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Measuring New Housing Prices in Pre-Sale Markets: A Repeat-Sales Approach Using Purchase Contract Cancellations

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In markets dominated by pre-sales, which is a structural feature of housing provision in emerging economies, constructing price indices is limited by the lack of resale history. Addressing this statistical blind spot, this study proposes a novel empirical strategy which exploits purchase contract cancellations to identify repeat-sales pairs. Utilizing a dataset of 25,049 pairs from Santiago (2013–2024) in Chile, this approach mitigates depreciation bias by comparing the same never-occupied unit over time. Results from geometric and arithmetic estimators reveal three key findings: (1) a distinct price hierarchy, where capital appreciation disproportionately favors entry-level housing and investment segments; (2) the index serves as a leading indicator, which anticipated the post-2021 market correction ahead of official administrative records; and (3) a 27% nominal loss rate in subsequent placements, which exposes the magnitude of price adjustments consistent with liquidity frictions. These findings validate cancellations not merely as administrative voids, but as real-time signals of financial distress, thus offering a replicable monitoring tool for global jurisdictions reliant on the pre-sale leverage model.

Keywords

Housing price index, Repeat sales, Contract cancellations, Pre-sale market, Leading indicator.

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1. Introduction

Accurately measuring housing price dynamics is a cornerstone of macroeconomic stability and national wealth assessment. In the Chilean case, this asset is critical due to both its aggregate magnitude and substantial weight in the domestic economy. Recent studies estimate the market value of the housing stock at 1.7 times the gross domestic product (GDP; Balsa and Vásquez, 2023b), thus establishing the housing stock as the principal capital asset of Chile. Household exposure is equally significant: according to the latest Household Financial Survey, the primary residence constitutes 59% of the real assets of households, while mortgage debt accounts for 80% of their total liabilities (Banco Central de Chile, 2025). Within this context, timely and accurate monitoring of value fluctuations is essential for prudential supervision. As Idrovo et al. (2021) emphasize, developing early warning indicators is crucial for detecting episodes of price exuberance and preventing imbalances that could jeopardize financial stability.

However, the construction of price indices for the new housing segment presents structural challenges that traditional literature has not resolved in a satisfactory manner. As noted in international best practice manuals (European Commission, 2013), conventional repeat-sales indices systematically exclude new construction due to a mechanical constraint: new units, sold for the first time, lack the prior transaction history required to form a sales pair. This limitation creates a statistical blind spot in dynamic markets where pre-sale or off-plan models predominate.

The central challenge lies in the nature of the data: unlike the resale market, the new housing market lacks the initial transaction history required for robust tracking. While the literature has proposed alternatives to overcome this limitation, which range from hedonic price models to median-based indicators and pseudo-sale matching techniques, these methods often face significant limitations. Hedonic models require costly attribute data that may exhibit parameter instability during volatile periods, whereas simple medians suffer from severe composition and spatial selection biases (Hill et al., 2018), particularly in segregated cities like Santiago. Furthermore, recent adaptations like pseudo-sales and traditional repeat-sales applications over long horizons struggle to disentangle pure price movements from unobserved heterogeneity and physical depreciation.

To bridge this gap, this study proposes a novel methodological strategy: the use of purchase contract cancellations as a source of high-frequency information for constructing price indices. In active pre-sale markets, units that initially contracted at the early project stages (period t) frequently re-enter the available inventory following a cancellation by the original buyer, only to be contracted again at an updated price (period $t+\tau$). This turnover generates a true repeat-sales pair for the same physical unit, thus transforming a single failed transaction into a valid longitudinal data point. By ensuring the asset remains new and never-occupied between transactions, the method strictly adheres to the constant-quality assumption and mitigates depreciation bias, thereby aligning with recent literature that highlights the superiority of actual transaction data over static valuations for price prediction (Birkeland et al., 2021).

To validate this proposal, the study utilizes a transactional database from the Chilean Chamber of Construction (CChC) that covers the Santiago metropolitan area for the period of 2013–2024. This market offers an ideal setting for empirical testing due to the depth of its pre-sale market and availability of accurate transactional records. Drawing on a robust and cleaned sample of 25,049 repeat-sales pairs, Jevons-type (geometric) and Laspeyres-type (arithmetic) indices are estimated by following the taxonomy of Shiller (1991) and the European Commission (2013) with the use of heteroscedasticity corrections to ensure estimator efficiency. This framework enables an analysis of price dynamics across a full cycle that comprises expansion, liquidity shock, and contractive adjustment.

While empirically tested in Santiago, Chile, the implications of this study extend to the Global South and major Asian economies, where the pre-sale model is the dominant form of housing provision. In these jurisdictions, the absence of immediate deed records creates a statistical blind spot. The methodology proposed here offers a replicable framework for any market where forward contracts are recorded prior to delivery.

Reliance on pre-sales is not unique to Chile but represents a structural financing mechanism across major emerging economies. Deng et al. (2025) document that pre-sale funds function as a critical substitute for bank credit, thus allowing developers to leverage buyer deposits as working capital to finance construction velocity and volume. Theoretical models by Chan et al. (2008) confirm that in such credit-constrained markets, pre-sales function as essential equity injections. Recent evidence by Chen et al. (2024) further reveals that developers use this liquidity to engage in multitasking by initiating concurrent projects before completing existing ones, thereby accelerating urban growth but amplifying systemic risk. In mature markets like Hong Kong, Li et al. (2023) find that this mechanism is also used strategically to hedge against price volatility. Consequently, the methodology proposed here offers a replicable framework for jurisdictions where the pre-sale leverage model creates a statistical blind spot in traditional deed-based indices.

This study contributes to the international real estate literature in three ways. First, the work formalizes a repeat-sales methodology free from depreciation bias, applicable to any market characterized by pre-sales and contract cancellations, thus overcoming the exclusion of new housing cited by statistical agencies. Second, the study empirically documents a statistically significant price hierarchy validated by confidence intervals, thus revealing that capital appreciation is concentrated in the entry-level housing and investment segments. This reveals a dual dynamic where both middle-income households (credit-constrained) and investors (yield-seeking) exert upward pressure on low-ticket asset prices, in contrast to the higher rigidity observed in the high-end segment. Finally, the research demonstrates that a cancellation-based index serves as a leading indicator, which anticipates market corrections ahead of official indices based on administrative records.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on housing price index construction and specific challenges of pre-sale markets. Section 3 describes the data and identification strategy based on cancellations. Section 4 presents the empirical results and calculated indices. Section 5 discusses the economic implications of the findings, and Section 6 concludes.

2. Literature Review

The construction of real estate price indices has sparked extensive econometric debate, primarily centered on the challenge of controlling for asset heterogeneity while maximizing the use of available information. This section reviews the methodological foundations, inherent limitations of the new housing market, and relevant international evidence in pre-sale contexts.

2.1 Fundamentals of Repeat-sales Method

The repeat-sales approach is grounded in the seminal work of Bailey et al. (1963), who propose the use of price variations of the same property across two distinct periods to estimate a geometric price index. This methodology, classified as a Jevons-type index in international manuals (European Commission, 2013), implicitly controls for time-invariant property characteristics. Subsequently, Case and Shiller (1987) refine this framework by identifying that the variance of the regression error term tends to increase with the interval between transactions (or holding period). To correct for this heteroscedasticity, they develop the weighted repeat sales method, which assigns lower weights to repeat-sales pairs with longer intervals, thereby enhancing estimator efficiency. Shiller (1991) further expands this framework by introducing arithmetic Laspeyres-type estimators, which are designed to track the performance of a real estate asset portfolio.

The validity of this methodology has been well-established across different geographical contexts that range from pioneering studies in the United Kingdom (Leishman and Watkins, 2002) to applications in Latin American markets like Colombia, where Escobar et al. (2006) demonstrate its utility given the scarcity of hedonic data. Similarly, comprehensive methodological reviews

(Nagaraja et al., 2014) conclude that, despite their modest data requirements, repeat-sales indices offer competitive performance relative to more complex models. In the Chilean context, while previous studies have developed housing quality and hedonic attributes indices to analyze local price determinants and construct aggregate market metrics (e.g., Cifuentes et al., (2020); Idrovo and Lennon (2011)), these approaches often require exhaustive structural data that may not be readily available at a high frequency.

The preference for this method over hedonic models (Rosen, 1974) is supported by practical constraints. As Shimizu and Karato (2016) note, collecting structural attribute data is often costly or incomplete. Furthermore, Chin and Chau (2003) document that the implicit prices of hedonic attributes are often unstable over time, thus potentially introducing bias if the model is not continuously respecified. By bypassing the need for attribute specification, the repeat-sales method offers a more robust price signal against structural changes in characteristic valuation.

2.2 Challenges of New Housing and Depreciation

Despite its theoretical advantages, the application of the repeat-sales method faces a structural constraint in the primary market. Epley (2016) identifies the exclusion of new construction as a critical limitation, and argues that, by definition, new units lack the prior sales history required for inclusion in traditional indices.

