretical implications for asset pricing models (Christie and Huang, 1995). Market regulators are concerned with herding/anti-herding as it signals potential market inefficiencies in aggregating private information, which could exacerbate market volatility, especially during crises, posing risks to the financial system (Bikhchandani and Sharma, 2001; Demirer and Kutan, 2006).

The selection of the Canadian real estate market as my focus of this study is driven by the global significance of this market and the fact that it remains relatively underexplored in academic literature. My sample covers a period of nearly four decades, during which real estate prices across the country, as well as in its distinct regions, have experienced diverse phases. Figure 1 illustrates the evolution of real estate prices nationwide and within each Canadian region over the sample period.



Source: Statistics Canada.

Figure 1. Evolution of monthly real estate prices in Canada and its regions (Feb 1986–Nov 2023, base month = 100: Feb 1986).

As shown in Figure 1, real estate prices in Canada have grown significantly more than the general price level of the economy over the last 20 years. The price dynamics in each region appear to be quite distinct. For instance, prices in the Prairie Region have quadrupled during the sample period, whereas in other regions, prices have increased by approximately 60% from 1986 to 2023. This apparent heterogeneity in real estate price dynamics supports my decision to focus on a regional level of analysis, as treating the Canadian real estate market as a homogeneous whole would overlook these significant regional variations.

My findings suggest that participants in Canada's regional housing markets exhibit significant anti-herding in most of the studied regions, as regional returns generally tend to deviate significantly from market consensus. Additionally, the phenomenon demonstrates a significant time-varying dynamic. While anti-herding appears to exist at significant levels only in bull markets in most regions, the differences in its intensity between bull and bear markets are only significant in the British Columbia region. Furthermore, anti-herding appears to be significantly less likely during periods of higher economic policy uncertainty. I attribute these results to the presence of strong private information due to the typical characteristics of real estate markets, such as asset heterogeneity, geographic segmentation, limited transparency, information asymmetries, illiquidity, and high transaction costs, which hinder the formation of competitive prices.

Three contributions of my study can be highlighted. First, my focus is on investigating herding/anti-herding tendencies within regional Canadian housing markets using direct housing price returns. It is worth noting that, with the notable exceptions of Ngene et al. (2017), Cakan et al. (2019), and Ngene and Gupta (2023), most studies on herding/anti-herding in the housing market rely not on direct housing prices but on Real Estate Investment Trusts (REITs) (see, for example, Philippas et al., 2013; Zhou and Anderson, 2013; Lesame et al., 2024). According to Ngene et al. (2017), REITs, being leveraged and tradable securities, are vulnerable to broader market sentiments. Several empirical studies have confirmed that investor sentiment plays a significant role in REITs return-generating process (e.g., Huerta et al., 2016; Hao et al., 2016; Chiang and Tsai, 2023). Additionally, the general herding tendencies observed among equities have the potential to distort and influence the behavior of REITs investors, particularly during periods of significant market volatility. On the other hand, direct real estate prices offer a more reliable reflection of the real estate market compared to REITs. Second, I am the first to delve into herding/anti-herding behavior in Canada's housing markets. This is an economically significant market on a global scale, yet it has been relatively underexplored in the literature compared to the housing markets of the US and UK. According to the business data platform Statista (Bowman, 2022), the Canadian real estate market is projected to reach a value of USD 8.80 trillion by 2025. This places it on par with the Australian real estate market (USD 8.06 trillion) and represents approximately one-third of the estimated value of the real estate markets in countries such as the UK (USD 23.94 trillion) and Japan (USD 25.27 trillion). Third, my sample spans nearly four decades, enabling a comprehensive examination of the herding/anti-herding phenomenon through various econometric techniques, including subsample analysis, rolling window regressions, quantile regressions, and probit regressions. Each of these econometric methods enables capturing various aspects of a complex and multifaceted phenomenon like herding/anti-herding in real estate markets. Specifically, subsample analysis, informed by Bai-Perron test results, and rolling window regressions account for potential structural breaks and regime shifts in the data. To further strengthen the robustness of my analysis and address the impact of outliers, I employ quantile regressions, which enable me to assess whether the dependence structure remains consistent across segments of the distribution. Last, I use probit regressions to investigate the relationship between the likelihood of herding/anti-herding behavior and levels of economic policy uncertainty in the Canadian economy.

The paper comprises five additional sections. In Section 2, I review studies and formulate the hypotheses to be tested. In Section 3, I introduce the data and outline the testing methodology. In Section 4, I present my findings of the empirical study, including robustness tests. In Section 5, I discuss the evidence provided in Section 4. Finally, in Section 6, I provide conclusions.

2. Literature review and development of hypotheses

One of the major concerns of Behavioral Economics is to understand how agents make decisions in contexts characterized by high levels of uncertainty, such as those found in speculative asset markets (Hirshleifer, 2015; Thaler, 2016). A critical decision these agents face is whether to rely on their private information or to make choices based on market consensus. When market consensus is considered in decision-making, dynamics of herding behavior or anti-herding behavior may emerge (Hirshleifer and Teoh, 2009; Spyrou, 2013). The literature has extensively documented varying degrees of herding/anti-herding behavior among investors across different asset classes, including stocks (Chang et al., 2000; Chiang and Zheng, 2010; Costa et al., 2024; Lobão et al., 2024), bonds (Galariotis et al., 2016a; Cai et al., 2019), exchange rates (Pierdzioch et al., 2012a; Sibande et al., 2023), derivatives (Gleason et al., 2004; Babalos and Stavroyiannis, 2015), and cryptocurrencies (Bouri et al., 2019; Kallinterakis and Wang, 2019).

However, the empirical research on herding/anti-herding behavior in real estate remains relatively limited with most researchers focusing primarily on US Real Estate Investment Trusts (REITs). For example, Philippas et al. (2013) and Zhou and Anderson (2013) investigated this phenomenon within the US, utilizing cross-sectional absolute deviation of REIT returns as a measure of herding. Philippas et al. (2013) observed significant levels of herding from 2004 to 2011, attributing this trend to positive feedback trading strategies employed by investors. Likewise, Zhou and Anderson (2013) corroborated the existence of herding in the US REIT market, noting an increase in herding intensity following the transition of US REITs into active self-managed entities in the early 1990s. Moreover, Yang et al. (2020) utilized data spanning 2000 through 2009 for twenty US cities to conclude that the real estate market demonstrates significant levels of anti-herding behavior. Further, Essa and Giouvris (2025) employed data for the period 2014–2022 and found significant differences depending on the sector to which the REITs belong: the Hotel, Retail, and Warehouse sectors exhibited significant anti-herding behavior, while herding behavior prevailed in the remaining sectors.

Some researchers have examined the intensity of herding in REITs among specific classes of investors. For instance, Ro and Gallimore (2014) analyzed trading data from 159 real estate mutual funds and found evidence of herding. Similarly, Lantushenko and Nelling (2016) investigated trading activity among 1,697 institutions, including banks, pension funds, mutual funds, and insurance companies, concluding that herding was common in the REIT market.

Research on herding in real estate outside the US is fairly limited. Lan (2014) identified a significant level of herding in the Chinese housing market during the period 1998–2013. Akinsomi et al. (2018a) studied 36 REITs listed in the UK from 2004 to 2016, revealing substantial evidence of herding during low volatility periods and anti-herding during high volatility periods. Akinsomi et al. (2018b) examined 31 Turkish REITs from 2007 to 2016, finding significant and persistent herding behavior during this period.

Based on the literature, I posit my initial research hypothesis as follows:

H1: The market displays significant levels of herding/anti-herding behavior.

The literature has shown that one of the major features of herding/anti-herding behavior lies in its variability over time. Instead of being a static phenomenon, consistently manifesting throughout a given period, the intensity and direction of the phenomenon (herding/anti-herding) seem to evolve with the passage of time. This dynamic pattern has been observed in various markets, including stocks (Stavroyiannis and Babalos, 2015), derivatives (Babalos and Stavroyiannis, 2015), and cryptocurrencies (Bouri et al., 2019). Similarly, it appears to exist in the housing market. For example, Ngene et al. (2017), considering direct US house prices for the period 1975–2015, demonstrated that the extent of herding/anti-herding differs among regimes. Akinsomi et al. (2018a) reached a similar conclusion in their study of UK REITs: While a static herding model dismisses the presence of herding in REITs markets, estimates from the regime-switching model reveal substantial evidence of herding under certain conditions. Babalos et al. (2015) applied a Markov-switching model to US REITs and concluded that although a static herding model rejects the existence of herding in REITs markets, estimates of the regime-switching model reveal substantial evidence of herding under the crash regime. Moreover, Lesame et al. (2024) demonstrated that investors in international REITs exhibited anti-herding behavior in the initial period of their sample (2018–2019), while herding behavior prevailed in the subsequent period.

Based on this literature, I propose the following research hypothesis:

H2: The intensity of herding/anti-herding behavior is time-varying.

Knowledge about the herding/anti-herding phenomena in real estate suggests that its intensity varies depending on the direction of returns. For instance, Zhou and Anderson (2013) examined US equity REITs finding evidence that herding becomes stronger in declining markets. Additionally, Ngene et al. (2017) found that bull housing markets generally exhibiting stronger herding effects than bear markets.

