Housing Crash, Gold Rush

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Abstract

Gold prices have more than doubled in recent years, coinciding with a historic collapse in China's housing market. We argue these are causally linked: as real estate prices fell roughly 20% from their 2021 peak, Chinese households reallocated savings into gold, causing China's domestic gold prices to lead global spot prices. Using administrative bank records of gold transactions, OLS and IV estimates show that housing price declines strongly predict gold purchases at the city and branch levels, and this effect is further amplified through social interactions. A quantitative exercise suggests that overall housing-market-driven demand from Chinese households contributed $100 to $366/oz to the global price rally. The negative relationship between housing prices and gold demand also extends to other major economies.

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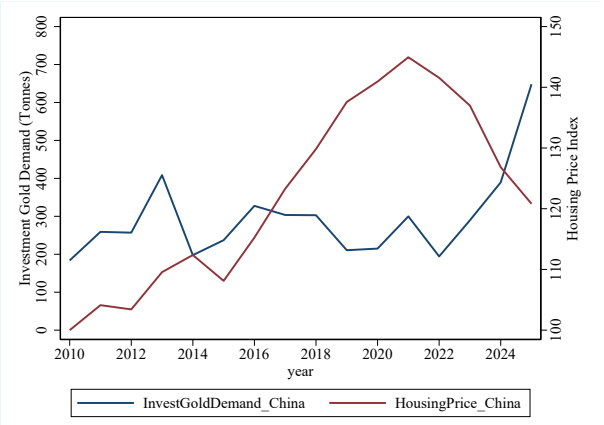
1. Introduction

Gold prices have surged dramatically in recent years, rising from around $2,000 per ounce in 2021–2023 to over $5,000 per ounce by early 2026, leaving investors and policymakers puzzled about the underlying causes (e.g., Erb and Harvey, 2024). Over the same period, as its economic growth slowed down, China's residential property market entered a historic downturn, with house prices peaking in 2021Q3 and declining for about 20% thereafter.

In this paper, we argue that these two phenomena are causally linked. We show that the collapse of the Chinese housing market prompted a large-scale reallocation of household savings from real estate to gold and that this shift in demand has significantly contributed to global gold price increases.



Panel A. China Investment Demand and Gold Price



Panel B. China Investment Demand and Housing Prices

Fig. 1. China's Gold Investment Demand, Gold Prices, and Housing Prices

Panel A plots China's annual investment gold demand (left axis, tons) and the year-end LBMA gold price (right axis, $/oz) from 2010 to 2025. Panel B plots China's annual investment gold demand (left axis, tons) and a national housing price index (right axis) over the same period. The housing price series is constructed as the annual average of quarterly real residential property price indices from the Bank for International Settlements (BIS), obtained from FRED.

We begin by documenting several stylized facts using country-level data on gold demand and real estate prices. First, China's investment demand for gold—through both physical purchases and ETFs—rose from 200–300 tons per year before 2022 to over 600 tons in 2025. Figure 1 illustrates this surge alongside two key macroeconomic trends: Panel A plots annual gold investment demand against the gold price, confirming that the rise in Chinese demand

coincides with the global gold price rally; Panel B plots demand against China's national housing price index, showing that the demand surge began precisely as housing prices peaked and began their sustained decline in late 2021. A time-series regression confirms that lagged housing returns are strongly and negatively associated with the Chinese gold investment demand, with the effect concentrated in periods of housing market distress. Furthermore, compared to other major economies, gold investment demand increased significantly more in China after 2021, even after absorbing global trends through country and year-quarter fixed effects.

Second, the dynamics of gold pricing also changed: we analyze the lead-lag relationship between Chinese and global spot gold prices. China's demand pressure spills over to global gold prices: the price premium between the Shanghai and London gold markets positively predicts subsequent London gold returns, and this predictive relationship strengthened markedly after 2021 but absent in prior periods.

These stylized facts point to a large-scale substitution from housing into gold among Chinese households. For decades, residential real estate has been the dominant savings vehicle for Chinese households, accounting for over 70% of household wealth (Xie and Jin, 2015), while China (alongside India) ranks as the world's largest retail gold market (World Gold Council, 2024). As housing returns disappointed, households reallocated savings into physical gold as an alternative safe-haven and wealth-preservation asset. Other investment outlets—most notably the equity market—featured limited participation and persistently poor returns (Allen, Qian, Shan, and Zhu, 2024). Given that China is now the world's second-largest economy and its households have accumulated substantial wealth, this flight to gold following a housing market bust can plausibly exert significant upward pressure on global gold prices.[1] Nevertheless, while compelling, the time-series evidence alone cannot fully rule out confounding factors, motivating our turn to micro-level cross-sectional analysis.