To overcome this barrier in emerging markets, recent studies in the literature have proposed pseudo-repeat sales techniques via spatial matching of similar units in adjacent buildings (Zhang et al., 2025; Guo et al., 2014). While these approaches which are based on spatial matching algorithms increase sample sizes, they fail to fully eliminate unobserved heterogeneity across distinct units. In this regard, the literature continues to refine these methods to navigate data constraints: Contat and Larson (2024) propose flexible aggregations to improve precision in submarkets, while Case et al. (1991) caution about the need to carefully select methodologies based on market homogeneity.

Additionally, the literature has raised concerns regarding the constant-quality assumption. Cannaday et al. (2005) demonstrate that, over long horizons, it is econometrically difficult to separate the pure effect of market appreciation from the negative impact of physical depreciation. This collinearity between age and time often induces a downward bias in long-term indices unless explicit corrections are applied. However, by focusing on new, never-occupied units, this study neutralizes this effect, thus aligning with rigorous robustness criteria.

2.3 Pre-sale Markets and Price Discovery

Price dynamics in markets dominated by pre-sales or off-plan sales, which is a common feature in Asian and Latin American economies, have been a central focus of debate. Tse et al. (1999) theoretically distinguish between owner-occupier and investment demands, thereby suggesting that transaction volumes and investment flows act as predictors of price cycles.

Regarding market response to crises, Leung et al. (2007) provide evidence on the instability of implicit prices during financial shocks, and find that attributes associated with luxury housing segments tend to exhibit more severe structural breaks than basic attributes. This suggests that aggregate indices may mask divergent dynamics across submarkets of different values.

In this context of friction and segmentation, the information transmission mechanism is critical. Ong and Sing (2002) introduce the concept of price discovery by analyzing the interaction between public and private markets, wherein certain market segments —typically the most liquid or least regulated, lead the adjustment, in anticipation of general trends. Complementing this view, Yiu (2009) documents how real interest rates act as the fundamental driver of price cycles, and finds that negative rates have an asymmetric and potent effect on housing bubble formation. This evidence supports the hypothesis that the recent cycle in Santiago is driven by extreme fluctuations in the real cost of financing. These studies suggest that, in investor-led markets, indicators based on high-frequency transactions can capture changes in fundamentals and sentiment ahead of official records — a hypothesis reinforced by recent evidence regarding the predictive superiority of actual transaction data over static appraisals (Birkeland et al., 2021).

Beyond price discovery, the literature emphasizes the role of pre-sales as a substitute for corporate finance. Chan et al. (2008) theoretically demonstrate that in markets with nascent financial systems, pre-sales provide the necessary working capital to reduce the weighted average cost of capital for developers. This structural dependency is empirically supported by Deng et al. (2025) in the context of China, where the pre-sale model has been shown to drive the high-turnover strategy of major developers, thus prioritizing sales velocity over profit margins to maintain liquidity.

2.4 Sample Selection Bias

Finally, index reliability depends critically on data representativeness. While indices based on online listings have proliferated due to their low cost, Lopez Ochoa (2023) shows that they suffer from severe spatial selection biases, thus systematically overrepresenting high-income areas. On the other hand, repeat-sales models face the risk that frequently transacted properties may differ from the total stock (Gatzlaff and Haurin, 1997). This challenge demands rigorous empirical validation to confirm that the sample of cancelled contracts is an unbiased reflection of the universe of sales.

Unlike the existing housing market, where a resale often signals user dissatisfaction with specific unit attributes, an asset typically does not yet exist physically or has not been inhabited in pre-sale markets. Therefore, cancellations are structurally driven by buyer-side financial shocks (credit denial, liquidity constraints) rather than asset-side idiosyncratic defects. This feature suggests that the assignment of cancellations is orthogonal to the unobserved physical quality of the unit.

3. Data and Methodology

3.1 Institutional Background of the Pre-sale Market

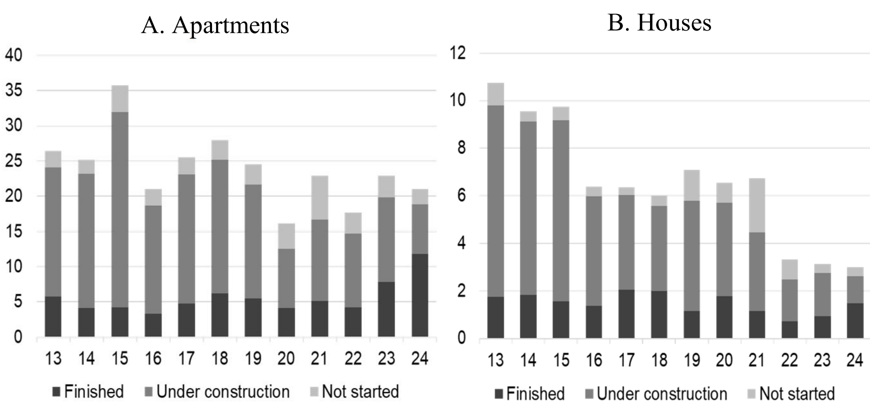
In the real estate market of Santiago, the pre-sale model known as “venta en verde” (off-plan sale during construction) or “venta en blanco” (pre-sale prior to construction), is the dominant mechanism for both acquiring new housing and financing real estate development. Unlike mature markets where buyers might simply pay a nominal, refundable reservation fee, the Chilean system relies on a legally binding forward contract known as the “promesa de compraventa” (promise of purchase and sale).

The financial mechanics of this contract are strictly regulated to protect market stability. During the validity of the promise, the buyer typically makes advance payments in installments, and these advances are intended to cover the down payment (usually 10% to 20% of the property value) that the financial institution will eventually require to issue the final mortgage upon delivery. Under Chilean Law No. 19932, developers are legally mandated to guarantee all advance payments received during the “verde” or “blanco” stages with an insurance policy or a bank guarantee. This legal framework ensures that the funds of the buyer are protected in the event of developer default or bankruptcy. A critical feature of this system, and the fundamental basis of the identification strategy in this study, is the strict penalty mechanism for contract cancellation (“desistimiento”). To ensure reciprocal compliance, the purchase promise includes a penalty clause typically backed by guarantee checks deposited by both parties at the time of signing. If a buyer cancels the contract without justified cause, the developer is entitled to cash this guarantee, which customarily ranges from 10% to 20% of the total asset value or the agreed-upon down payment. Consequently, when a contract is cancelled and the unit returns to the inventory of the developer, it is rarely a costless administrative event or a mere change in consumer preference regarding the asset. Facing such severe financial penalties, a cancellation serves as a signal of buyer-side financial distress. These cancellations normally occur near the delivery date when the buyer fails to secure the final mortgage approval due to macroeconomic shocks,

tighter credit standards, or a deterioration in household income. This institutional reality confirms that the cancellation records analyzed in this study are real-time indicators of liquidity constraints and market clearing dynamics, thus fully validating the econometric design.
When analyzing the composition of these forward contracts, it is evident that off-plan sales during the construction phase ("venta en verde") constitute the fundamental pillar of the Chilean real estate market, which have historically constituted the vast majority of transaction volume across both housing segments, as shown in Figure 1. Pre-sales prior to construction ("venta en blanco") exhibit an asymmetric dynamic: while their presence is marginal in the house market (Panel B), they represent a significant fraction of promises in the apartment segment (Panel A). This structural difference responds to the longer development horizons and complex financial structuring typically required to trigger construction loans for high-rise projects compared to horizontal developments.

Together, the dominance of these two pre-sale modalities throughout the entire 2013–2024 cycle underscores a critical market reality: price formation occurs long before the physical completion of the asset. This definitively reinforces the methodological imperative of utilizing purchase promises to capture the true real-time price signal, rather than relying on final deeds that suffer from severe administrative lags.

Figure 1 Evolution of Purchase Promises by Construction Status (Thousands of Units)



3.2 Data and Sources

The empirical analysis draws on the transactional database from the CChC. This dataset is constructed from monthly information reported by a representative panel of real estate developers that are operating in Santiago.

A critical distinction of this study relative to the traditional studies in the Chilean literature (Parrado et al., 2009) and official indices (Balsa and Vásquez, 2023a) lies in the timing of the data capture. While public administrative records (Property Registrar or Internal Tax Service) register transactions at the deed signing stage which is a legal event that may occur 12 to 24 months after the economic agreement depending on construction progress, the CChC data records purchase promises (contracts) in the actual month in which they are signed. These are legally binding forward contracts that fix the price and quantity months or years before delivery, which differ from non-binding reservation fees common in other jurisdictions. This characteristic yields a significant time advantage. By using the price at the promise stage, the model captures supply and demand conditions in real-time relative to the economic decision, thereby avoiding the administrative lag inherent in deed-based indices, which reflect past pricing. In pre-sale markets, where cost volatility and financial conditions are high, the purchase promise serves as the most reliable proxy for the current market price.

The dataset covers the period from January 2013 to December 2024 (144 months), which spans a full real estate cycle that includes expansion, liquidity shocks, and contractive adjustment phases. It is noteworthy that, although systematic recording with unique unit identifiers began in January 2010, the timeframe of the study is selected to ensure stability of the initial estimates. Data from 2010 to 2012 serve exclusively as a burn-in period (inventory accumulation). This strategy allows for the build-up of a critical mass of initial promises susceptible to subsequent cancellation, thus ensuring that by the 2013 start date, the model has sufficient sample density to avoid the artificial volatility associated with thin markets, which is a common issue in the early stages of such indicators.