The propensity for imitation is expected to be stronger when market uncertainty levels are higher. Market participants have reasons to doubt their private information in such circumstances, making them more likely to follow the market consensus. The relationship between uncertainty and the prevalence of herding has been corroborated in stock and cryptocurrency markets (Bouri et al., 2019; Aharon, 2021), for instance. Regarding the real estate market, Ngene et al. (2017) demonstrated that increases in uncertainty, captured by the Economic Policy Uncertainty (EPU) index, tend to amplify herding and anti-herding behaviors in different sub-periods. Cakan et al. (2019) analyzed the South African real estate market, providing evidence of herding during high volatility regimes only, consistent with the notion that the phenomenon is primarily driven by increased market uncertainty. Huang et al. (2020) emphasized that economic policy uncertainty played a role in explaining the evolution of herding in the US REITs market. This finding was later corroborated by Essa and Giouvris (2025). Finally, Ngene and Gupta (2023) concluded that EPU intensifies herding behaviors in regional UK housing markets. Based on this literature, I propose the following research hypotheses:

H3: The intensity of herding/anti-herding behavior varies depending on whether market prices are rising or falling.

H4: Greater uncertainty results in an intensification of herding behavior.

Evidence suggests that herding/anti-herding behaviors may synchronize across geographic regions, which has significant implications for diversification benefits across these markets. Economou et al. (2011) analyzed the stock markets of Portugal, Spain, Greece, and Italy, concluding that herding dynamics in one market affect the others. Mobarek et al. (2014) extended this analysis to a broader set of European stock markets, finding notable cross-country herding effects. Moreover, Yasir and Önder (2023) reported significant herding spillover effects in the stock markets of the BRIC countries and Turkey under various regimes.

To the best of my knowledge, the possibility of synchronization in herding/anti-herding dynamics across geographic areas has not been studied in the context of real estate markets. Therefore, I propose the following research hypothesis:

H5: The herding/anti-herding dynamics are synchronized across the regions under study.

3. Methodology and data

3.1. Methodology

In my analysis, I apply the following herding/anti-herding behavior detection model recently proposed by Ngene and Gupta (2023):

$$AD_{i,t} = \gamma_0 + \gamma_1 |R_{i,t}| + \gamma_2 R_{i,t}^2 + \varepsilon_{i,t} \tag{1}$$

where $AD_{i,t} = |R_{i,t} - R_{m,t}|$ represents the absolute deviation of the observed returns of the real estate market in region i at period t ($R_{i,t}$) from the market return at the same period ($R_{m,t}$). Herding behavior is considered to exist if γ_2 is significantly negative, while a significantly positive γ_2 suggests the occurrence of anti-herding behavior.

My empirical study can be divided into seven parts. In the first part, I utilize OLS regression to estimate Equation (1) over the sample period to verify the presence of herding/anti-herding behavior in each of the regions considered. In this estimation, as well as in all OLS regressions conducted in my analysis, standard errors are calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors.

Given indications in the literature that there may be structural breaks in the intensity of herding/anti-herding behavior (e.g., Babalos and Stavroyiannis, 2015; Ngene et al., 2017; Bouri et al., 2019), I proceed, in the second part of my my analysis, to study the dynamics of the phenomenon over time. Thus, I first apply rolling window regressions to examine whether herding/anti-herding exhibits significant differences in intensity and direction over time. The rolling window regressions consider a two-year window of data (24 monthly observations) with a one-month step. Next, to formally test the possibility of structural breaks in the relationship between the dependent variable and the explanatory variables of Equation (1), I apply the Bai-Perron test and estimate Equation (1) for each of the sub-periods indicated by the test. This procedure ensures that each of the sub-samples considered is homogeneous in terms of the intensity and nature of herding or anti-herding phenomena.

In the third part of my study, I utilize the quantile regression method to estimate Equation (1). This method offers a more suitable approach to handling outliers in the data and enables an analysis of the intensity of herding/anti-herding behavior across the distribution of regional return deviations from market returns. Formally, I estimate the following model:

$$AD_{i,t} = \gamma_0 + \gamma_1 \left| R_{i,t}(\tau) \right| + \gamma_2 \left[R_{i,t}(\tau) \right]^2 + \varepsilon_{i,t} \tag{2}$$

where τ denotes the quantiles to be considered in the regression estimation, in this case $\tau = 0.10, 0.20, \ldots, 0.80, 0.90$. The regression coefficients for each τ illustrate the co-movement between the explanatory variables and $AD_{i,t}$. If the values of the coefficients remain consistent across quantiles, the dependence structure of the data is deemed constant. Should they rise (fall) across quantiles, the dependence structure is considered increasing (decreasing). If they exhibit similarity (disparity) for high (low) quantiles, the dependence structure is termed symmetric (asymmetric).

The linear regression model predicts the average value of the dependent variable based on specified levels of the independent (exogenous) variables. However, ordinary least squares (OLS) estimators, which rely on the conditional mean distribution, may overlook crucial information present in extreme market conditions, particularly outliers in the upper and lower tails (Zhou and Anderson, 2013; Lan, 2014; Aharon, 2021). In contrast, quantile regression provides robustness against non-normality, making it well-suited for analyzing market data, which often contains notable outliers. Additionally, it enables the evaluation of the relationship between absolute return deviations and market movements across points of the dependent variable's distribution. Furthermore, quantile regression is not only suitable for handling outliers in the data, as it remains robust against heteroscedasticity and skewness, which are common characteristics of the data under scrutiny. Additionally, it does not require distribution assumptions about the population and can estimate parameters non-parametrically, providing a more comprehensive understanding of the impact of linear and nonlinear returns on the absolute deviation of returns across conditional distributions.

In the fourth part of my empirical study, I examine the dynamics of herding/anti-herding behavior under varying market conditions. I analyze how being in either a rising or declining market affects the formation of herding/anti-herding behavior. Rather than dividing the sample based on the sign of market returns and estimating Equation (1) separately, as done by Chang et al. (2000) for example, I adopt the more robust approach introduced by Chiang and Zheng (2010), who employ a single-model strategy using dummy variables. Specifically, I investigate the asymmetric impact of market return sign by estimating the following model for each region *i*:

$$AD_{i,t} = \gamma_0 + \gamma_1(1-D)R_{i,t} + \gamma_2(1-D)\left[R_{i,t}\right]^2 + \gamma_3 DR_{i,t} + \gamma_4 D\left[R_{i,t}\right]^2 + \varepsilon_{i,t} \tag{3}$$

In Equation (3), I account for asymmetry in both linear and nonlinear terms by defining *D* as a binary variable. *D* assumes a value of 1 if $R_{i,t}$<0, and 0 if $R_{i,t}$>0. Significantly negative (positive) values of γ_2 would signal the existence of significant herding (anti-herding) on months of positive returns, whereas negative (positive) and significant values of γ_4 would imply that herding (anti-herding) is significant on months of negative returns.

Equation (3) will be estimated using the OLS method and also by quantile regression, given the advantages of the latter method in dealing with possible outliers.

In the fifth part of my empirical study, I examine the potential effects of uncertainty on the intensity of herding/anti-herding behavior. Since the results of anti-herding are predominant in the findings, I will analyze the impact of uncertainty on the probability of anti-herding occurrence. For this purpose, my econometric modeling will proceed as follows. First, for each of the regions under analysis, I will extract the estimates of the coefficient γ_2 from Equation (1) obtained from the rolling window regressions mentioned above. Second, I will generate a binary variable from these γ_2 estimates that will take the value of one if the estimated γ_2 is positive and significant at the statistically significance level of 5% (corresponding to the situation of anti-herding), and zero otherwise. Third, I will estimate a Probit model for each of the regions under study, where the dependent variable will be the binary variable described in the previous step, and the explanatory variable will be the Economic Policy Uncertainty (EPU) index relative to Canada:

$$Prob(anti-herding)_{i,t} = \gamma_0 + \gamma_1 EPU_t + \varepsilon_{i,t} \tag{4}$$

The dependent variable of the Probit regression is going to be estimated using a rolling window regression that considers 24 months of data with a one-month step. If I consider the explanatory variable as the EPU referring to the last month of those 24 months, I are assuming that the observed uncertainty levels in the previous 23 months of estimation were not relevant in determining the anti-herding behaviors of market participants. To address the possibility that EPU values in the estimation period of the rolling windows regressions may be relevant, and to increase the robustness of my results, I will consider two models of Equation (4): In model (1), I utilize the EPU value corresponding to the final moment of the estimation period of the rolling window regression, while for model (2), I employ the average value of EPU over the data period considered for the regression, spanning the 24-month period.

In the sixth part of the empirical study, I investigate the existence of cross-regional effects of herding/anti-herding. Thus, inspired by the model applied by Economou et al. (2011) to several European stock markets, I estimate the following regression for each of the regions *i*:

$$AD_{i,t} = \gamma_0 + \gamma_1\left|R_{i,t}\right| + \gamma_2 R_{i,t}^2 + \sum_{j=1}^{4} \delta_j\, AD_{j,t} + \varepsilon_{i,t} \tag{5}$$

In this equation, compared to Equation (1), I add as explanatory variables the absolute deviations of the returns of each region relative to the market observed in the remaining regions.