We use a unique administrative dataset from a major state-owned commercial bank in China, covering all branch-level physical gold transactions (bars and coins) nationwide from January 2007 to June 2025. The bank accounts for approximately 12.9% of national gold

[1] Although some unique institutional features make this housing-induced-reallocation-to-gold effect particularly pronounced in China, we provide evidence in Section 5.2 that the housing–gold substitution is also present in other major economies.

investment demand during 2021–2025, and its transaction time series closely mirrors the aggregate patterns reported by the World Gold Council, confirming the dataset's representativeness.

We aggregate net gold purchases (purchases minus sales) to the city level across 296 prefecture-level cities. In this city-level panel, lagged housing returns strongly and negatively predict net gold purchases, remaining the dominant explanatory factor in a horse race against local GDP growth and abnormal investor attention (proxied by change in Baidu search volume). The analysis includes time fixed effects to absorb macroeconomic influences such as inflation and gold price fluctuations, as well as city fixed effects to control for unobserved local heterogeneity.

To address potential endogeneity—such as omitted factors jointly affecting housing prices and local gold demand—we employ a sensitivity-based instrumental variable (IV) approach following Guren, McKay, Nakamura, and Steinsson (2021). Specifically, we instrument local housing returns with the interaction between each city's pre-determined exposure to aggregate housing shocks and national housing returns, thereby isolating plausibly endogenous variation in local housing conditions. The IV estimates indicate that a one–standard deviation decline in housing returns increases city-level gold purchases by approximately 17–18% of a standard deviation.

A back-of-the-envelope calculation based on this estimate suggests that the housing market collapse generated about 199.8 additional tons of gold investment demand nationwide over 2021–2025. Using our instrument, we also estimate the price-to-investment-demand elasticity to be -0.814, consistent with the literature's range between -0.3 to -1.1 (Immanuvel and Lazar, 2021). This implies that the housing-induced flight to gold contributed approximately \$68–\$251 per ounce to the global price rally.

To further strengthen the causal interpretation, we replicate the analysis at the branch level (12,509 branches). By incorporating city-by-month fixed effects, we absorb all time-varying shocks common to a city and identify the housing–gold relationship from within-city cross-branch variations. Both OLS and IV estimates show that branches serving neighborhoods experiencing larger housing downturns exhibit significantly greater increases in gold purchases.

Beyond the direct effect of housing returns, we find evidence that this effect is amplified through social interactions. Branches whose peers recently earned higher gold returns or engaged in net buying exhibit a stronger gold-purchasing response to housing downturns. This pattern holds for both existing investors and first-time entrants, suggesting that word-of-mouth communication and social learning magnify the initial flight-to-gold response and extend it beyond households directly affected by housing losses. Quantitatively, given that the average peer gold return before 2021 is 18.9%, the estimated social amplification implies that peer effects multiply the baseline response by a factor of 1.46. Accounting for this social amplification, the total contribution of the Chinese housing channel to the global gold rally reaches approximately \$100–\$366 per ounce, or 5.6% to 20.4% of the gold price at China's housing market peak time.

Finally, we show that the housing-induced flight-to-gold phenomenon extends beyond China. Using country-level data, we document a negative relationship between housing price changes and gold investment demand across several major countries, including the United States, Singapore, Canada, and the United Kingdom.

Contribution to the literature. This paper contributes to several strands of the literature. First, we contribute to the literature on the determinants of gold demand and prices. Prior work has emphasized safe-haven demand (Baur and McDermott, 2010; Baur and Lucey, 2010), interest rates (Jermann, 2025), rare-disaster and tail-risk channels (Barro and Misra, 2016; Huang and Kilic, 2019), and de-dollarization motives of central banks (Erb and Harvey, 2024) as drivers of gold demand. Barro and Misra (2016); Erb and Harvey (2025); Fang, Liu, and Roussanov (2026) examine the inflation-hedging motive but find little evidence. More broadly, our findings connect to the macroeconomic literature on "flight to safety" episodes, where severe localized economic distress triggers massive hoarding of safe assets (Baele, Bekaert, Inghelbrecht, and Wei, 2020; Caballero and Krishnamurthy, 2008).