The total universe of records since the start of individualized collection (January 2010) exceeds 218,000 promises. However, after applying the stabilization period filter, the effective sample for analysis (January 2013 – December 2024) consists of 182,563 signed purchase promises for new housing, which comprise 143,176 apartments and 39,387 houses. For each observation, key hedonic variables (floor area, typology, and municipality) and the unique identifier of the unit are available, thus enabling the traceability of its commercial history to identify market re-entry events.

To ensure robustness and mitigate recording errors, a two-stage protocol for statistical cleaning is implemented which include outlier filtering and tail trimming. Bourassa et al. (2013) show that outlier removal significantly improves the accuracy of repeat-sales indices, a practice recommended by international institutions (European Commission, 2013). Following Case and Shiller (1987), transaction pairs with studentized residuals that exceed a threshold of $|t|>3$ in a preliminary regression are removed, which discards implausible price variations. For tail trimming, observations in the top and bottom 1% of the price and size distributions are excluded to remove unrepresentative extreme values.

3.3 Identification Strategy

Applying the repeat-sales method to a new housing market requires overcoming the lack of a prior resale history. To this end, this study implements an identification strategy based on tracking purchase contract cancellations.

In real estate markets characterized by pre-sale or off-plan transactions, the commercialization process is non-linear. A significant proportion of contracted units return to the available inventory due to failed financial closings of the original operation. A repeat-sales pair is defined when the following chronological sequence occurs for the same housing unit *i*:

1) Period t_1 (original promise): Unit *i* is contracted by an initial buyer at a price $P_{i,t}$.

2) Cancellation event: The promise is annulled (rescinded) prior to the final deed transfer, and the unit returns to the active inventory of the developer.

3) Period t_2 (subsequent placement): The same unit *i* is contracted again by a different buyer at an updated market price $P_{i,\tau}$, where τ represents the period of subsequent placement ($\tau > t$).

Applying this algorithm to the database yields 25,049 valid transaction pairs (18,621 apartments and 6,428 houses). This figure represents approximately 14% of the total flow of promises, a sample size sufficient enough to ensure the stability of monthly estimators and overcome inference issues in thin markets (Francke, 2010).

The fundamental methodological advantage of utilizing cancellations instead of secondary market resales is to preserve the quality of the asset. Classic repeat-sales studies (Case and Quigley, 1991; Cannaday et al., 2005) warn that long-term indices are often downward-biased due to physical depreciation (age effect) or upward-biased from unobserved renovations (McMillen and Thorsnes, 2006).

In the proposed design, the underlying asset remains strictly new and never-occupied between t and τ. The passage of time does not imply wear from use or functional obsolescence, but rather progress in the construction cycle of the project. Consequently, the price differential ($P_{i,\tau}$ / $P_{i,t}$) only captures the variation in market conditions and premium for reduced delivery risk, free from the idiosyncratic noise associated with physical wear or property improvements. This allows for the robust assumption that $\Delta Quality_i \approx 0$, which meets the theoretical assumption of Bailey et al. (1963) with more rigor than standard applications in used housing.

3.4 Econometric Models

To construct the price indices, three distinct estimators are used, following the classification outlined in international statistical manuals (European Commission, 2013). This strategy allows assessment of result sensitivity across different weighting and aggregation schemes. Specifically, both geometric and arithmetic indices are estimated. Goetzmann (1992) suggests that geometric methods may be more robust to data errors, while Shiller (1991) and Hansen (2009) argue in favor of arithmetic indices to accurately reflect changes in portfolio wealth.

3.4.1 Geometric Repeat Sales

The first estimator corresponds to the classical model proposed by Bailey et al. (1963), known in the index number literature as a Jevons-type index. The logarithmic variation in the price of property i is modeled as a linear function of the time dummy variables:

$$\ln(P_{i\tau}/P_{it}) = \sum_{j=1}^{T} \beta_j D_{ij} + \epsilon_{i\tau} \tag{1}$$

where P_{it} and $P_{i\tau}$ represent the transaction prices at the original promise (t) and subsequent placement (τ), respectively. D_{ij} is a dichotomous variable that has the value –1 if j=t, +1 if j=τ, and 0 otherwise. The estimated coefficients $\widehat{\beta_J}$ denote the logarithm of the price level in period j, and the index is recovered via exponentiation: $I_t^{GRS} = exp(\hat{\beta}_t)$.

3.4.2 Arithmetic Repeat Sales

While the geometric estimator captures the central tendency of prices, Shiller (1991) argues that it may underestimate the variation in the aggregate value of the real estate stock due to Jensen's inequality (Wang and Zorn, 1997). To address this and reflect changes in portfolio wealth, arithmetic indices (Laspeyres-type) are estimated under two specifications. Unlike the logarithmic model, coefficients here represent direct cumulative returns.

1) Equally weighted (EW) arithmetic repeat sales (ARS): This model estimates the average arithmetic return for a representative unit. The rate of price change is regressed on time dummy variables:

$$P_{i\tau}/P_{it} - 1 = \sum\nolimits_{j=1}^{T} \gamma_j \, D_{ij} + \nu_{i\tau} \tag{2}$$

The left side of Equation 2 denotes the nominal return of unit *i* between *t* and *τ*. The estimated coefficients $\widehat{\gamma_j}$ are interpreted as the average cumulative variation relative to the base period. Consequently, the index level in period *t* is obtained by adding one to the coefficient: $I_t^{EW} = 1 + \widehat{\gamma_t}$.

2) Value weighted (VW) ARS: To replicate total real estate wealth variation, the instrumental variable estimator in Shiller (1991) is used. The estimation employs the original matrix of time dummies (*D*) as instruments for the price-weighted variables ($P_{it} \cdot D_{ij}$). This procedure ensures estimator consistency by eliminating the endogeneity that arises from the correlation between the initial price and stochastic error term.

$$P_{i\tau} - P_{it} = \sum_{j=1}^{T} \lambda_j \left(P_{it} \cdot D_{ij}\right) + \xi_{i\tau} \tag{3}$$

In Equation 3, the dependent variable is the monetary change, and the regressors are the time dummies scaled by the purchase price (P_{it}). This implicitly assigns greater weight to high-value transactions. The estimated coefficient $\widehat{\lambda_j}$ represents the percentage change in the aggregate portfolio value, and the index is obtained analogously as: $I_t^{VW} = 1 + \hat{\lambda}_t$.

3.4.3 Correction for Heteroskedasticity

The literature indicates that the error term variance in repeat-sales models is not constant but tends to increase with the interval between transactions (Case and Shiller, 1987). To correct for this heteroskedasticity and obtain efficient estimators, weighted least squares (WLS) is employed. Although some studies suggest the impact is marginal in large samples (Hansen, 2009), others (Englund et al., 1998; Yeon, 2016) emphasize the importance of controlling the error structure to avoid spurious inference in volatile markets. This study adopts the weighted specification to prioritize statistical robustness over computational simplicity.

The procedure is executed in three stages as follows:

1) The GRS model is estimated via ordinary least squares.

2) The squared residuals ($\hat{e}^2$) are modeled as a function of the time elapsed between contracts ($\tau - t$), which yields the adjusted variance $\hat{\sigma}^2$.

3) All models (GRS, EW, and VW) are re-estimated, by weighting each observation by the inverse of the estimated standard deviation ($w_i = 1/\sqrt{\widehat{\sigma_i^2}}$). This correction ensures that repeat-sale pairs with excessively long or noisy holding periods exert less influence on the final index, thereby improving the accuracy of the confidence intervals.

3.5 Estimation and Normalization Procedures

The indices are estimated at a monthly frequency for the period of January 2013 (*t=1*) to December 2024 (*t=144*). To avoid perfect collinearity in the matrix of the time dummies, the first period is omitted from the regression, thus normalizing the index to a base of 100 in January 2013 ($I_{2013m1} = 100$).

Computationally, the implementation of arithmetic estimators (ARS) and their weighted variants requires the inversion of large-dimensional matrices. To ensure numerical accuracy and the exact replicability of the instrumental variable estimator proposed by Shiller (1991), the models are estimated by using direct matrix algebra (Mata language in Stata 18), thus avoiding the approximations inherent in standard regression commands.

Additionally, to mitigate high-frequency noise without incurring the detection lag associated with quarterly aggregation, which is standard in national accounts but detrimental to early warning indicators, the final series are smoothed with a three-period centered moving average. This approach optimizes the trade-off between signal stability and timeliness, thus preserving the monthly frequency essential for macroprudential monitoring (European Commission, 2013).

4. Empirical Results

4.1 Descriptive Statistics and Sample Characterization

The final dataset, consolidated following the application of the outlier detection criterion in Case and Shiller (1987) and a 1% trimming of prices and floor areas, comprises 25,049 repeat-sales pairs. The statistical properties of the sample are analyzed below to validate its econometric suitability and representativeness regarding the total universe of purchase promises.