Finally, as a robustness test to my main result that anti-herding is predominant in the Canadian housing market, I estimate Equations (1) and (2) for all census metropolitan areas in Canada with more than one million inhabitants in 2021, namely Toronto (Ontario), Montreal (Quebec), Vancouver (British Columbia), Ottawa-Gatineau (Ontario), Calgary (Alberta), and Edmonton (Alberta).

3.2. Data

The data regarding the Canadian housing market prices are obtained from the Statistics Canada website, the official statistical information agency of the country. The values of the New Housing Price Index (NHPI), referring to houses only, are downloaded on a monthly basis for the five regions of Canada - Atlantic Region, Quebec, Ontario, Prairie Region, and British Columbia - covering the period from January 1986 to November 2023. The national-level New Housing Price Index (NHPI) for Canada, used as the reference market return in my calculations of regional deviations, is published by Statistics Canada. This index reflects the aggregate performance of new housing prices across all regions of Canada, ensuring that the measure of regional deviations is relative to a comprehensive market benchmark. The selected sample period is the longest for which monthly frequency data on real estate prices is available for the five Canadian regions mentioned. My decision to base the analysis of herding/anti-herding behavior on regional divisions is motivated by the fact that Canada is a geographically large country with heterogeneous economic regions (see Figure 1). This highlights that treating the Canadian housing sector as a single entity may overlook important regional dynamics (Allen et al., 2009). Moreover, Wakerly et al. (2006) demonstrated that fluctuations in Canadian regional output are significantly influenced by a significant and asymmetric range of disaggregate propagation and growth mechanisms. Given the varied responses of regions to macroeconomic shocks, I anticipate diverse reactions and instances of herding/anti-herding among housing market participants across regions. Table 1 presents the five regions considered and the provinces associated with each region.

Table 1. Regions included in the sample.

Region	Provinces
Atlantic Region	Newfoundland and Labrador, Prince Edward Island, Nova Scotia, New Brunswick
Quebec	Quebec
Ontario	Ontario
Prairie Region	Manitoba, Saskatchewan, Alberta
British Columbia	British Columbia

Additionally, monthly index values for the same time frame are retrieved for the census metropolitan areas of Toronto, Montreal, Vancouver, Ottawa-Gatineau, Calgary, and Edmonton. According to Statistics Canada, “The New Housing Price Index is a monthly series that measures changes over time in the builders’ selling prices of new residential houses, where detailed specifications pertaining to each house remain the same between two consecutive months. The survey covers the following dwelling types: new single homes, semi-detached homes, and townhomes (row or garden homes)”. Monthly logarithmic returns are calculated based on the index values for the different geographic areas.

The values of the Economic Policy Uncertainty (EPU) Index for Canada are obtained from the Federal Reserve Bank of St. Louis website. These are monthly frequency data that cover the period from February 1986 to November 2023. The index, constructed by Scott Baker, Nick Bloom, and Stephen J. Davis, is based on newspaper articles regarding policy uncertainty. Specifically, the authors count the number of news articles containing terms such as uncertain or uncertainty, economic or economy, as well as policy-relevant terms like ‘policy’, ‘tax’, ‘spending’, ‘regulation’, ‘central bank’, ‘budget’, and ‘deficit’. In the case of Canada, data from five Canadian newspapers are considered: The Gazette, The Vancouver Sun, The Toronto Star, The Ottawa Citizen, and The Globe and Mail. Additionally, articles from the Canadian Newswire are included. Each paper-specific monthly series is normalized to have a standard deviation of 1 prior to 2011, and then the values are aggregated across papers on a monthly basis. Finally, the series are further normalized to a mean of 100 prior to 2011. Baker et al. (2016) provide additional details about the method of computation of the EPU index.

Table 2 reports the descriptive statistics of the AD measure and the monthly returns observed in each of the five Canadian regions under scrutiny.

Table 2. Descriptive statistics.

		N	Mean	Median	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Atlantic Region	AD_i	454	0.0037	0.0025	0.0042	0.0000	0.0390	2.9205	14.7061
	R_i	454	0.0018	0.0009	0.0040	−0.0206	0.0223	1.5718	7.5736
Quebec	AD_i	454	0.0033	0.0021	0.0038	0.0000	0.0412	3.4951	23.6481
	R_i	454	0.0028	0.0017	0.0051	−0.0126	0.0580	3.5283	28.8771
Ontario	AD_i	454	0.0024	0.0019	0.0024	0.0000	0.0142	1.4909	2.3569
	R_i	454	0.0029	0.0022	0.0068	−0.0301	0.0442	0.5084	7.7551
Prairie Region	AD_i	454	0.0043	0.0025	0.0053	0.0000	0.0376	2.5553	8.0847
	R_i	454	0.0031	0.0020	0.0079	−0.0214	0.0518	2.3673	9.4726
British Columbia	AD_i	454	0.0049	0.0032	0.0049	0.0000	0.0391	2.2821	7.7611
	R_i	454	0.0010	0.0000	0.0084	−0.0474	0.0437	0.1686	5.2623

Notes: This table reports descriptive statistics for the measure of absolute deviation (AD_i) of real estate returns of region i with respect to the market return during the period February 1986–November 2023. The AD measure is defined as $AD_{i,t} = |R_{i,t} - R_{m,t}|$, where $R_{i,t}$ is the return observed in region i at period t and $R_{m,t}$ is the market return at the same period.

The average monthly returns for all regions are positive, reflecting a growth in housing prices in the period under analysis. The Prairie Region exhibits the highest mean monthly return (0.31%), while the lowest mean monthly return is observed in British Columbia (0.10%). Notably, British Columbia also experiences the most volatile monthly returns, as indicated by the standard deviation. All statistical series exhibit positive skewness, and except for the absolute deviation measure for the Ontario region, it is observed that the distributions are leptokurtic.

4. Results

4.1. Static analysis of herding/anti-herding behavior

Table 3 presents the results of estimating Equation (1) for each of the five regions under study using an OLS regression with robust estimators.

Table 3. Estimates of herding/anti-herding behavior in the full sample period.

	Atlantic Region	Quebec	Ontario	Prairie Region	British Columbia
γ_0	0.003***	0.002***	0.001***	0.002***	0.003***
γ_1	0.032	0.202***	0.251***	0.338***	0.335***
γ_2	29.004	8.155***	1.753	7.144***	8.014***
Adjusted R^2	18.75%	34.03%	45.58%	58.57%	53.51%

Notes: This table reports the estimated coefficients for the model $AD_{i,t} = \gamma_0 + \gamma_1|R_{i,t}| + \gamma_2 R_{i,t}^2 + \varepsilon_{i,t}$, where $AD_{i,t}$ stands for absolute deviation of returns of observed in each region i ($R_{i,t}$) with respect to the market return in month t ($R_{m,t}$). The sample period spans February 1986 to November 2023. The significance of the coefficients is assessed using Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors. *** denotes statistical significance at the 1% level.

The results suggest that anti-herding behavior is present during the sample period for the regions of Quebec, Prairie Region, and British Columbia, as in these cases, the value of the coefficient γ_2 is positive and statistically significant at the 1% significance level. However, in the cases of the Atlantic Region and Ontario, although the value of γ_2 is positive, it is not statistically different from zero, indicating that there are no signs of either herding or anti-herding behavior in these two regions.

The existence of anti-herding behavior in the housing market of some regions of Canada is consistent with similar evidence found in the UK and US markets. For example, Akinsomi et al. (2018a), using a similar static model to the one applied in my empirical study, documented significant anti-herding in the market of listed REITs in the UK. Similarly, in the case of the US, Ngene et al. (2017) found that in six out of nine regions analyzed, anti-herding behavior occurred in some periods of their sample. Moreover, Pollock et al. (2024) concluded that anti-herding behavior is predominant in most of the 20 largest urban areas in the US.

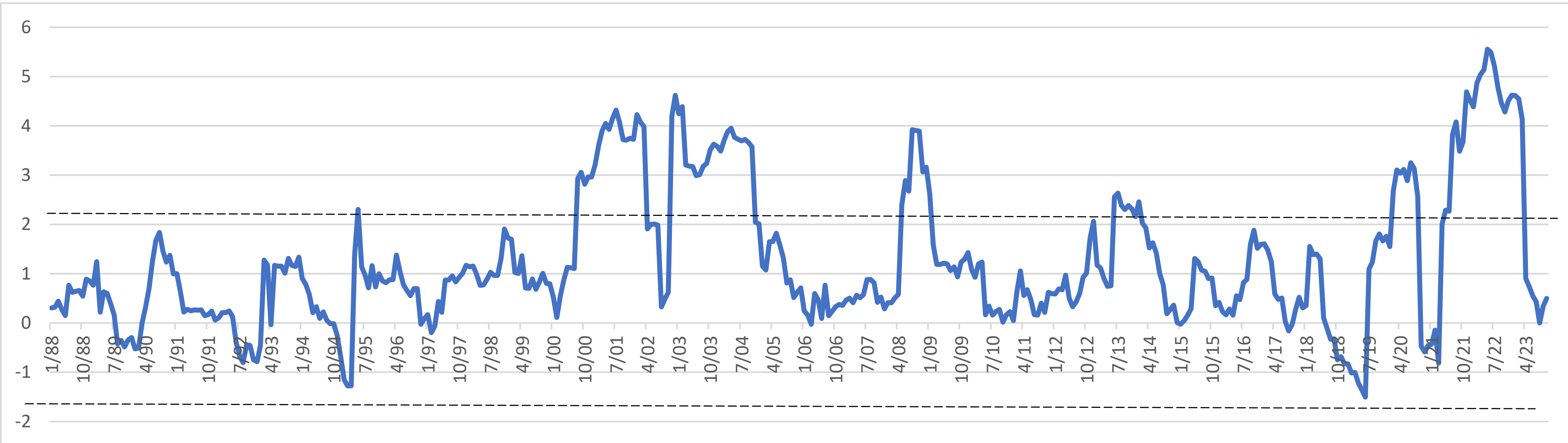
4.2. Time-varying nature of herding/anti-herding behavior

It is important to verify if the dynamics of herding/anti-herding vary significantly over my sample period. To do so, I begin by presenting, in Figure 2, the t-statistic values for coefficient γ_2 obtained for each region from a rolling window regression over a 24-month period with a one-month step.