Erb and Harvey (2013, 2024) systematically examine the canonical explanations for gold's elevated real price–inflation hedging, currency hedging, real interest rates, and safe-haven demand—and find limited empirical support for any of them as reliable drivers. They end with what they call "the golden dilemma:" the real price of gold is historically high and may

mean-revert, yet demand from prominent emerging markets, particularly China, could push it even higher. They raise this possibility but can neither identify a specific mechanism nor measure its magnitude.

We provide an answer to the question with direct empirical evidence. China's housing market collapse triggered a large-scale portfolio reallocation from real estate into gold, generating a quantitatively first-order demand shock that spills over into global prices. Furthermore, unlike earlier research relying on aggregate time-series data, we use branch-level transaction records to rule out confounding factors and establish causal estimates. To the best of our knowledge, we provide the first micro-level evidence on household gold purchase behavior and identify a new, quantitatively important channel: the substitution from real estate into gold in response to housing market distress, particularly in economies where real estate constitutes the primary household savings vehicle.

Second, we contribute to the literature on household portfolio choice in the presence of housing. A foundational literature establishes that housing—as a large, illiquid, and risky asset—profoundly shapes the broader composition of household portfolios, often crowding out other investments (Cocco, 2005; Chetty, Sándor, and Szeidl, 2017). While a growing body of work documents the centrality of housing in Chinese household portfolios and the real effects of housing shocks on consumption and precautionary savings (e.g., Painter, Yang, and Zhong, 2022; Fang, Wang, and Yang, 2022), we extend this literature by tracing the direct reallocation of household savings across asset classes. We provide micro-level evidence that households substitute away from real estate and into alternative wealth-preservation assets in response to housing market deterioration.

Third, we contribute to the macro-finance literature on the demand for safe assets. A large body of work identifies U.S. Treasuries and the U.S. dollar as the primary global safe assets and emphasizes their role in stabilizing financial markets (e.g., He, Krishnamurthy, and Milbradt, 2016; Jiang, Krishnamurthy, and Lustig, 2021; Baele et al., 2020). However, recent literature has increasingly questioned the resilience of this safe-asset architecture (e.g., Duffie, 2023; Chen, Jiang, Lustig, Van Nieuwerburgh, and Xia, 2025). Several papers provide early evidence consistent with this view. For example, during the tariff shock in April 2025, the U.S. dollar depreciated and the convenience yield on 1-year Treasuries fell relative to

foreign-currency safe assets (Jiang, Krishnamurthy, Lustig, and Richmond, 2025), while the negative correlation between the U.S. dollar and U.S. Treasuries with equity market returns weakened (Hu, Jin, and Pan, 2023). Against this backdrop, our paper highlights the growing importance of gold as an alternative safe asset. While we focus on the housing distress shocks faced by the Chinese households, the underlying mechanism is more general and can help rationalize the rising gold demand among the U.S. investors since 2025.[2]

Fourth, we contribute to the literature on commodity markets, financialization, and the global transmission of demand shocks. Prior research highlights how non-commercial investor flows can financialize commodity markets and drive significant, sometimes disconnected, price rallies (Basak and Pavlova, 2016; Cheng and Xiong, 2014; Singleton, 2014). By documenting that Chinese retail demand pressures spill over into London gold benchmark prices, we provide micro-founded evidence for the global price impact of localized retail commodity demand.

Finally, by documenting the peer amplification mechanism, we contribute to the literature on social finance and the diffusion of financial decisions within social networks. While early work established the role of word-of-mouth in stock market participation(e.g., Hong, Kubik, and Stein, 2004; Shue, 2013), recent literature emphasizes how social networks shape retail investor behavior and propagate macroeconomic expectations, particularly regarding housing and local economic conditions (Bailey, Cao, Kuchler, and Stroebel, 2018; Kuchler and Stroebel, 2021). Our results demonstrate that social learning and peer effects can significantly magnify the aggregate impact of local macroeconomic shocks on global asset prices.