4.1.1 Price Distribution and Heterogeneity

Table 1 summarizes the statistical moments of the transaction prices. Despite the cleaning process, the price distribution maintains a marked positive skewness, with means (CLF[1] 3,036 and 3,113; approximately $121,400 and $124,500 USD) that consistently exceed the medians (CLF 2,435 and 2,515; approximately $97,400 and $100,600 USD), thus confirming the influence of a high-value segment on the arithmetic average. Similarly, high kurtosis (9.82 and 9.13) indicates a leptokurtic distribution with heavy tails, which reveals

[1] The Unidad de Fomento (CLF) is a Chilean inflation-adjusted unit of account. For ease of interpretation by international readers, the USD equivalents provided are based on the approximate exchange rate at the end of the sample period (December 2024), where 1 CLF ≈ 40 USD.

significant dispersion in asset value. This distributional structure justifies the methodological preference for the geometric repeat sales (GRS) estimator, which has a logarithmic transformation that normalizes residuals, thereby mitigating the bias that simple arithmetic averages would introduce in a sample with such heterogeneity.

4.1.2 Representativeness and Selection Mechanism

To rule out potential quality biases within the cancellation subsample, Table 2 contrasts its attributes against the total universe of promises. A notable typological homogeneity is evident: the average number of bedrooms and bathrooms is virtually the same between the sample and universe (1.90 vs. 1.89 for apartments and 3.07 vs. 3.09 for houses). This finding is fundamental, as it dismisses the concern that cancellations are concentrated in atypical or marginal units; on the contrary, they affect the standard market product. This typological homogeneity supports the hypothesis that cancellations are driven by macro-financial constraints rather than idiosyncratic unit defects, thus mitigating concerns about negative selection bias based on unobservable quality.

This representativeness aligns with international evidence (Clapp et al., 1991; Wallace and Meese, 1997), which suggests that market arbitrage tends to balance the prices of high-turnover properties and the broader stock over the long term. However, a structural gap is observed in the total price: canceled units are 13% lower priced than the market average (CLF 2,969 vs. 3,416; approximately $118,700 vs. $136,600 USD). This differential confirms that the selection mechanism is not driven by the intrinsic quality of the asset (price per sq. meter is similar), but rather by budget constraints: cancellations disproportionately affect lower-ticket segments, where demand is more sensitive to bank borrowing limits.

4.1.3 Changes with Time and Construction Cycle

The changes of the sample with time (Table 3) reveals a structural regime shift. After remaining stable at approximately 12% during the expansionary phase, the incidence of cancellations surged to 30% in 2024 (reaching 37% in the housing segment). This sharp rise serves as an indicator of systemic financial stress, which is closely correlated with the tightening of credit conditions.

Regarding the holding period (Table 4), the median of 15 months aligns with the typical pre-sale construction cycle. The low incidence of short-term transactions (< 6 months: 21.2%) mitigates concerns regarding speculative noise, thus confirming that the index captures asset appreciation driven by the reduction of delivery risk rather than short-term arbitrage. This result distinguishes the current sample from the speculative issues identified by Jansen et al. (2008) and Steele and Goy (1997).

Table 1 **Summary of Price Variables**

		Obs.	Mean	St. Dev.	Median	Min.	Max.	Skewness	Kurtosis
Total	Price #1	25,049	3,036	1,972	2,435	744	16,540	2.29	9.82
	Price #2	25,049	3,113	1,955	2,515	1,012	15,589	2.21	9.13
Apartments	Price #1	18,621	2,731	1,735	2,260	744	15,770	2.77	13.06
	Price #2	18,621	2,799	1,713	2,339	1,012	13,886	2.77	13.00
Houses	Price #1	6,428	3,917	2,322	3,416	900	16,540	1.57	6.44
	Price #2	6,428	4,023	2,297	3,582	1,100	15,589	1.38	5.51

Notes: For reference, 1 CLF was approximately equivalent to 40 USD at the end of the sample period (December 2024). Housing prices measured in CLF (Unidad de Fomento). #1 corresponds to the original promise, #2 corresponds to the subsequent placement.

Table 2 **Distribution of Repeat-sales Sample**

		Obs.	Price	Floor area	Unit price	Bedrooms	Baths
Total	Repeat sales	25,049	2,969	59.3	53.0	2.20	1.60
	Promises	182,563	3,416	62.3	54.3	2.15	1.64
Apartments	Repeat sales	18,621	2,683	49.1	56.2	1.90	1.37
	Promises	143,176	3,186	53.8	57.7	1.89	1.45
Houses	Repeat sales	6,428	3,795	88.6	43.5	3.07	2.28
	Promises	39,387	4,254	93.4	42.2	3.09	2.30

Notes: For reference, 1 CLF was approximately equivalent to 40 USD at the end of the sample period (December 2024). Price corresponds to the transaction price measured in CLF; Floor area is measured in square meters; and Unit price is calculated as transaction price divided by floor area.

Table 3 Observations of Repeat-sales by Year

		2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Total
Total	RS	836	1,708	2,395	2,094	2,147	2,113	1,784	1,694	2,159	1,801	2,881	3,437	25,049
	P	16,570	17,328	23,347	13,947	16,299	18,671	16,192	11,042	14,689	10,081	12,791	11,606	182,563
	%	5%	10%	10%	15%	13%	11%	11%	15%	15%	18%	23%	30%	14%
Apartments	RS	517	1,015	1,377	1,424	1,545	1,735	1,483	1,331	1,638	1,401	2,311	2,844	18,621
	P	10,643	12,302	18,560	10,818	13,265	15,635	12,972	8,090	11,441	8,360	11,073	10,017	122,086
	%	5%	8%	7%	13%	12%	11%	11%	16%	14%	17%	21%	28%	15%
Houses	RS	319	693	1,018	670	602	378	301	363	521	400	570	593	6,428
	P	5,927	5,026	4,787	3,129	3,034	3,036	3,220	2,952	3,248	1,721	1,718	1,589	36,080
	%	5%	14%	21%	21%	20%	12%	9%	12%	16%	23%	33%	37%	18%

Notes: RS refers to the repeat-sale sample; P refers to the total promise sample; and % represents the incidence rate of cancellations.

Table 4 Holding Period between Original Promise and Subsequent Placement (Months)

	Obs.	Mean	Std. Dev.	Median	P25	P75	Short-term	Long-term
Total	25,049	17.9	14.2	15	7	26	21.2%	27.6%
Apartments	18,621	18.8	14.8	16	7	28	21.6%	31.1%
Houses	6,428	15.2	11.8	13	7	21	20.2%	17.3%

Notes: P25 and P75 refer to the 25th and 75th percentiles; Short-term indicates the share of transactions with a holding period below 6 months; and Long-term indicates the share with a holding exceeding 24 months.

4.1.4 Spatial Distribution and Risk Map

Finally, the analysis of the spatial dimension (Table 5) rules out severe geographic biases that could invalidate the generalizability of results. The distribution of the repeat-sales sample replicates the structure of the universe of purchase promises with high fidelity, thus preserving proportionality in municipalities with the highest real estate activity, such as Santiago and Estación Central.

Table 5 Spatial Distribution of Repeat-Sales and Promises

	Repeat sales	Share	Promises	Share	Cancellation Rate
Santiago	2,671	10.7%	25,282	13.8%	10.6%
Estación Central	2,442	9.7%	16,223	8.9%	15.1%
Puente Alto	2,224	8.9%	9,238	5.1%	24.1%
Ñuñoa	1,662	6.6%	14,091	7.7%	11.8%
La Florida	1,609	6.4%	11,139	6.1%	14.4%
Independencia	1,394	5.6%	8,647	4.7%	16.1%
Lampa	1,331	5.3%	9,008	4.9%	14.8%
San Miguel	1,321	5.3%	13,942	7.6%	9.5%
La Cisterna	1,287	5.1%	7,117	3.9%	18.1%
Macul	1,176	4.7%	8,638	4.7%	13.6%
Quinta Normal	996	4.0%	5,408	3.0%	18.4%
Padre Hurtado	682	2.7%	3,470	1.9%	19.7%
Maipú	612	2.4%	3,960	2.2%	15.5%
Colina	592	2.4%	4,435	2.4%	13.3%
San Joaquín	559	2.2%	2,735	1.5%	20.4%
Buin	421	1.7%	2,776	1.5%	15.2%
Las Condes	406	1.6%	6,527	3.6%	6.2%
Quilicura	396	1.6%	2,161	1.2%	18.3%
Renca	394	1.6%	3,074	1.7%	12.8%
Cerrillos	373	1.5%	1,340	0.7%	27.8%
Peñalolén	349	1.4%	2,002	1.1%	17.4%
Providencia	300	1.2%	3,361	1.8%	8.9%
San Bernardo	275	1.1%	2,793	1.5%	9.8%
Huechuraba	257	1.0%	2,450	1.3%	10.5%
Recoleta	224	0.9%	2,551	1.4%	8.8%
La Granja	195	0.8%	943	0.5%	20.7%
Lo Barnechea	194	0.8%	3,391	1.9%	5.7%
Pudahuel	159	0.6%	864	0.5%	18.4%
Peñaflor	148	0.6%	1,926	1.1%	7.7%
Vitacura	100	0.4%	993	0.5%	10.1%
Pedro Aguirre Cerda	84	0.3%	427	0.2%	19.7%
Conchalí	83	0.3%	579	0.3%	14.3%
Talagante	78	0.3%	291	0.2%	26.8%
La Reina	55	0.2%	726	0.4%	7.6%
La Pintana	0	0.0%	55	0.0%	0.0%
Total	25,049		182,563		13.7%

However, examining the implied cancellation rate by municipality reveals a pattern of financial segregation. Consolidated high-income municipalities in the eastern zone of Santiago (Las Condes, Vitacura, Lo Barnechea) exhibit single-digit cancellations rates (< 10%), which show demand with high credit resilience. In contrast, peripheral or emerging areas like Cerrillos (27.8%), Puente Alto (24.1%), or San Joaquín (20.4%) present rates triple those of the high-end sector. This spatial gradient confirms that the cancellation sample, while geographically representative, captures with higher intensity the dynamics of submarkets exposed to budget constraints, consistent with the price hierarchy subsequently observed in the indices.