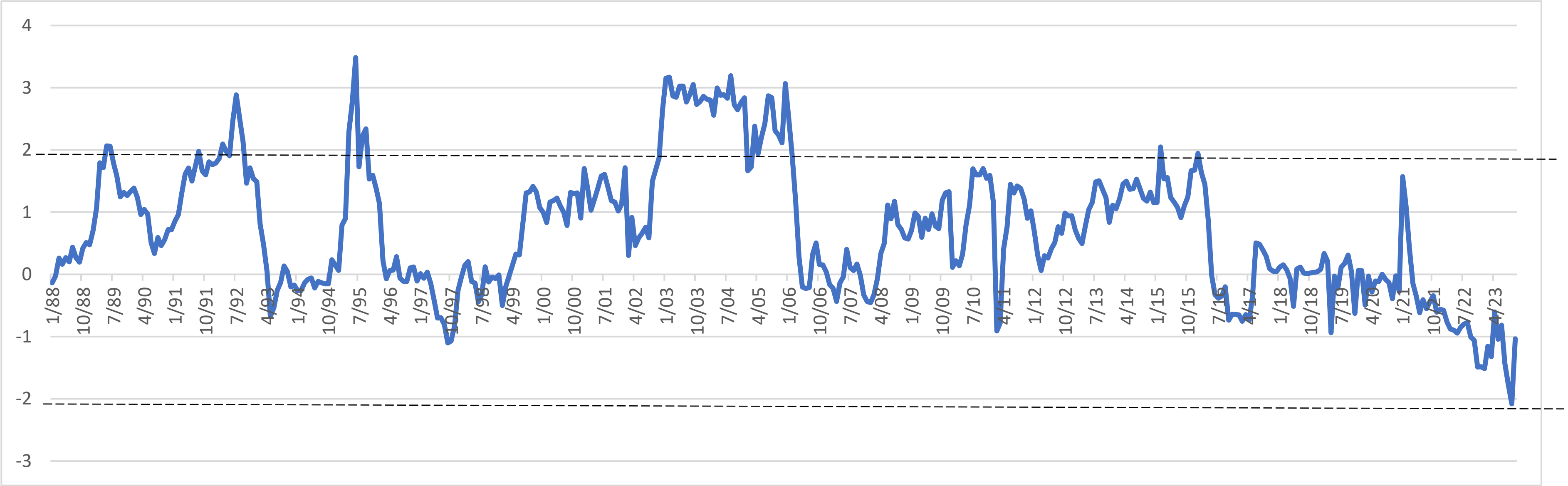
Figure 2 reveals several interesting insights. First, it indicates that herding behavior is very rare throughout the sample period. Significant herding behavior is observed in the Atlantic Region in February 1995, in Ontario in September 2023, in the Prairie Region between May and October 2011, and in British Columbia in March 1998. No observations of herding behavior occurs in the Quebec region throughout the sample period. Second, it is evident that anti-herding behavior is quite frequent and can persist for relatively long periods. However, the incidence of anti-herding varies from region to region. While it represents only 11.63% and 20.93% of all observations in the Ontario and Atlantic regions, respectively, it reaches almost one-third of observations (32.79%) in the Prairie Region. Third, the figure demonstrates that the phenomenon of herding/anti-herding is highly dynamic, varying markedly over time, suggesting the existence of structural breaks in the data.

Atlantic Region

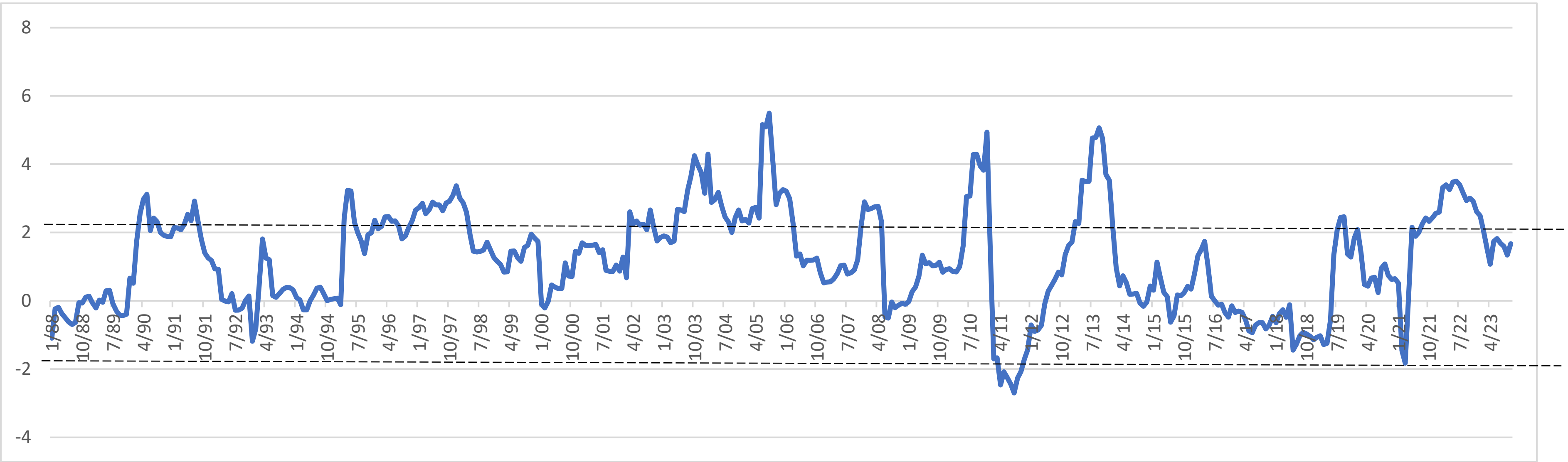
Quebec



Ontario



Prairie Region



British Columbia

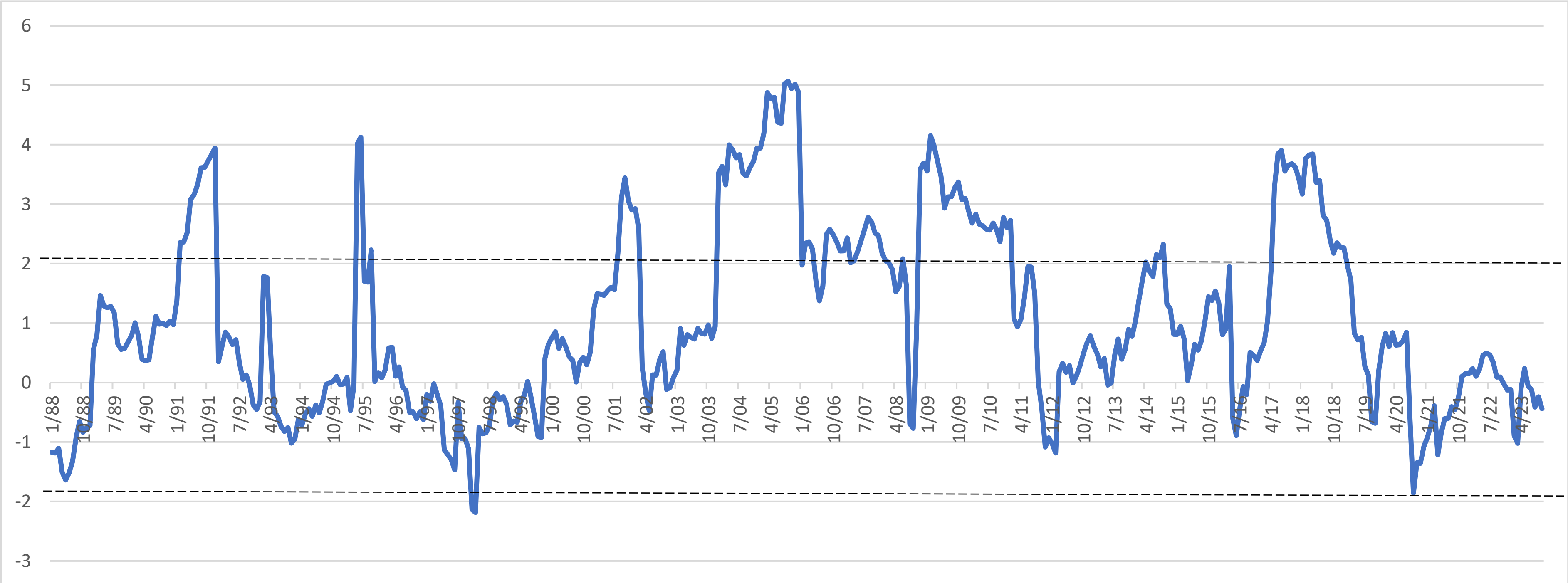


Figure 2. Rolling t-statistics.