[2]While the U.S. gold ETF net demand was negative during 2021–2024 (–345 tons in total), it rose to 437 tons in 2025. Anecdotes attribute this shift to investors seeking safe assets beyond U.S. Treasuries and the U.S. dollar amid heightened trade and policy uncertainty (Rogelberg, 2025).

2. Data and Variables

2.1. Public Country-level Data

For country-level analysis, we use several public data series. We obtain quarterly global and country-level gold demand by category (investment, jewelry, technology, and central bank demand) from the World Gold Council. We obtain London Bullion Market Association (LBMA) benchmark gold prices from Bloomberg and use them to construct gold returns and gold price-premium measures. We obtain country-level residential property price indices, 10-year Treasury yields, and GDP growth from FRED. Variable definitions are provided in Appendix A.

Figure 2 plots the time series of gold demand by type in China. Alongside Chinese households, the demand from People's Bank of China (PBC) in the aim for de-dolloarization may have contributed to the post-2021 gold rally (Erb and Harvey, 2024). To assess the relative importance of this channel, Figure 2 compares the magnitude of household investment demand with the reported gold purchases of the PBC. Between 2021 and 2025, total household investment demand amounts to 1,738 tons, whereas central bank purchases total only 363 tons over the same period. The increase in household investment demand is also larger than that of the PBC. Specifically, household investment demand rises from an annual average of 256.2 tons during 2015–2020 to 310.2 tons during 2021–2025, implying an increase of approximately 54 tons per year. In comparison, the PBC's annual gold purchases increase by 35.43 tons, from 37.20 tons to 72.63 tons over the same periods. Even allowing for the possibility that the PBoC may under-report its purchases, the figure suggests that Chinese household demand represents a quantitatively important component of the recent surge in gold demand and is comparable to other prominent channels.

[Insert Figure 2 Around Here]

Figure 3 presents aggregate trends in global gold demand and supply by category. Panel A decomposes total demand into jewelry, technology, investment, and central bank purchases. Jewelry demand consistently represents the largest component of global gold demand, except in 2025. However, its share declines as gold prices rise after 2021. In contrast, global

investment demand increases sharply only in 2025 but remains relatively subdued during 2021–2024. The fact that global investment demand does not follow the same pattern as the surge observed in China highlights the distinctive role of Chinese household demand in the recent price dynamics. Central bank purchases remain relatively small prior to 2018 but increase markedly in recent years. Technology demand is comparatively stable and represents a small share of total demand throughout the sample.

Panel B reports the composition of global gold supply, including mine production, net producer hedging, and recycled gold. Mine production constitutes the dominant source of supply and remains relatively inelastic over the sample period. Recycled gold fluctuates more substantially and tends to increase during periods of elevated prices, consistent with supply responses to higher gold prices. Net producer hedging remains quantitatively small relative to other supply components.

[Insert Figure 3 Around Here]

2.2. Administrative Gold Transaction Data

We obtain a large dataset of physical gold transaction records from a major state-owned commercial bank in China. The bank conducts retail physical gold transactions through thousands of branch locations nationwide, making it one of the main intermediaries for retail physical gold investments in China.

The dataset includes both retail purchases from the bank and sales to the bank, allowing us to measure net investment flows for each investor (purchases minus sales). Each transaction is identified by a unique investor ID and includes the date of transaction (recorded daily), weight of gold (in grams) transacted, and the total transaction amount in RMB. We aggregate all transactions into monthly measures at both the city and branch levels. The city-level sample covers 296 prefecture-level cities between January 2015 and June 2025, while the branch-level sample includes 12,509 branches in these cities between June 2017 and June 2025.[3] This structure allows us to exploit variation in gold demand both across cities and across branches within the same city.

[3]The branch sample starts from 2017 because the branch identifiers are only available from 2017 onward.

To assess the representativeness of the data, we compare gold demand recorded by the bank with national statistics. Panel A of Figure 4 plots three series: China's total gold investment demand, cumulative gold holdings in Chinese gold ETFs, and aggregate net gold purchases processed through our bank. Between 2021 and 2025, net gold purchases at the bank total 200.32 tons, accounting for 12.91% of China's physical investment demand. This volume is also comparable to the entire ETF channel, of which cumulative increases amount to 186.95 tons. Moreover, the time-series pattern of our bank's data closely tracks national investment demand, including the surge after 2021. Together, these patterns indicate that our data capture a substantial share of gold demand in China and reflect economically meaningful variation in national investment activity.