4.2 Estimation of Price Indices

Based on the identified and cleaned repeat-sales pairs, three indices are estimated: the GRS, ARS-VW, and ARS-EW. Figures 2, 3, and 4 show the changes in these indices in levels, along with their respective confidence intervals normalized to the start of the period (Panel A), as well as their annual variations (Panel B).

Figure 2 Aggregate Repeat-Sale Housing Price Index

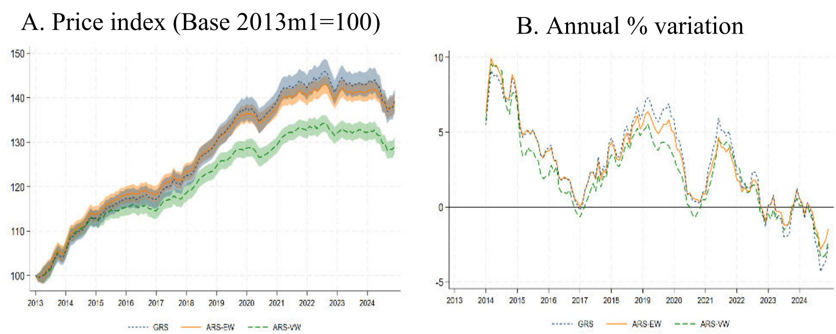


Figure 3 Repeat-sale Apartment Price Index

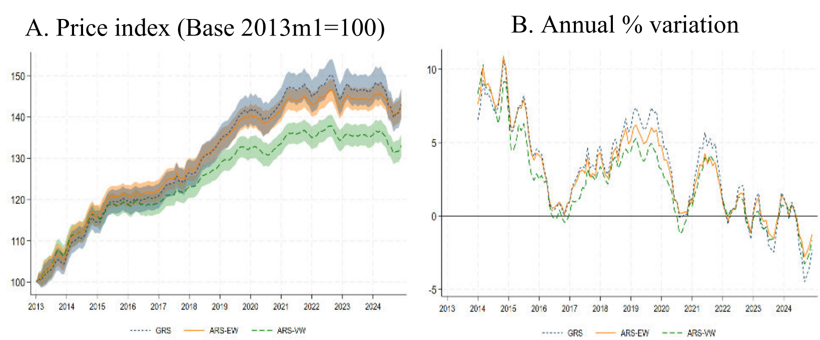
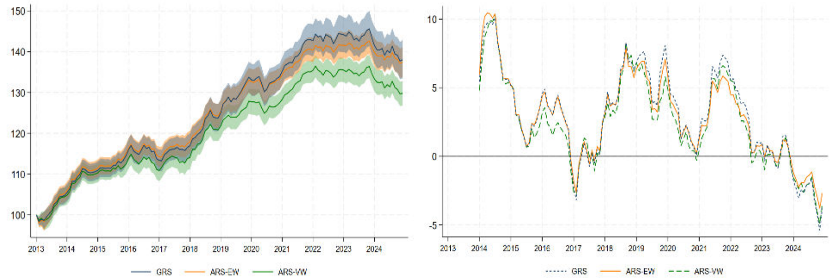


Figure 4 Repeat-sale House Price Index

A. Price index (Base 2013m1=100) B. Annual % variation



4.2.1 Econometric Validation and Model Robustness

The reliability of the indices is supported by the statistical robustness of the underlying regression models. Table 6 summarizes the goodness-of-fit metrics for the three estimators (GRS, ARS-EW, and ARS-VW) calculated on the cleaned sample by using WLS correction.

The results confirm the statistical validity of the constructed series:

1) Global significance: All of the models for the aggregate market exhibit highly significant F-statistics ($p < 0.01$), which allows for the rejection of the null hypothesis that prices follow a random walk without a time trend.

2) Precision hierarchy: The EW arithmetic index consistently exhibits the highest adjusted R^2 (0.178 for the total, 0.177 for apartments, and 0.243 for houses). This confirms that the price signal is higher when analyzing the average behavior of units, thus minimizing the noise introduced by the variance of high-value assets. Furthermore, data cleaning allows the WV model to achieve significance (F=16.4), which validates its use for wealth trend analyses, although its lower fit (R^2=0.081) signals higher idiosyncratic dispersion in the luxury housing segment.

3) Temporal stability: Over 96% of the monthly coefficients are individually significant, which shows that the index maintains its robustness even during periods with less transaction activity.

4.2.2 Structural Hierarchy in Price Levels

Analyzing the long-term trajectory (Figure 1a) reveals a persistent hierarchy in the magnitude of cumulative appreciation, thus challenging the intuition that capital gains are concentrated in premium assets: ARS-EW ≈ GRS > ARS-VW.

The ARS-EW leads growth during the expansionary phase. Since this estimator assigns equal weight to every unit, its outperformance indicates that the percentage capital gains are maximized in the lower-value, smaller-size housing segment. This aligns with the transition of the market toward a rental investment model, where high demand for small apartments exerts more upward pressure on prices compared to the high-value housing segment (which dominates the VW index).

Conversely, the ARS-VW consistently tracks the lower bound. This reveals that high-net-worth portfolios (houses and luxury apartments in the eastern zone of Santiago) experience more moderate growth, which act as a drag on aggregate appreciation. This structure is mirrored with nuances across the submarkets: a hierarchy inversion is observed in apartments (Figure 2a) starting in 2021 (GRS > ARS-EW), which signals potential distressed sales in the entry-level housing segment, whereas in houses (Figure 3a), the hierarchy remains stable, with the VW index showing a significant lag, which is consistent with the slower appreciation rate of high price points.

4.2.3 Adjustment Cycle and Capitulation Signal

The index dynamics undergo a structural regime shift starting in 2021, which coincides with the end of the liquidity shock and onset of the contractionary monetary cycle. This adjustment manifests in two phenomena captured in the annual variation panels (Figures 2b, 3b, and 4b): nominal contraction and hierarchy inversion. In terms of nominal contraction, annual variations across all three indices crossed into the negative territory starting in the second half of 2022, and accumulated there throughout 2023 and 2024. This confirms that the market not only decelerated but experienced a nominal price correction. As for hierarchy inversion, at the margin of the crisis, the GRS tends to fall more sharply than ARS-EW. Econometrically, this implies negative skewness in the return distribution: a subset of transactions is closing with aggressive nominal discounts, which exceed fundamental price levels. However, the relative resilience of the EW index suggests some downward rigidity in the bulk of the mass market, which is possibly sustained by the safe-haven demand for low price points, while the volatility-adjusted central trend (GRS) captures the effective price capitulation at closing.

4.3 Heterogeneity Analysis

To determine the microeconomic determinants behind the index hierarchy and adjustment dynamics, the price differential ($P_{i\tau}/P_{it}$) is analyzed, which is disaggregated by the direction of changes, structural attributes, and location.

4.3.1 Adjustment Mechanisms: Rigidity versus Flexibility

Table 7 breaks down the distribution of the nominal returns and classifies transactions according to the direction of price adjustment, and reveals two divergent market equilibrium mechanisms: price adjustment in apartments and nominal rigidity in houses. The apartment market shows greater flexibility; notably, 29% of the canceled units are re-contracted at a nominal price lower than the original price, with a median return that is marginally positive (0.9%). This willingness to discount aligns with the cost structure of high-rise construction, where the financial carrying cost of finished inventory incentivizes rapid liquidation to release productive capital. On the other hand, the housing segment exhibits strong downward nominal rigidity. The median return is exactly 1, and 31% of the transactions close with no price change. This behavior suggests a structural resistance among developers to validate nominal drops in high price points, and instead, they opt to adjust via quantity (higher cancellation rates) rather than price.