Notes: The figure shows the rolling t-statistics of γ_2 based on a rolling-window estimation of the model $AD_{i,t} = \gamma_0 + \gamma_1 |R_{i,t}| + \gamma_2 R_{i,t}^2 + \varepsilon_{i,t}$ with a window of 24 monthly observations and a step of one month. The dashed horizontal lines represent the critical values of 5%, which correspond to t-statistics of -1.96 and +1.96.

To formally test the existence of structural breaks in the relationship defined by Equation (1), I apply the Bai-Perron test. The results of the Bai-Perron test are presented in Table 4.

Table 4. Significant structural breaks.

	Atlantic Region	Quebec	Ontario	Prairie Region	British Columbia
# of significant breaks	3	1	2	1	4
1st	10/1991	10/1991	1/2002	7/1993	12/1991
2nd	2/2001		6/2009		1/2001
3rd	6/2011				11/2007
4th					8/2017

Notes: This table reports the estimated points of structural breaks identified by Bai-Perron tests of L+1 vs. L sequentially determined breaks, considering a trimming of 0.15 and a significance level of 0.05. The breaking variables are $|R_{i,t}|$ and $R_{i,t}^2$.

The table confirms the presence of structural breaks in the data for all regions included in the sample. The number of structural break points varies from one in the case of Quebec and the Prairie Region to four in the case of British Columbia. In the Atlantic Region, Quebec, and British Columbia, a significant structural break is observed in the latter months of 1991. At the beginning of 2001, another structural break is observed in the Atlantic Region and British Columbia.

The existence of structural breaks in the data supports the notion that the estimates of γ_2 vary significantly from sub-period to sub-period. To account for this variation, it is advisable to estimate Equation (1) for each of the sub-periods identified from the results of the Bai-Perron test. Table 5 presents these estimates.

The results provide a clearer picture of the incidence of herding/anti-herding behavior. First, as can be inferred from the results displayed in Figure 2, there is no sub-period where herding behavior predominates. In fact, despite finding negative values for γ_2 in some sub-periods and regions, these values are always statistically nonsignificant at conventional levels of significance. An examination of each region individually reveals distinct scenarios. For example, although the results presented in Table 3 suggest that anti-herding did not exist in the Atlantic Region, analysis by sub-periods reveals that this phenomenon is significant, albeit with varying intensities, in the initial part of the sample until mid-2011. In Quebec, anti-herding behavior is observed only after October 1991. Confirming the results displayed in Section 4.1, Ontario seems to be the region where anti-herding is rarer, as it does not predominate at statistically significant levels in any of the identified sub-periods. Conversely, in the Prairie Region, anti-herding is significant before and after the structural break identified by the Bai-Perron test. Last, in the case of British Columbia, significant anti-herding is observed from the beginning of the sample until the end of 1991, and during the period January 2001 to August 2017. Interestingly, it is noteworthy that anti-herding appears to be relatively less common in the most recent period of my sample, as in the period after 2017, the phenomenon only affects two of the scrutinized regions (Quebec and Prairie Region).

Overall, my results confirm H2, which posits that the intensity of the phenomenon under study is time-varying. In this regard, the evidence presented in this section is consistent with the findings of authors such as Babalos et al. (2015) and Ngene et al. (2017) for the USA, Akinsomi et al. (2018a) for the UK, and Lesame et al. (2024) for a set of international markets.

Table 5. Estimates of time-varying herding/anti-herding behavior using sub-sample periods.

Regimes		Atlantic Region	Quebec	Ontario	Prairie Region	British Columbia
1	γ_0	0.007***	0.007***	0.001***	0.006***	0.007***
	γ_1	−0.742*	−0.623	0.318***	−0.019	−0.13
	γ_2	97.375***	37.187	−0.342	22.077**	16.348***
	Adjusted R^2	28.95%	0.89%	64.72%	18.35%	35.23%
2	γ_0	0.002***	0.002***	0.003***	0.001***	0.001***
	γ_1	0.49***	0.273***	−0.303	0.35***	0.837***
	γ_2	23.808**	7.082***	22.695	7.062***	−2.736
	Adjusted R^2	58.29%	50.01%	−0.21%	80.64%	79.47%
3	γ_0	0.004***		0.001**		0.003***
	γ_1	−0.197		0.398***		−0.164
	γ_2	37.306***		−3.552		18.584***
	Adjusted R^2	21.04%		53.23%		27.61%
4	γ_0	0.002***				0.002***
	γ_1	0.324**				0.466***
	γ_2	-7.088				7.227***
	Adjusted R^2	9.85%				88.48%
5	γ_0					0.001**
	γ_1					0.516***
	γ_2					−7.432
	Adjusted R^2					29.38%

Notes: This table reports the estimated coefficients for the model $AD_{i,t} = \gamma_0 + \gamma_1 |R_{i,t}| + \gamma_2 R_{i,t}^2 + \varepsilon_{i,t}$, applied to each of the sub-periods identified by the Bai-Perron test. Here, $AD_{i,t}$ represents the absolute deviation of returns observed in each region *i* ($R_{i,t}$) with respect to the market return in month *t* ($R_{m,t}$). The sample period spans from February 1986 to November 2023. The significance of the coefficients was assessed using Newey–West heteroscedasticity and autocorrelation consistent (HAC) standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.3. Herding/anti-herding across regional deviation levels

In this section, I analyze the presence of herding/anti-herding behavior using quantile regressions, which generates more robust estimates in the presence of outliers in the data and enables me to understand how the phenomenon varies depending on the levels of deviation of regional returns relative to national market returns. Table 6 displays the estimates of Equation (2).

Table 6. Estimates of herding/anti-herding behavior using quantile regressions.

Region		0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Atlantic Region	γ_0	0.001	0.001	0.001***	0.001***	0.002***	0.003***	0.003***	0.005***	0.008***
	γ_1	0.172*	0.424***	0.22***	0.218**	0.075	0.025	0.266*	−0.026	−0.633***
	γ_2	−1.413	−11.833	9.038	8.168	26.163	31.549*	32.104***	52.46	93.941***
Quebec	γ_0	0.001	0.001	0.001***	0.001***	0.002***	0.002***	0.002***	0.003***	0.006***
	γ_1	0.026	0.092	0.113**	0.127***	0.185***	0.263***	0.378***	0.415***	0.276***
	γ_2	11.812***	10.66***	10.033***	9.627***	8.552***	7.155***	5.085***	4.127***	5.764***
Ontario	γ_0	0.001	0.001	0.001	0.001	0.001***	0.001***	0.001***	0.002***	0.003***
	γ_1	0.038	0.111***	0.234***	0.37***	0.361***	0.348***	0.335***	0.348***	0.214***
	γ_2	6.406***	4.786***	2.582	−1.12	−1.185	−1.128	0.154	0.118	3.273
Prairie Region	γ_0	0.001	0.001	0.001***	0.001***	0.001***	0.002***	0.002***	0.004***	0.006***
	γ_1	0.048	0.234***	0.298***	0.362***	0.405***	0.384***	0.471***	0.435***	0.422***
	γ_2	13.068***	9.485***	8.03***	6.711***	5.735***	7.553***	5.294***	5.424**	6.397*
British Columbia	γ_0	0.001	0.001***	0.001***	0.001***	0.002***	0.002***	0.003***	0.004***	0.006***
	γ_1	0.041	0.114	0.273***	0.287***	0.422***	0.499***	0.527***	0.51***	0.539***
	γ_2	13.403***	11.297***	7.573***	10.694***	7.731***	5.913***	5.049***	5.01***	3.86**

Notes: This table reports the estimated coefficients for the model $AD_{i,t} = \gamma_0 + \gamma_1 |R_{i,t}(\tau)| + \gamma_2 [R_{i,t}(\tau)]^2 + \varepsilon_{i,t}$, where $AD_{i,t}$ represents the absolute deviation of returns observed in each region *i* with respect to the market return in month *t* and τ denotes the quantiles to be considered in the regression estimation, $\tau = 0.10, 0.20, \ldots, 0.80, 0.90$. The sample period spans February 1986 to November 2023. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The results reveal that the intensity of the phenomenon, captured by the values of γ_2 across quantiles, significantly varies depending on the levels of deviations of regional returns relative to market returns. Several insights can be drawn from the statistical analysis of Table 6. First, it should be noted that among all quantiles considered in all regions under study, there is not a single one indicating the presence of herding behavior at statistically significant levels. Instead, signals of anti-herding behavior are quite pronounced, particularly in the regions of Quebec, Prairie Region, and British Columbia. This finding corroborates the evidence presented in earlier sections.