Notably, the volume of physical gold demand from this single source already exceeds the total ETF demand in China, suggesting that physical gold is the dominant channel of household gold investment. This contrasts sharply with the U.S., where a significant proportion of gold is purchased through intermediary financial vehicles (Erb and Harvey, 2024).

[Insert Figure 4 Around Here]

Our primary measure of gold demand is *NetBuyValue*, defined as the real net value of gold purchases (in millions of RMB) at the city–month or branch-month level. It is calculated as the total value of gold purchases minus the total value of gold sales, aggregated across all investors within the respective unit. To account for inflation, we deflate the variable to constant 2014 RMB using the CPI. For a quantity-based alternative, we construct *NetBuy*, defined as the net weight of gold purchased (total kilograms bought minus kilograms sold) within a city-month or branch-month.

2.3. Housing Price Data

To measure local housing market conditions, we use proprietary internal data provided by the bank that were developed for mortgage origination and credit risk assessment. For each property transaction backed by a mortgage originated by the bank, the dataset records both the bank's appraisal value of the property and its size. We compute the price per

square meter for each transaction and construct housing indices by averaging these values at the city–month or branch–month level.

Nominal housing price growth is computed at the monthly frequency and converted into year-over-year housing returns. Real housing returns, denoted as $HousingRet_{c,t}$, are constructed as nominal housing price growth minus year-over-year CPI inflation.The systematic housing return, $HousingRet_t^{Systematic}$, is defined as the average $HousingRet_{c,t}$ across all cities in month t.

To assess the quality of our housing price indices, we compare our index aggregated to the national level with the residential property price index for China published by the Bank for International Settlements (BIS), obtained from FRED. Panel B of Figure 4 plots our national housing price index alongside the BIS housing price index. Both series exhibit similar trends over 2015–2020 and a downturn starting in 2021Q3. The strong co-movement between the two series supports the validity and credibility of the housing price indices constructed from the bank's internal data.

2.4. Summary Statistics

Panel A of Table 1 describes the distribution of city–month characteristics. On average, cities purchase 5.06 kilograms of gold each month, with a median purchase volume of 1.15 kilograms. Average monthly net purchase value is 1.98 million RMB, while the median value is 0.36 million RMB. The average number of traders per city-month is 78.8, while the median is 24. Typical transaction sizes are modest, with a median average deal size of 0.058 kilograms (58 grams) and a median average deal value of 20,800 RMB.

[Insert Table 1 Around Here]

Panel B of Table 1 summarizes averages for key variables prior to and after the housing peak, at 2021Q3. Housing returns decline sharply after 2021Q3: the mean housing return changes from 0.063 pre-2021 to -0.021 post-2021, and the instrumented mean changes from 0.060 to -0.035. Gold demand increases since 2021: average *NetBuyValue* expands from 0.762 to 4.116 million RMB, and average *NetBuy* increases from 2.808 kilograms to 9.256

kilograms, along with the average number of net purchasers increasing from 40.2 to 69.8. These changes motivate our focus on the structural break around 2021.

Panel C of Table 1 compares cities with low and high housing elasticity. By construction, high-elasticity cities have larger elasticity estimates. Other observable fundamentals differ modestly and are controlled for in the regression analysis.

Appendix Table B1 reports branch–month summary statistics. As shown in Panel A, the mean branch-month net purchase is 0.105 kilograms. Panels B–C report time-series comparisons and within city–time comparisons of treatment and control branches. Appendix Table B2 reports country–quarter summary statistics for the macro variables used in the cross-country analyses.

3. Empirical Strategy

Our empirical objective is to estimate the effect of housing returns on household physical gold demand.

3.1. Baseline City-Level Specification

We start from the city–month panel and estimate:

$$GoldDemand_{c,t} = \alpha_c + \gamma_t + \beta\, HousingRet_{c,t-1} + X'_{c,t}\delta + \varepsilon_{c,t}, \tag{1}$$

where $GoldDemand_{c,t}$ is a city–month measure of net physical gold demand (e.g., *NetBuyValue* or *NetBuy*). The lagged housing return $HousingRet_{c,t-1}$ captures local housing market performance. City fixed effects α_c absorb time-invariant differences across cities, and time fixed effects γ_t absorb nationwide shocks common to all cities, including aggregate macro conditions and nationwide gold price movements. The control vector $X_{c,t}$ consists of city-level observables such as GDP growth and changes in gold-related attention.