4.3.2 Profitability Gradient

An analysis of the physical and monetary attributes (Table 8) confirms that capital appreciation is not homogeneous, but rather, follows an inverse correlation pattern with asset value. Price monotonicity is observed; there is a strictly declining relationship observed between the initial price and appreciation rate. The first quintile (properties under CLF 1,650; approximately $66,000 USD) records the highest percentage of average growth (8.6%), while the fifth quintile (over CLF 4,00; approximately $160,000 USD) exhibits virtually a stagnation (0.7%). Then there is a small-scale premium; the smallest units (first floor area quintile and one-bedroom units) systematically yield higher returns (5.8% and 5.1%, respectively) than larger family units after disaggregating by floor area and type of unit. This finding validates the hypothesis that the expansionary cycle is driven by demand for entry-level housing units, where liquidity and subsidies sustain price dynamism.

Table 6 **Estimation Results**

	Total			Apartments			Houses		
Estimator	GRS	ARS EW	ARS VW	GRS	ARS EW	ARS VW	GRS	ARS EW	ARS VW
Obs.	25,049	25,049	25,049	18,621	18,621	18,621	6,428	6,428	6,428
Adj. R^2	0.171	0.178	0.081	0.172	0.177	0.037	0.232	0.243	0.221
F-stat	37.05***	38.81***	16.39***	28.07***	29.04***	5.99***	14.56***	15.40***	13.74***
Min t-stat	0.251	0.001	0.098	0.364	0.589	0.430	0.076	0.019	0.224
% sign.	97.2%	97.2%	97.2%	96.5%	96.5%	97.2%	97.2%	97.2%	95.8%

Notes: *** denotes statistical significance at the 1% level (p-value< 0.01). Min t-stat reports the lowest t-statistic observed among time dummies. % sign. indicates the percentage of monthly coefficients that are statistically significant at the 5% level ($|t| > 1.96$).

Table 7 **Price Differentials between Periods**

	Obs.	Mean	Std. Dev.	Median	P25	P75	Lower price	Same price	Higher price
Total	25,049	1.040	0.117	1.004	0.996	1.094	26.9%	21.2%	51.9%
Apartments	18,621	1.042	0.122	1.009	0.987	1.103	28.9%	17.9%	53.2%
Houses	6,428	1.038	0.102	1.000	1.000	1.069	20.9%	30.7%	48.4%

Notes: Price differential is calculated as the ratio between the subsequent placement price and the original promise price.

Table 8 Price Differentials by Price, Floor Area and Bedrooms

Category	Group	Obs.	Range (CLF)	Mean
Price (CLF)	Q1	5,019	744 – 1,651	1.086
	Q2	5,021	1,652 – 2,185	1.059
	Q3	4,991	2,186 – 2,792	1.032
	Q4	5,013	2,793 – 3,957	1.020
	Q5	5,005	3,958 – 16,540	1.007
Floor area (sq. m^2)	Q1	5,024	20.9 – 37.4	1.058
	Q2	5,046	37.4 – 46.0	1.048
	Q3	4,965	46.0 – 53.9	1.040
	Q4	5,020	53.9 – 81.6	1.028
	Q5	4,994	81.6 – 198	1.031
Bedrooms	1	5,782		1.051
	2	9,577		1.037
	3	8,712		1.038
	4	896		1.044
	5	82		1.041

Notes: For reference, 1 CLF was approximately equivalent to 40 USD at the end of the sample period (December 2024). Q1-Q5 refer to quintiles of the respective distribution. Range indicates the minimum and maximum for each quintile. Mean is the average price differential (ratio between the subsequent placement price and the original promise price) for that group.

4.3.3 Temporal and Spatial Validation

Finally, Table 9 provides evidence on the non-speculative nature of the transactions and spatial segregation of performance. There is the absence of short-term arbitrage. In the first holding period quintile (1 to 5 months), the average appreciation is minimal (1.1%), thus refuting the presence of speculative purchases (Steele and Goy, 1997). Capital gains accrue progressively over time (reaching 7.3% in the fifth quintile), thereby confirming that the index captures the maturation of the construction cycle. Then there is geographic segregation. Spatially, capital gains are concentrated in the Pericentro zone (5.5%), which are municipalities that are undergoing urban renewal and high investment density. In contrast, the high-income Eastern zone (Oriente) records the least appreciation (1.8%), thus reinforcing the conclusion that the price dynamics of wealth assets have decoupled from those of the average housing market, thereby justifying the need to monitor both indices separately.

Table 9 Price Differentials by Holding Period and Location

Category	Group	Obs.	Range	Mean
Holding period	Q1	5,313	1 – 5	1.011
	Q2	4,843	6 – 11	1.026
	Q3	5,350	12 – 19	1.039
	Q4	4,693	20 – 29	1.058
	Q5	4,850	30 – 106	1.073
Location	1 Centro	2,671		1.041
	2 Pericentro	8,569		1.055
	3 Periferia	5,341		1.033
	4 Satelital	5,159		1.040
	5 Oriente	3,309		1.018

Notes: Holding period refers to the time (months) elapsed between original promise and subsequent placement. Location is defined as follows: Centro=Municipality of Santiago; Pericentro=Municipalities contiguous to Santiago; Periferia=Municipalities contiguous to Pericentro; Satelital=Municipalities outside the Vespucio Road Ring; and Oriente=High-income eastern municipalities. Q1-Q5 refer to quintiles of the respective distribution. Range indicates the minimum and maximum for each quintile. Mean is the average price differential (ratio between the subsequent placement price and the original promise price) for that group.

4.4 Comparative Analysis

To assess the external validity and practical utility of the proposed index, the changes of the GRS estimator which is selected for its statistical robustness and conservative nature, is contrasted with major market benchmarks for new housing: the Housing Price Index (IPV) from the Central Bank, Real Housing Price Index (IRPV) from the CChC, and listing prices from GfK-Nielsen IQ.

Widely cited indicators that incorporate secondary market transactions (the Centro Latinoamericano de Políticas Económicas [Center for Economic and Social Politics] TocToc (a real estate agency in Chile)) are deliberately excluded from this analysis. Price dynamics in the used housing market are driven by depreciation, remodeling, and immediate liquidity factors that structurally differ from the pre-sale market. This segmentation ensures a homogeneous validation, by focusing exclusively on price formation in the primary market across different methodologies and data capture points.

The comparison is conducted along two dimensions: the changes in the annual average price levels (Figures 4, 5, and 6) and dynamics of cyclical variations (Table 10).

Table 10 Comparison of Annual Variations

Group	Period	GRS	IRPV	IPV	GFK
Total	2014-2019	4.7%	6.8%	5.9%	7.8%
	2020-2021	4.3%	9.2%	3.7%	7.4%
	2022-2024	-1.1%	-0.7%	2.7%	1.4%
Apartments	2014-2019	5.0%	7.2%	6.4%	7.7%
	2020-2021	4.1%	7.7%	3.3%	5.8%
	2022-2024	-0.9%	-1.1%	1.5%	1.4%
Houses	2014-2019	4.4%	5.7%	5.2%	6.1%
	2020-2021	5.9%	12.7%	4.2%	6.7%
	2022-2024	-1.5%	0.9%	n.a.	-0.3%

Notes: GRS=Geometric Repeat Sales; IRPV=Real Housing Price Index (Chilean Chamber of Construction); IPV=Housing Price Index (Central Bank of Chile); GFK=Housing Listing Price Index (GfK-Nielsen IQ).

4.4.1 Decomposition of Price Gap

A comparison of the indices (Figures 5, 6, and 7) reveals a structural price hierarchy, which allows for the decomposition of real estate appreciation components including the listing price ceiling (GfK), IRPV and IPV, and GRS. The GfK index consistently reaches the upper bound, which shows a variation that exceeds 100% during the period of 2013–2024. As a simple average of listings, this indicator not only captures price inflation but also quality improvements (the progressive incorporation of superior finishes and amenities in new projects), thereby inflating the average price per square meter.