Second, situations can be distinguished in the regions under analysis. Thus, in the regions of Quebec, Prairie Region, and British Columbia, there is significant anti-herding at conventional levels of statistical significance in all quantiles considered. In contrast, in the Ontario and Atlantic Region, anti-herding is observed in only two and three quantiles, respectively. This evidence is consistent with the data presented in Tables 3 and 5, as they confirm that signals of anti-herding behavior are more pronounced in the regions of Quebec, Prairie Region, and British Columbia. Furthermore, the comparison with previously obtained results also highlights that in the Ontario region, which appears to show no significant anti-herding, the phenomenon exists, but only when the divergence, in absolute terms, between the returns of the region and market returns is very low.

Third, there appears to be a significant decreasing dependence structure in all regions except the Atlantic Region. This means that the intensity of anti-herding tends to be higher in cases where the returns of regional markets move in tandem with the national market. In contrast, in the Atlantic Region, there is an increasing dependence structure, as the intensity of anti-herding seems to be higher and more significant as I approach the upper tail of the distribution of absolute deviations from the market. In all cases, the dependence structure appears asymmetric, as the values of the extreme quantiles are significantly different in all regions: They are higher in the upper tail of deviations in the Atlantic Region and higher in the lower tail of deviations in the remaining regions.

4.4. Herding/anti-herding behavior across varying market conditions

In this section, I analyze the differential impact on the dynamics of herding/anti-herding resulting from whether a regional market is experiencing upward or downward price trends. Table 7 presents the results of estimating Equation (3) through an OLS regression.

The findings suggest that anti-herding behavior is evident in bull markets within the Quebec, Prairie Region, and British Columbia regions. However, in bear markets, anti-herding does not reach statistically significant levels. Additionally, the results reaffirm the lesser occurrence of anti-herding in the Atlantic Region and Ontario. Considering the coefficient values, it can be concluded that anti-herding is particularly intense in the bull markets of Quebec and British Columbia. However, the results of the Wald tests suggest that, except for the British Columbia region, there are no significant differences in the intensity of the phenomenon in bull and bear markets. In the mentioned region, anti-herding is significantly more intense in markets with a rising price trend.

Table 7. Estimates of herding/anti-herding behavior in rising and declining regional markets.

		Atlantic Region	Quebec	Ontario	Prairie Region	British Columbia
Up market	γ_0	0.001***	0.002***	0.001***	0.001***	0.002***
	γ_1	0.415***	0.116***	0.326***	0.426***	0.28***
	γ_2	−1.166	9.829***	−0.17	5.868***	9.023***
Down market	γ_3	0.978***	0.273	0.422***	0.679***	0.672***
	γ_4	1.693	17.494	−2.436	−2.943	2.067
Adjusted R^2		14.09%	9.71%	37.59%	28.67%	33.59%
	$\gamma_1 - \gamma_3$	−0.563***	−0.157	−0.096*	−0.253**	−0.392***
	$\gamma_2 - \gamma_4$	−2.859	−7.665	2.267	8.811	6.956***

Notes: This table reports the estimated coefficients for the model $AD_t = \gamma_0 + \gamma_1(1-D)|R_{i,t}| + \gamma_2(1-D)R_{i,t}^2 + \gamma_3 D|R_{i,t}| + \gamma_4 D R_{i,t}^2 + \varepsilon_t$, where $AD_{i,t}$ represents the absolute deviation of returns observed in each region i ($R_{i,t}$) with respect to the market return in month t ($R_{m,t}$) and D is a dummy variable that takes the value 1 on days with negative returns in region i and the value 0 on days with positive returns in region i. The sample period spans February 1986 to November 2023. The significance of the coefficients is assessed using Newey–West heteroscedasticity and autocorrelation consistent (HAC) standard errors. The table also illustrates the difference between γ_1 and γ_3, as well as between γ_2 and γ_4, alongside the statistical significance of these differences measured by Wald tests for the null hypotheses $\gamma_1 - \gamma_3 = 0$ and $\gamma_2 - \gamma_4 = 0$ in the estimated model. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.5. EPU and herding/anti-herding behavior

In this section, I analyze the effect of economic policy uncertainty on the dynamics of herding/anti-herding behavior by estimating the Probit model presented in Equation (4). Table 8 presents the results of these estimations.

The results suggest a negative relationship between EPU levels and the probability of anti-herding behavior occurrence in four of the regions under analysis: Atlantic Region, Ontario, Prairie Region, and British Columbia. However, in the case of the Quebec region, the found relationship is positive: The higher the EPU, the more likely anti-herding behavior is to occur. Both models support the direction of the relationship between the variables in all regions, except for the Prairie Region. In this region, a significantly negative relationship is seen when considering the observed EPU index value at month t. However, the coefficient capturing the relationship when considering the average of the EPU index over the previous 24 months is not statistically significant at conventional levels of statistical significance.

The result obtained for most regions, that anti-herding behavior is more likely to be observed in tranquil periods when EPU is lower, is consistent with findings reported by Cakan et al. (2019) and Ngene and Gupta (2023) for the housing markets of South Africa and the UK, respectively. In the case studied by these authors, herding was found to be less likely when a lower EPU was observed. Considering that anti-herding and herding behaviors can be considered on a continuum, my results, interpreted with those of Cakan et al. (2019) and Ngene and Gupta (2023), suggest that a higher level of EPU not only makes herding more likely but also decreases the probability of anti-herding behavior occurrence.

Table 8. Estimates of the impact of EPU on the probability of observing anti-herding behavior.

Region		Model (1)	Model (2)
	γ_0	−0.387***	−0.246*
Atlantic Region	γ_1	−0.003***	−0.004***
	McFadden R^2	3.31%	4.25%
	γ_0	−0.981***	−1.152***
Quebec	γ_1	0.002**	0.003***
	McFadden R^2	1.42%	2.98%
	γ_0	−0.281	−0.257
Ontario	γ_1	−0.007***	−0.007***
	McFadden R^2	11.70%	9.05%
	γ_0	−0.188*	−0.479***
Prairie Region	γ_1	−0.002***	0.001
	McFadden R^2	1.28%	0.02%
	γ_0	−0.302**	−0.139
British Columbia	γ_1	−0.002***	−0.003***
	McFadden R^2	1.42%	2.66%

Notes: This table reports the estimated coefficients for the Binary Probit model $Prob(anti-herding)_{i,t} = \gamma_0 + \gamma_1 EPU_t + \varepsilon_{i,t}$, where EPU_t stands for the Economic Policy Uncertainty Index relative to the Canadian Economy created by Baker et al. (2016) observed in month t. Model (1) includes the EPU observed in month t as the explanatory variable, while Model (2) incorporates the mean value of EPU observed over the 24-month period leading up to month t. The dependent dummy variable takes a value of 1 during periods of statistically significant anti-herding (i.e., for months when the rolling t-statistic on $\gamma_2 > 1.96$ in the model $AD_{i,t} = \gamma_0 + \gamma_1 |R_{i,t}| + \gamma_2 R_{i,t}^2 + \varepsilon_{i,t}$, and the value zero otherwise. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.6. *Cross-regional effects of herding/anti-herding behavior*

Table 9 presents the estimates of Equation (5), which aims to capture the synchronicity in the absolute deviations of regional returns from overall market returns.

The enhanced explanatory capability of these models becomes apparent when contrasting their adjusted R2 values with those presented in Table 3. Across most cases, I observe a robustly statistically significant positive association among the $AD_{i,t}$ measures across regions. Particularly noteworthy is the strongest relationship observed between the Atlantic Region and Ontario, along with the absolute deviation measures observed between Ontario and the Prairie Region.

Table 9. Estimates of herding/anti-herding behavior incorporating other regions' AD.

	Atlantic Region	Quebec	Ontario	Prairie Region	British Columbia
γ_0	0.001*	0.001***	0.001	0.001	0.002***
γ_1	−0.007	0.038	0.197***	0.249***	0.301***
γ_2	21.006	10.545***	−0.611	6.416***	8.219***
γ_3 [Atlantic Region]	–	0.276***	0.079***	0.201***	−0.074
γ_4 [Quebec]	0.159	–	0.014	0.008	−0.038
γ_5 [Ontario]	0.602***	0.198**	–	0.589***	0.433***
γ_6 [Prairie Region]	0.153***	0.062*	0.147***	–	0.024
γ_7 [British Columbia]	0.034	0.006	0.069***	0.004	–
Adjusted R^2	51.53%	52.57%	60.92%	71.99%	56.63%

Notes: This table reports the estimated coefficients of the model $AD_{i,t} = \gamma_0 + \gamma_1|R_{i,t}| + \gamma_2 R_{i,t}^2 + \sum_{j=1}^{4} \delta_j\, AD_{j,t} + \varepsilon_{i,t}$, where $AD_{i,t}$ represents the absolute deviation of returns observed in each region i ($R_{i,t}$) with respect to the market return in month t ($R_{m,t}$) and $AD_{j,t}$ the corresponding measures of absolute deviation in each of the four other regions, apart from region i. The sample period spans February 1986 to November 2023. The significance of the coefficients is assessed using Newey–West heteroscedasticity and autocorrelation consistent (HAC) standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.7. Robustness tests

The primary result of my empirical study is the significant presence of anti-herding behavior, observed in four of the five analyzed regions (with Ontario being the exception), at least in some sub-periods. Given that significant anti-herding behavior may arise due to the large size of the considered regions, potentially harboring significantly heterogeneous herding/anti-herding dynamics within, I test the robustness of my results by investigating the phenomenon in the Canadian census metropolitan areas (CMA) with a population exceeding one million inhabitants according to 2021 data. The metropolitan areas meeting this criterion are as follows: Toronto (Ontario), Montreal (Quebec), Vancouver (British Columbia), Ottawa-Gatineau (Ontario), Calgary (Alberta), and Edmonton (Alberta).