A key endogeneity concern is that local housing returns may be influenced by local shocks that also affect gold demand. For example, a negative local income shock to households, not related to real estate sector, may lead to housing demand falling and depress households'

investment in gold and other assets, causing a positive comovement that attenuates the estimated housing-gold relationship toward zero. This motivates the identification strategies below.

3.2. Identification: Sensitivity-Based IV at the City Level

To isolate plausibly exogenous variation in housing returns, we construct a sensitivity-based instrument following Guren et al. (2021). The approach combines aggregate shocks to the housing market with cross-city differences in exposure to these shocks.

The systematic housing return, $HousingRet_t^{Systematic}$, is defined as the average housing return across all cities in month t. The exposure coefficient for each city is estimated using an expanding-window regression based only on observations available prior to month t:

$$\begin{aligned} HousingRet_{c,\tau} = \alpha_c + \beta_{c,t-1}\, HousingRet_{\tau}^{Systematic} \\ + \pi_1\, GDPGrowth_{c,\tau} + \pi_2\, \Delta \log Attention_{c,\tau} + u_{c,\tau}, \quad \tau \leq t-1. \end{aligned} \tag{2}$$

The expanding window begins in November 2014 and we require at least 12 monthly observations for estimation. The coefficient $\beta_{c,t-1}$ captures the predictable sensitivity of city c's housing market to aggregate housing fluctuations. We then construct the instrument:

$$Z_{c,t} = \beta_{c,t-1} \times HousingRet_t^{Systematic}. \tag{3}$$

In the second stage, we instrument $HousingRet_{c,t-1}$ with $Z_{c,t}$ in equation (6). Identification comes from cross-city differences in exposure $\beta_{c,t-1}$ interacting with time variation in aggregate housing shocks. The identifying assumption is that, conditional on city and time fixed effects and observable controls, aggregate housing shocks do not differentially affect city-level gold demand in proportion to $\beta_{c,t-1}$ except through their impact on local housing returns.

3.3. Difference-in-Differences Design: Post-2021 Housing Regime Shift

We also implement a difference-in-differences design exploiting the post-2021 deterioration of China's housing market. The timing of the treatment is motivated by the introduction of the "Three Red Lines" policy, a major regulatory tightening targeting highly leveraged real estate developers. The policy was announced in August 2020 by the Ministry of Housing and Urban–Rural Development together with the People's Bank of China and imposed explicit balance-sheet constraints on property developers. In particular, developers were required to satisfy three leverage-related thresholds: (i) a liability-to-asset ratio below 70% (excluding advance proceeds), (ii) a net-debt-to-equity ratio below 100%, and (iii) cash reserves covering at least 100% of short-term debt.

Depending on how many of these thresholds a firm violated, developers were classified into four regulatory categories that imposed increasingly tight caps on the growth of interest-bearing liabilities. Highly leveraged developers were therefore severely constrained in their ability to refinance or expand borrowing. As the Chinese real estate sector is both highly leveraged and tightly connected to the broader economy, the policy triggered a substantial contraction in developer financing and investment activity (Chen, Du, and Ma, 2024).

Following the policy implementation, housing market conditions deteriorated markedly. National housing prices peaked around 2021Q3 and subsequently entered a prolonged decline. Motivated by this structural break, we define $Post_t$ as an indicator equal to one for months from 2021 onward.

We define treatment intensity using pre-determined exposure: we compute each city's pre-2021 average housing elasticity and classify cities in the top quartile as $HighExposure_c$. We estimate:

$$GoldDemand_{c,t} = \alpha_c + \gamma_t + \theta \left(HighExposure_c \times Post_t \right) + X'_{c,t}\delta + \varepsilon_{c,t}. \tag{4}$$

The coefficient θ assesses whether gold demand rises more after 2021 in cities that are more exposed to systematic housing fluctuations.

3.4. Branch-Level Estimation with City-by-Time Fixed Effects

Finally, we implement the main specifications at the branch–month level as a sharpening exercise. The branch-level regressions include branch fixed effects and city-by-time fixed effects. We also include time-varying branch characteristics such as average age, male share, log average assets under management, and log average wage. This design absorbs all time-varying shocks common within a city and exploits within-city cross-branch variation, helping to alleviate concerns that unobserved city-level shocks drive the relation between housing returns and gold demand.