Figure 5 Comparison of Aggregate Housing Price Indices

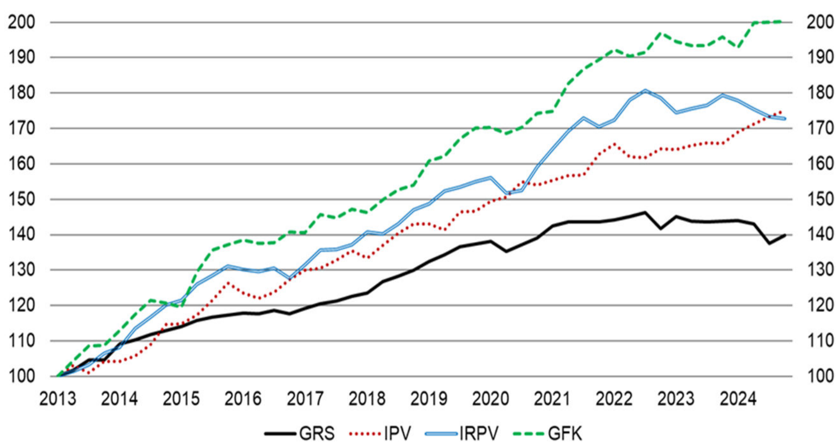


Figure 6 Comparison of Apartment Price Indices

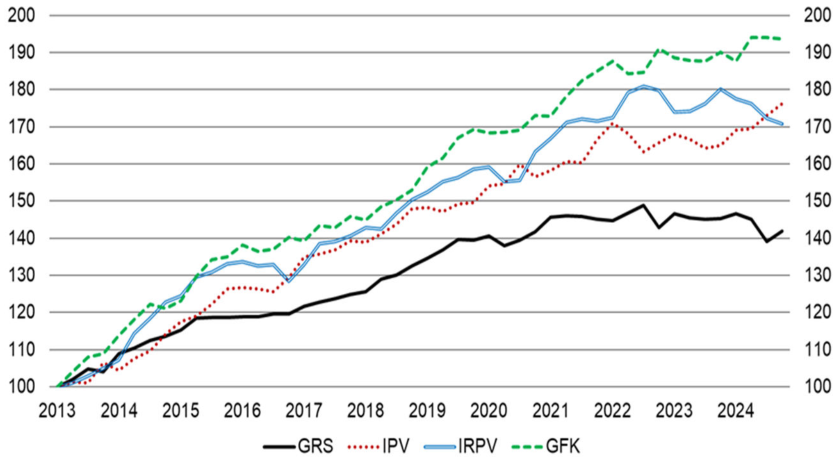
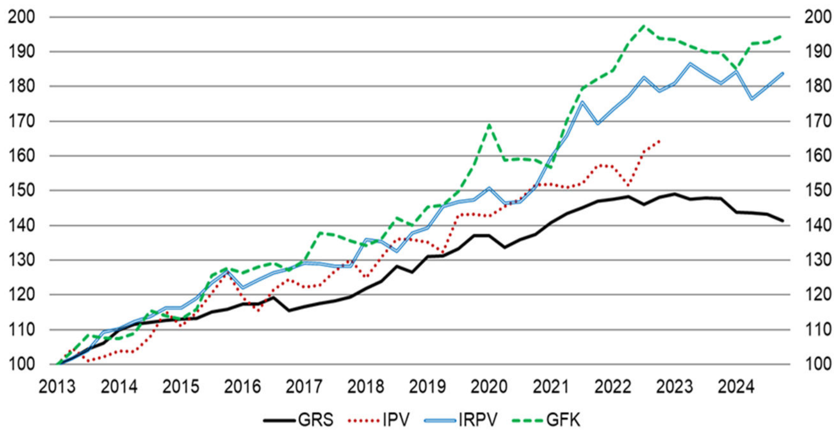


Figure 7 Comparison of House Price Indices



Positioned at the intermediate-high level, the traditional indices IRPV (hedonic) and IPV (stratified) indices show a convergent trajectory, thus accumulating significantly more appreciation than the GRS. The gap between these indices and the GfK suggests that both hedonic and stratification methods effectively discount part of the quality effect. However, the remaining positive gap relative to the GRS indicates that they fail to fully purge the quality effect. Stratification (IPV) controls for compositional changes across municipalities or typologies but does not capture standard improvements within the stratum. The GRS, by comparing the same physical unit, eliminates this residual quality bias.

Finally, the GRS or actual closing price index sits at the base of the hierarchy. The distance of over 30 points relative to IPV/IRPV quantifies a negotiation and lag premium. The GRS captures the subsequent placement price in real-time (avoiding the administrative lag of the IPV) and reflects the actual transaction value (removing the listing expectations of the IRPV), thus providing the most conservative and clean measure of constant-quality asset value.

4.4.2 Rigidity versus Adjustment in the Crisis

At the recent margin, the divergence between indicators becomes critical, which reveals a structural dichotomy in the reading of a cycle (Table 10). On the one hand, indices that have nominal rigidity or registration inertia remain in positive territory: the GfK (0.8%) reflects the resistance of the asking prices to decline, while the IPV (2.7%) continues to capture deed prices agreed upon in the past. Conversely, indices based on real-time deal closings, which in this case are both the GRS (-1.1%) and IRPV (-0.7%) indices, exhibit synchronized correction. This alignment confirms that the adjustment of the Chilean real estate market is an ongoing phenomenon at the promise stage, executed via transactional discounts obscured by listing prices, which official records will take quarters to reflect. The GRS, by showing the steepest decline, suggests that market clearing via cancellations is occurring at values even lower than the hedonic averages of new purchase promises.

4.4.3 GRS as a Leading Indicator

The temporal divergence observed between the GRS and IPV index of the Central Bank confirms the utility of contract cancellations as an early warning mechanism. While administrative deed records suffer from a temporal blind spot due to contract lags (12 to 24 months), the proposed index captures price discovery at the instantaneous transactional margin.

By anticipating the turning point of the cycle several quarters ahead of official figures, the GRS not only corrects current price measurement but also allows for projecting the future convergence trajectory of administrative indices. This predictive capability positions the GRS as a critical tool for financial stability monitoring, thus enabling the detection of value corrections in mortgage collateral before they materialize in bank balance sheets or national accounts.

To statistically validate the forward-looking nature of pre-sale prices and their predictive capacity, Table 11 presents a cross-correlation function analysis, which contrasts the annual variations of the GRS against the displaced variations of the IPV, GfK, and hedonic pre-sale index of the (IRPV).

Table 11 Cross-correlations of Annual Price Variations

Lag (k)	-4	-3	-2	-1	0	1	2	3	4
Aggregate housing									
GRS_t, IPV_{t+k}	0.23	0.30	0.34	0.32	0.32	0.36	0.47	0.46	0.39
GRS_t, GFK_{t+k}	0.05	0.15	0.34	0.50	0.68	0.67	0.56	0.44	0.28
GRS_t, $IRPV_{t+k}$	0.10	0.19	0.38	0.61	0.81	0.76	0.54	0.38	0.25
Apartments									
GRS_t, IPV_{t+k}	0.26	0.37	0.44	0.43	0.38	0.46	0.53	0.48	0.43
GRS_t, GFK_{t+k}	0.19	0.25	0.41	0.55	0.73	0.77	0.66	0.51	0.32
GRS_t, $IRPV_{t+k}$	0.16	0.23	0.40	0.62	0.82	0.80	0.59	0.41	0.26
Houses									
GRS_t, IPV_{t+k}	0.09	0.16	0.02	0.04	-0.05	-0.09	0.23	0.21	0.32
GRS_t, GFK_{t+k}	-0.08	0.03	0.13	0.22	0.44	0.44	0.36	0.36	0.24
GRS_t, $IRPV_{t+k}$	-0.14	0.03	0.40	0.62	0.64	0.59	0.31	0.17	0.18

The results confirm a structural lead-lag relationship between forward contracts and final deeds. The contemporaneous correlation between the aggregate GRS and official IPV is moderate (0.32), thus reflecting the temporal blind spot inherent in administrative records. The correlation maximizes when the IPV is displaced by 2 to 3 quarters into the future. This quantitative evidence proves that the instantaneous price discovery captured at the purchase promise stage today reliably anticipates the trajectory that official deeds will register 6 to 9 months later. Furthermore, the aggregate GRS exhibits strong contemporaneous correlation with both the hedonic IRPV and listing price records (GfK). However, as discussed in the comparative analysis, listing indices (GfK) exhibit strong downward nominal rigidity during liquidity shocks. By stripping away both registration inertia (IPV) and unexecuted asking prices (GfK), the GRS emerges as a real-time reflection of actual market clearing prices.

The robustness of this forward-looking capability becomes even more evident when disaggregating the cross-correlation analysis by submarkets. As illustrated in Table 11, the predictive power of the GRS is driven by the apartment segment. For apartments, the correlation with the official IPV peaks strongly at the second lag and remains highly significant at the third lag. This precisely mirrors the structural reality of high-rise developments, which are deeply reliant on early-stage pre-sales due to their lengthy construction cycles, making their promise prices an exceptionally clean leading indicator.

In contrast, the cross-correlation between the GRS and IPV for the housing segment is weaker and more dispersed. This econometric result perfectly aligns with the microeconomic findings detailed in previous sections. Since the house market exhibits strong downward nominal rigidity, the pure price signal is more muted. Consequently, while the GRS is a highly accurate forecasting tool for the dynamic apartment market, it also accurately diagnoses the frictional, rigid pricing behavior inherent to the housing segment.

5. Discussion

The results obtained provide new evidence on the price dynamics in new housing markets, thus validating the utility of contract cancellations as a superior source of transactional information in contexts of high uncertainty. The following sections interpret the findings through the lens of the economic theory, assess the methodological robustness against international standards, and discuss the implications for financial stability.

5.1 Economic Interpretation: Segmentation and Financial Friction

The documented price hierarchy (ARS-EW ≈ GRS > ARS-VW) and the divergence between the typologies are not random phenomena, but rather a reflection of the structural segmentation of demand and transmission mechanisms of the monetary policy.

5.1.1 Duality of Demand (Investment versus Owner-occupancy)

The superiority of the EW index over the VW index during the expansionary phase suggests that capital gains are disproportionately concentrated in the entry-level housing segment. Following the theoretical framework of Tse et al. (1999), who distinguish between owner-occupier and investment demands, these results indicate that the real estate boom in Santiago was driven by an investment component (buy-to-let) and by middle-income households who accessed the market by purchasing smaller units. High liquidity incentivized mass entry into this housing segment, which exerted higher upward pressure on small unit prices compared to the high-net-worth housing segment, where demand responds to more rigid fundamentals. This divergence aligns with evidence from Melser (2023), who documents that selection bias and price heterogeneity vary significantly across different market segments, thus justifying a disaggregated analysis.