Table 10 presents the results of estimating Equation (1) via OLS for the mentioned CMAs.

The results indicate that anti-herding was observed in all CMAs, as γ_2 is significantly positive in all cases at the 1% level of statistical significance.

I also conduct the estimation of Equation (2) using quantile regressions. The results, not reported here due to space constraints, generally corroborate the findings reported in Table 10. However, there is one exception: While Table 10 indicates significant anti-herding in the Toronto CMA, the quantile regression shows a γ_2 not statistically different from zero at the median level at conventional levels of statistical significance. This contradictory result highlights the lesser prevalence of anti-herding behaviors in the Ontario region, where the Toronto CMA is located, a point I mention in sections 4.1. and 4.2.[1].

[1] To assess the presence of herding/anti-herding in the Canadian real estate market as a whole, I also estimate the conventional OLS model proposed by Chang et al. (2000), $CSAD_{i,t} = \gamma_0 + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_{i,t}$, where $CSAD_{i,t}$ represents the cross-sectional absolute return dispersion of the observed returns in the real estate markets of each of the

Table 10. Estimates of herding/anti-herding behavior in the most populated census metropolitan areas (CMA).

	Toronto (Ontario)	Montreal (Quebec)	Vancouver (British Columbia)	Ottawa-Gatineau (Ontario)	Calgary (Alberta)	Edmonton (Alberta)
γ_0	0.001***	0.002***	0.002***	0.002***	0.001***	0.002***
γ_1	0.327***	0.232***	0.412***	0.429***	0.562***	0.384***
γ_2	6.522***	6.909***	7.469***	4.912***	3.726***	7.760***
Adjusted R^2	37.24%	12.93%	31.51%	27.83%	38.47%	24.78%

Notes: This table reports the estimated coefficients for the model $AD_{i,t} = \gamma_0 + \gamma_1 |R_{i,t}| + \gamma_2 R_{i,t}^2 + \varepsilon_{i,t}$, where $AD_{i,t}$ stands for absolute deviation of returns of observed in each census metropolitan area i ($R_{i,t}$) with respect to the market return in month t ($R_{m,t}$). The sample period spans February 1986 to November 2023. The significance of the coefficients is assessed using Newey–West heteroscedasticity and autocorrelation consistent (HAC) standard errors. *** denotes statistical significance at the 1% level.

5. Discussion

My results are consistent with the fact that, overall, participants in Canada's regional housing markets exhibit significant anti-herding behavior, meaning they deviate from the market consensus more than rationality would dictate. Additionally, my findings suggest a notable time-dependent aspect to this phenomenon. Although anti-herding seems to occur significantly only in bull markets across most regions, the disparities in its strength between bull and bear markets are statistically significant solely in the British Columbia region. Overall, anti-herding demonstrates an asymmetric and declining dependence structure. Furthermore, my study indicates that anti-herding behavior is more prevalent during periods of low economic policy uncertainty.

Moreover, the following question arises: How may I interpret the prevalence of anti-herding in light of the literature on the phenomenon? The literature suggests that anti-herding behavior is more commonly observed in mature markets than in emerging ones (Chang et al., 2000; Gleason et al., 2004). Authors such as Klein (2013) conjecture that anti-herding behavior is more likely to be found in more sophisticated markets, and over time, there is a tendency for markets to progress from a state where herding is more prevalent to one where anti-herding predominates. Moreover, given indications that herding tends to be more prevalent in assets with high market liquidity (e.g., Galariotis, 2016b; Vo and Phan, 2019), this could help explain not only why herding is relatively less common in illiquid housing markets but also potentially

geographic areas around the market return, $CSAD_{i,t} = \frac{\sum_{i=1}^{N} |R_{i,t} - R_{m,t}|}{N}$, with $R_{i,t}$ being the observed return in the housing market of geographic area i in month t, N the number of geographic areas considered, and $R_{m,t}$ the market return. I calculate this regression considering the five regions (Atlantic Region, Quebec, Ontario, Prairie Region, and British Columbia) and the six CMAs (Toronto, Montreal, Vancouver, Ottawa-Gatineau, Calgary, and Edmonton). Additionally, following Pochea et al. (2017), I also estimate the regressions by adding the 1-month lag variable $CSAD_{i,t-1}$ to the independent variables of the models to mitigate multicollinearity among explanatory factors. In all cases, the regressions confirm the existence of significant anti-herding behavior in the Canadian housing market at the 1% statistical significance level. The results of the mentioned regressions are available upon request.

account for increased instances of anti-herding such as those observed in the market under study. In this context, finding anti-herding in a mature real estate market like Canada's would not be completely surprising. Additionally, anti-herding behaviors have been observed across various agents who attempt to predict market developments in mature markets. These agents include macroeconomic forecasters (Batchelor and Dua, 1990), stock analysts (Naujoks et al., 2009), oil-price forecasters (Pierdzioch et al., 2010), or real estate forecasters in Canada, Japan, and the US (Pierdzioch et al., 2012b).

The primary models of herding transmission mentioned in the literature are based on informational cascades, reputational concerns, and informational inefficiencies in prices (Hirshleifer and Teoh, 2009; Spyrou, 2013). However, the following question arises: What are the reasons that might justify anti-herding behavior? Although anti-herding behavior has not been as extensively studied in the literature as herding behavior, five causes can be identified for market agents exhibiting anti-herding behavior: localized herding, excessive flight to quality, overconfidence, highly competitive preferences, and strong private information.

First, localized herding occurs when a group of investors simultaneously buy and sell certain assets against the broader market trend in an attempt to capitalize on market movements, resulting in increased dispersion of returns as they oppose the predominant consensus (Gebka and Wohar, 2013; Gemayel and Preda, 2018). Given the illiquidity and transaction costs inherent in housing markets, this approach appears impractical and costly within these markets. Consequently, this factor seems unlikely to significantly contribute to the observed anti-herding in my sample.

Regarding the excessive flight to quality, periods characterized by high volatility and uncertainty often prompt portfolio rebalancing (Caballero and Krishnamurthy, 2008; Guerrieri and Shimer, 2014). This entails investors reallocating their capital from riskier positions or markets to more secure ones, which frequently includes housing. If assets originate from non-housing liquidations, funds could swiftly be reinvested into property. On a national scale, this could lead to opposing price movements for risky and safe assets, potentially resulting in a divergence from market consensus. However, only a limited number of individuals possess enough liquid assets to acquire additional properties. Furthermore, I would expect these flight-to-quality effects to be more pronounced during periods of heightened uncertainty and market stress, which contrasts with the observation that in my sample, anti-herding seems to strengthen when political uncertainty levels are lower. Additionally, selling housing is neither costless nor immediate if market conditions warrant a shift into other asset classes. These factors lead me to believe that this explanation may not have been the primary driver behind the results obtained in my sample.

Another explanation for anti-herding lies in the overconfidence of market participants, particularly after periods of high positive returns. Individuals may attribute their success to their own skills rather than overall market conditions, leading them to overemphasize their own views and disregard market signals when making subsequent decisions. This overconfidence may result in overly dispersed returns, as individuals tend to be extremely confident in their abilities and are less likely to follow the opinions of others (Sornette and Zhou, 2006; Ekholm and Pasternack, 2008; Pollock et al., 2024). In the real estate market of the UK, a market of similar maturity to Canada, homeowners are generally overconfident except during down markets or recessions (Hwang et al., 2020). Taking these factors into consideration, while it is reasonable to assume that participants in the Canadian housing market might exhibit overconfidence, it is important to be cautious in assigning significance to this explanatory factor. This is because it is challenging to reconcile with the observation that, in my sample, the intensity of anti-herding seems to rise in bull markets only in the British Columbia region.

Research has associated highly competitive preferences among individuals with increased risk-taking and a pursuit of status (Friedman and Savage, 1948; Koedijk et al., 2013). Consequently, in certain scenarios, an investor striving for status may opt to display significant deviation from the average investor. This is what I expect to observe, particularly in the real estate market, given that housing can be socially perceived as a signal of value, thus functioning as a strong positional good and a source of status (Foye et al., 2018). Therefore, if contrarian behavior becomes prevalent enough, it may give rise to anti-herding behavior. While it is plausible to consider that this mechanism could be present in the market under analysis, it is challenging to assert that it is widespread enough to generate anti-herding behavior as frequently as observed in the Canadian housing market.

Taken together, these arguments suggest that anti-herding behavior in real estate markets is best understood through an integrated framework that combines insights from behavioral asset pricing theory and models of information asymmetry. Bounded rationality and behavioral biases, such as overconfidence and status-seeking, influence how market participants process and weigh information, while the presence of strong, location-specific private information shapes the incentives to deviate from the market consensus. In segmented housing markets, where transparency is limited and information acquisition is costly, agents may rationally place greater emphasis on their private signals, leading to systematic departures from herding behavior. Although behavioral factors may amplify these deviations in certain market conditions, my analysis indicates that informational considerations play a dominant role in explaining the prevalence of anti-herding observed in the Canadian housing market.