4. Results

Figure 1 shows that the surge in Chinese gold demand after 2021 coincides with the housing market bust and may contribute to movements in global gold prices. In this section, we formally test these implications using regression analysis. Section 4.1 presents country-level evidence based on international data while Sections 4.2 - 4.6 present city- and branch-level evidence using our gold transaction data.

4.1. Country-Level Evidence

China's Gold Demand Relative to Other Countries. We begin by examining whether the surge in China's gold investment demand after 2021 is stronger, on average, than that observed in other countries. We estimate the following country–quarter panel regression:

$$InvestVal_{c,t} = \alpha_n + \gamma_t + \beta\, China_c \times Post21_t + \Delta Treasury_{c,t} + MKTYOY_{c,t} + \varepsilon_{c,t}, \quad (5)$$

where $InvestVal_{c,t}$ is the inflation-adjusted dollar value of gold investment demand (USD billions) in country c during quarter t. Because gold demand can be negative, we transform investment demand using the inverse hyperbolic sine (IHS) instead of the logarithmic transformation to mitigate the influence of extreme observations.[4] $China_c$ is a dummy equal to

[4]Following the World Gold Council, we define bars-and-coins gold demand as investment demand. We exclude ETF demand because gold ETFs are small in many countries and, in countries with large ETF

one for China. $Post21_t$ is a dummy equal to one for quarters after 2021Q3. The sample includes 19 countries between 2010Q1 and 2025Q4, the period for which the gold demand data are available. We control for quarterly changes in the 10-year government bond yield ($\Delta Treasury_{c,t}$) and lagged year-over-year stock market returns ($MKTYOY_{c,t}$).

Panel A of Table 2 presents the results. The coefficient on the interaction term is 0.386 and highly significant at the 1% level (t-value = 11.65). This number indicates that China's quarterly gold demand increased by approximately 47% ($e^{0.402} - 1$) relative to that of other countries after 2021. This translates into an increase of approximately USD 1.37 billion per quarter, which is 2.45 standard deviations of the cross-country distribution. Consistent with Figure 1, the results suggest that the post-2021 surge in China's gold demand is both economically meaningful and distinct from contemporaneous developments in other major economies.

[Insert Table 2 Around Here]

Housing Returns and Gold Demand in China. We next examine whether housing returns affect gold demand in China using the following aggregate time-series regression:

$$InvestVal_t = \alpha + \beta\, LowHousing_t \times HouseYOY_t + HouseYOY_t + LowHousing_t + Controls, \tag{6}$$

where $HouseYOY$ is the lagged year-over-year housing return. $LowHousing$ is a dummy equal to one if the housing price index falls within the bottom quartile of the sample distribution.

The results are reported in Panel B of Table 2. In column (1), the coefficient on lagged housing returns is negative and statistically significant (t-value = -2.60), indicating that periods of weak housing-market performance are associated with stronger gold demand in China. Column (2) shows that this relationship becomes substantially stronger during housing market downturns. The coefficient on the interaction term, $LowHousing \times HouseYOY$, is -11.671 (t-value = -2.28), suggesting that the sensitivity of gold demand to housing returns is amplified when housing returns are at low levels.

markets, ETF shares can be traded by investors worldwide and therefore do not necessarily reflect domestic gold demand. Nevertheless, our main findings remain unchanged when ETF demand is included.

This state-dependent pattern resembles the relationship between Treasury yields and gold returns documented by Jermann (2025) for the U.S. market. They show that investors enter the gold market when Treasury yields are low, strengthening the negative relation between gold returns and Treasury yields. Analogously, our results suggest that Chinese households are more likely to increase gold purchases when housing-market conditions deteriorate, leading to a stronger negative relation between gold demand and housing returns during downturns.

Interestingly, changes in Treasury yields are not statistically significant in China. One interpretation is that housing-market performance serves as a more salient benchmark for Chinese households than government bond yields. This interpretation is consistent with evidence that housing wealth constitutes a large share of household portfolios in China and that housing-price shocks have meaningful effects on household behavior (e.g., Painter et al. (2022); Fang et al. (2022)). In this sense, our housing-benchmark hypothesis complements the interest-rate channel proposed by Jermann (2025) by highlighting the role of housing-market conditions in shaping household demand for gold.