It is important to note that the initial growth (2013-2015) should not necessarily be interpreted as a speculative bubble. Idrovo et al. (2021) conclude that appreciation in Chile during this period of time was aligned with the fundamentals of economic prosperity and favorable credit conditions. The GRS index corroborates this view, which shows a linear positive trend that is only structurally disrupted by the rate shock of 2021.

5.1.2 Decoupling of Fundamentals and Price Adjustment

The observed regime shift that started in 2022, characterized by a surge in the cancellation rate (from 12% to 30%) and a nominal contraction of indices, validates the decoupling of the fundamentals hypothesis described by Hui and Yue (2006). The tightening of financial conditions generated an unsustainable gap between contract prices agreed at the promise stage and the actual borrowing capacity of households at the time of the deed transfer.

The high incidence of downward nominal adjustments in subsequent placements (26.9%) highlights the rationality of developers in the face of this constraint. Unlike the secondary market, where households exhibit loss aversion, development firms face increasing financial carrying costs on finished stock. In this scenario, liquidating units through explicit discounts becomes the optimal strategy to release productive capital. This liquidity pressure aligns with the multitasking hypothesis proposed by Chen et al. (2024). They argue that developers rely on pre-sale proceeds from current projects to finance the initiation of concurrent new developments. When pre-sales are weak, which is manifested here by a surge in cancellations, the cross-funding chain breaks, thus forcing the liquidation of inventory to cover immediate liabilities and avoid project abandonment. This price adjustment phenomenon is captured more sharply in the apartment market, whereas the housing segment shows more nominal rigidity, which is consistent with the notion that luxury attributes are more sensitive to negative wealth effects but slower to adjust their nominal valuation (Leung et al., 2007).

5.2 Methodological Validation and Compliance with Standards

The robustness of the proposed index lies in its capacity to overcome the structural limitations of the repeat-sales method identified in both the academic literature and statistical manuals. These include neutralization of depreciation bias, stability, and sampling efficiency.

The classic critique that repeat-sales indices fail to separate price variation from physical deterioration (Cannaday et al., 2005) is addressed by the sampling design. By restricting analysis to the pre-sale market, the unit subject to subsequent placement remains strictly new and never-occupied. The median time interval (15 months) corresponds to construction progress rather than asset use, thereby ensuring that the price differential only reflects the market valuation of the constant-quality asset.

The choice of the repeat-sales method is further justified by the temporal instability of implicit prices in hedonic models, a limitation documented by Chau et al. (2003). By bypassing attribute specification and comparing the same unit, the proposed index avoids biases derived from changes in the valuation of specific characteristics during periods of market turbulence.

Finally, in terms of sampling efficiency, the study overcomes data scarcity as a constraint which often destabilizes local repeat-sales indices (Francke, 2010) with over 25,000 repeated-sales pairs identified after cleaning, thus achieving statistical significance that exceeds 95% in monthly estimators. The robustness of the initial estimates is reinforced by the data collection strategy which started in 2010, by utilizing the period of 2010–2012 as an inventory accumulation phase. This ensures that the 2013 base index is built upon a mature transactional volume, thereby avoiding the artificial volatility typical of series inception in thin markets.

5.3 Public Policy Implications: Value of a Leading Indicator

The most significant contribution to macroprudential supervision is the confirmation of the GRS index as a leading indicator.

A comparison with official records shows that the repeat-sales index anticipates the turning point of the real estate cycle several quarters ahead of the IPV index. While administrative records suffer from a temporal blind spot due to deed registration lags (12 to 24 months), the proposed index captures price discovery at the instantaneous transactional margin. This information transmission dynamic mirrors the findings of Ong and Sing (2002), where more liquid markets with lower information barriers anticipate general trends.

This anticipatory capacity is consistent with Li et al. (2023), who find that developers strategically accelerate pre-sales during periods of high price volatility to transfer risk to buyers. Since developers use pre-sales as a hedging instrument against uncertainty, a spike in contract cancellations signals the failure of this hedging strategy in real-time, thus providing regulators with an immediate proxy for financial stress that deed-based indices would only capture with a lag of several quarters.

Furthermore, the capacity of the GRS index to isolate pure price variation allows the filtering out of exogenous components such as quality changes and the impact of regulatory shocks. When contrasted with the GfK supply index and the hedonic IRPV, it becomes evident that the repeat-sales method eliminates both the upward bias from construction improvements inherent in hedonic models and speculative component of asking prices when the same physical unit is compared. This purity of the transactional signal aligns the index with recent evidence on the predictive superiority of actual transaction data over static or supply-based valuations (Birkeland et al., 2021).

The divergence observed post-2016 relative to the IRPV empirically illustrates this quality: while the hedonic index captures the structural pass-through of value-added taxes to prices, which is an increase estimated between 9.6% and 12.6% by Lozano and Idrovo (2024), the moderation of the GRS reveals that effective demand does not fully validate the said surcharge. This suggests that the supply side is forced to adjust margins in the final closing price, a market dynamic perceptible only when discounting the inflationary noise of costs and quality.

5.4 Limitations and Future Research Directions

While the findings presented are robust, the study is subject to limitations inherent to the methodology and data which provide opportunities for future research.

As is characteristic of repeat-sales methods, the estimation utilizes all available historical information, which means that the inclusion of new future data will generate retrospective revisions of the index values (Clapp and Giaccotto, 1999; Clapham et al., 2006). For operational implementation aimed at real-time monitoring or use in financial contracts, future applications should adopt local or semiparametric estimation techniques (Clapp, 2004), movement splice methods, or rolling windows to stabilize the published series and prevent the rewriting of historical series.

Although the municipality-level analysis ruled out severe selection bias, the aggregate index may obscure price contagion dynamics between adjacent neighborhoods. A natural extension of this work would involve applying spatial dynamic factor models, following the recent methodology of Francke et al. (2025). This approach would allow for modeling how financial stress in investment-driven municipalities is spatially transmitted to consolidated residential areas.

Finally, the high-frequency price signal derived from contract cancellations has high predictive value. Future research could integrate this index as an exogenous variable in automated valuation models or hybrid hedonic estimates (Jones, 2010). As Birkeland et al. (2021) suggest, combining pure transactional data with machine learning algorithms could substantially improve the accuracy of bank appraisals and mortgage portfolio risk management in emerging markets.

6. Conclusion

This study addresses the structural challenge of measuring price changes in a new housing market by proposing a novel methodology based on purchase contract cancellations. Utilizing a robust sample of 25,049 repeat-sales pairs in Santiago during the period of 2013–2024, the research offers conclusions that contribute both to the econometric literature and the understanding of real estate cycles in emerging economies where pre-sales constitute the primary mechanism of housing supply.

First, the research validates the methodological soundness of using cancellations to overcome the lack of resale history, a classic limitation in the price index literature (Epley, 2016). By comparing the original promise price with that of the subsequent placement of the same never-occupied physical unit, the method ensures strict adherence to the constant-quality assumption, thus mitigating the depreciation bias that affects used housing indices. The high statistical significance of estimators (over 95%) confirms that this information source is a reliable and efficient proxy for market prices.

Beyond technical validation, the empirical evidence reveals a structural price hierarchy that reflects the demand segmentation. The systematic superiority of the EW over the VW index indicates that capital gains in the last decade were concentrated in the entry-level housing and investment segments, driven by rental demand and household liquidity. In contrast, the high-net-worth housing segment was an anchor of stability, and showed more moderate appreciation, which is consistent with demand less exposed to the volatility of short-term capital flows.

From a public policy perspective, the most relevant finding is the confirmation of the proposed index as a leading indicator. While the IPV (based on deeds) of the Central Bank maintained a positive inertia during the 2022–2024 crisis, the repeat-sales index detected the turning point and nominal contraction several quarters in advance. This temporal advantage confirms that records of promises and cancellations capture real-time price discovery, thus eliminating the administrative lag inherent in the deed registration process.

The analysis of the recent crisis illuminates adjustment mechanisms in response to financial friction. The structural increase in the cancellation rate (from a historical 12% to 30% in 2024), alongside the high incidence of nominal losses (26.9%) in subsequent placements, validates the credit channel hypothesis. Current price adjustment is not attributable to a shift in preferences but rather to an ex-post liquidity constraint: the escalation in financing costs between promise and delivery excludes a substantial portion of demand, thus compelling developers to liquidate inventory at discounts to release productive capital.

Finally, notable heterogeneity in the supply response is observed. While the apartment market shows downward flexibility by accepting discounts to rotate stock, the housing segment exhibits strong nominal rigidity, and primarily adjusted through quantity (higher cancellation rates) rather than price. These findings highlight the critical need to incorporate high-frequency indicators based on promises and cancellations into financial stability monitoring panels. In markets where pre-sales predominate, relying solely on deed-based indices can generate a false sense of security during the initial phase of a correction, thereby delaying the macroprudential policy response to asset price misalignments.

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