In my view, the existence of strong private information is the primary justification for the anti-herding documented in my empirical study. Given the characteristics of real estate markets (asset heterogeneity, geographic segmentation, limited transparency, information asymmetries, illiquidity, high transaction costs, and the lack of easily accessible and frequent pricing), the aggregation of information through market mechanisms is relatively less efficient than in financial asset markets. I acknowledge that market-wide herding measures are inherently subject to endogeneity and may capture informational inefficiencies rather than pure behavioral deviations; however, these features are intrinsic to real estate markets and constitute a central mechanism through which strong private information can generate persistent deviations from market consensus. Such inefficiencies are well documented in the literature, which reports substantial departures from informational efficiency in real estate markets (Case and Shiller, 1990; Beracha et al., 2012; Nneji et al., 2013; Fabozzi et al., 2020; Trojanek et al., 2023). Additionally, the expense and time involved in physically visiting properties contribute to a significant acquisition cost for information, leading investors to develop strong private knowledge about local markets. Given that property values are heavily influenced by location, possessing private information about specific areas is crucial for making informed investment decisions.

The literature has shown that anti-herding effects are likely to occur in contexts where there is strong private information (Daniel et al., 1998; Avery and Chevalier, 1999; Levy, 2004). For instance, in Daniel et al.'s (1998) model, agents tend to overreact to private information while underreacting to public news. Since private information is typically accessible primarily to local agents, whereas public news reaches individuals regardless of their location, this leads to exaggerated responses to private, location-specific information, causing asset prices to deviate from the market consensus. The finding that housing markets in Canada display a high degree of geographic segmentation highlights the importance of local private information to market participants (Allen et al., 2009). The connection between overreaction to private information and anti-herding has been empirically confirmed (Broughton and Lobo, 2018). Theoretical models also suggest that anti-herding becomes more frequent when agents are better able to assess the value of their private information, which is likely to occur when there is less economic policy uncertainty, as observed in my empirical study. For example, in Avery and Chevalier's (1999) model, herding occurs when agents lack private information about their abilities. However, as the market matures and agents gain more experience, becoming aware of the value of this private information, they tend to exhibit anti-herding behavior more often. Overall, the tendency to herd or anti-herd appears to depend on how accurately individuals evaluate the information they possess (Ottaviani and Sorensen, 2006). These effects may be strengthened by reputational mechanisms that increase the incentives for agents to signal their private information and deviate from the market consensus, even if they are unaware of the value of that information (Prendergast and Stole, 1996; Effinger and Polborn, 2001).

6. Conclusions

In this study, I examine, for the first time, the occurrence of herding and anti-herding behavior in Canada's regional housing markets, analyzing data spanning February 1986 to November 2023. I employ a diverse set of econometric techniques, including sub-sample analysis, rolling window regressions, quantile regressions, and probit regressions, enabling a more robust and comprehensive characterization of the phenomenon under study. Unlike most researchers in this field, I utilize direct housing prices instead of REIT returns. This methodological choice offers a significant advantage, as direct housing prices provide a more reliable reflection of the housing market compared to REITs. Direct housing prices are less susceptible to broader market sentiments and the herding/anti-herding dynamics affecting the stock market.

My results are highly suggestive of the presence of anti-herding in most of the regions studied and during most of the examined sub-periods. Ontario stands out as the only region where market participants do not exhibit anti-herding in any of the considered sub-periods. The phenomenon displays marked dynamics over time, with periods of prolonged anti-herding and others where it is absent. Interestingly, there is a notable absence of herding periods in the analyzed regional markets. While anti-herding appears to exist at significant levels only in bull markets in most regions, the differences in its intensity between bull and bear markets are statistically significant only in the British Columbia region. Overall, anti-herding demonstrates an asymmetric and declining dependence structure in most regions, and it is more likely to occur during periods of lower economic policy risk. These findings are consistent with the existence of strong private information resulting from the regional segmentation of the Canadian housing market.

The presence of anti-herding behavior in regional real estate markets in Canada aligns with similar findings in the UK and US. For instance, Akinsomi et al. (2018a) identified significant anti-herding in the UK market of listed REITs using a static model similar to the one used in my empirical study. Likewise, Ngene et al. (2017) demonstrated that anti-herding behavior occurs in some periods across six of the nine regions analyzed in the US. Moreover, Pollock et al. (2024) found that anti-herding behavior is predominant in US metropolitan housing markets, which the authors attribute to the interaction between price appreciation and overconfidence.

The implications of widespread anti-herding behavior in a housing market are significant for stakeholders. For academia, the prevalence of anti-herding behavior suggests that traditional rational asset valuation models may be inadequate to assess housing prices. This observation encourages the incorporation of behavioral factors into valuation models to better capture the observed price dynamics in the market.

The implications for real estate market participants are equally important. While the literature has shown that herding behavior can increase market volatility and contribute to speculative bubbles and crashes (Lux, 1995; Hott, 2009), leading to deviations of housing market prices from fundamentals (Hott, 2012), the consequences of anti-herding are less explored. However, it is evident that excessive deviations of returns from the market consensus increase the risk of some investors buying or selling properties at prices that are either too high or too low (Merli and Roger, 2013). This is particularly relevant given the substantial sums typically involved in these transactions relative to individuals' available income. Furthermore, price deviations from equilibrium present profit opportunities for those who view real estate as a speculative asset. Moreover, the presence of herding and especially anti-herding can be associated with idiosyncratic risk and diversifiable risk (Gebka and Wohar, 2013). Thus, holding investment positions in the housing markets of only a few regions in Canada may not ensure efficient portfolio diversification.

Finally, the observation of widespread anti-herding behavior in the real estate market is also of interest to market regulators and policymakers. This behavior signals potential market inefficiencies in aggregating private information, which could exacerbate market volatility, particularly during crises, thereby posing risks to the financial system. Since anti-herding undermines market participants' ability to diversify risk (Gebka and Wohar, 2013), large institutional investors in the real estate market may face unmanageable levels of risk during adverse economic conditions. Significant losses in this context could lead to contagion effects that heighten the fragility of the financial system and increase systemic risk (Hautsch et al., 2015; Helwege and Zhang, 2015). In terms of housing policy, given that the observed anti-herding behavior appears to be linked to the presence of strong private information in the real estate market, as discussed in the previous section, my findings suggest that regulators and policymakers should enhance the dissemination and accessibility of market information to participants. In particular, establishing standardized regional real estate data disclosure frameworks would help harmonize information availability across provinces and reduce fragmentation in market signals. In parallel, the implementation of AI-based public information systems could improve the real-time processing and dissemination of housing market indicators, thereby lowering information acquisition costs and mitigating asymmetries between informed and less-informed participants. Finally, encouraging cross-provincial coordination in data collection and dissemination would support more coherent price discovery at the national level and limit the scope for localized informational advantages. Together, these measures would lower the costs of acquiring information and facilitate more efficient price formation through market mechanisms.

My results should be interpreted with some qualifications. While my analysis relies on the NHPI, I assume that the newly built segment is broadly representative of the Canadian housing market. Therefore, my conclusions are primarily applicable under the premise that trends observed for new houses reflect the dynamics of the overall housing market. An additional potential concern in the empirical analysis relates to the endogeneity between economic policy uncertainty (EPU) and real estate market behavior. While fluctuations in EPU may influence housing market dynamics by affecting expectations, investment timing, and risk perceptions, developments in the real estate market can also feed back into policy uncertainty through their impact on macroeconomic stability, fiscal conditions, and regulatory responses. This bidirectional relationship raises the possibility that observed associations may reflect simultaneous causality rather than a purely exogenous effect of policy uncertainty on market behavior. To mitigate this concern, researchers could employ identification strategies such as instrumental variable approaches, lag structures, or natural experiments linked to exogenous policy shocks.

Beyond this issue, there are several additional avenues to be pursued in the exploration of herding and anti-herding behavior in real estate markets. For instance, it would be valuable to investigate the relationship between the dynamics of herding and anti-herding in real estate markets and those in stock markets. Such an analysis could highlight behavioral differences between participants in these distinct markets. It would also be worthwhile to investigate whether the anti-herding dynamics in relation to market consensus identified in my study are prevalent at a micro-level among subsets of investors operating in the Canadian real estate market. Another valuable line of inquiry would involve exploring the impact of macroeconomics conditions (economic growth, interest rates, inflation, etc.) on the dynamics of herding/anti-herding behavior. A further avenue for research could be to examine the influence of herding/anti-herding on generating predictability patterns in real estate prices, such as the momentum effect or price overreaction.

Use of AI tools declaration

The author declares that Generative AI tools were used solely for language editing purposes, including grammar correction, punctuation, and improvements to sentence clarity and readability. These tools were not used for the generation of ideas, research design, data analysis, interpretation of results, or the drafting of scientific content. All intellectual contributions, analyses, and conclusions presented in this manuscript are the sole responsibility of the author.

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Conflict of interest

The author declares no conflicts of interest in this paper.

Data availability statement

The data used to support the findings of this study are publicly available.

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