China Gold Prices and International Gold Prices. The evidence so far suggests that China's housing downturn after 2021 may have contributed to the substantial surge in its gold investment demand. Because China's gold market is partially segmented from the international market, we further examine whether this increase in demand has strengthened China's price impact on the global gold market. Specifically, we test whether the Shanghai-London gold price premium predicts subsequent London gold returns using daily data.

For a given day t, the Shanghai-London price premium, $Premium_t$, is defined as the log difference between the London AM gold price (available at 10:30 a.m. London time) and the Shanghai PM gold price (available at 7:00 a.m. London time) on the same calendar day, measured at the beginning of day t. Two London gold returns follow this premium. The first is the London intraday return on day t ($Ret_t^{Intraday}$), defined as the log difference between the London PM price (3:00 p.m. London time) and the London AM price (10:30 a.m. London time) on day t. The second is the London AM-to-AM daily return over day t (Ret_t), defined as the log difference between the London AM price on day $t+1$ and the

London AM price on day t.

The results are reported in Table 3. Under the null hypothesis, the premium should not predict subsequent London returns—either $Ret_t^{Intraday}$ or Ret_t—if demand pressures originating in China do not spill over to international prices. However, consistent with the enhanced price-impact interpretation, the coefficients on the premium in the baseline specifications are positive and statistically significant for both subsequent intraday returns (0.030 with $t = 2.90$, column (1)) and AM-to-AM returns (0.049 with $t = 2.82$, column (3)). Moreover, the predictive relationship becomes stronger after China's national housing-price peak: the interaction term $Premium \times PostPeak$ is positive and statistically significant for both intraday and AM-to-AM returns (0.057 with $t = 2.47$; 0.068 with $t = 1.70$). We define $PostPeak$ as one for observations in or after October 2021, following BIS residential property price data showing that China's national house price index peaks in 2021Q3. In terms of economic magnitude, after the peak a 1 percentage point increase in the premium predicts a 0.10 percentage point increase in AM-to-AM London gold returns (0.10%= 1% $\times$ $(0.029 + 0.068)$). Overall, these results suggest that demand spillovers from China to global gold prices.[5]

[Insert Table 3 Around Here]

4.2. City-Level Evidence on Housing Returns and Alternative Determinants of Gold Demand

With city-year month panel, we are able to further examine which factors have the strongest explanatory power for household gold demand. Table 4 reports two sets of city–month panel regressions. Panel A conducts a horse-race exercise without time fixed effects, which allows both time-series and cross-city variation in the candidate variables to contribute to the estimates. Panel B then adds time fixed effects to absorb aggregate shocks and test whether the housing-return effect remains strong after relying on within-city variation.

[5]It is worth noting that our estimates should be interpreted as a lower bound on the spillover effect. London AM benchmark prices are settled roughly two hours post the Shang- hai PM fixing, which means that some information from Shanghai prices may already be incorporated into London prices before the subsequent returns are to be realized.

We organize the candidate variables into two groups. The first group consists of major asset-market performance and macroeconomic indicators, including lagged housing returns, lagged stock market returns, changes in the yield of the Chinese 10-year government bond, GDP growth, and geopolitical risk. The second group captures behavioral and speculative forces. We use changes in gold-related attention to proxy for investor salience, following Da, Engelberg, and Gao (2011). We use past gold returns to capture return extrapolation, as in Greenwood and Shleifer (2014); Barberis, Greenwood, Jin, and Shleifer (2018). We also include People's Bank of China (PBOC) gold demand to capture speculative responses to official-sector purchases, which households may interpret as a signal of future demand and resale value (Harrison and Kreps, 1978; Scheinkman and Xiong, 2003).

[Insert Table 4 Around Here]

Panel A shows that housing returns have the strongest explanatory power among these candidate variables. When each variable is entered separately without time fixed effects, lagged housing returns generate the largest R^2 (5.97%), slightly exceeding GDP growth (5.76%) and clearly exceeding geopolitical risk (3.33%), past gold returns (3.12%), PBOC gold demand (2.28%), gold-related attention (1.56%), Treasury-yield changes (0.09%), and stock returns (0.02%). The coefficient on lagged housing returns is negative and highly statistically significant (-8.685, $t = -13.09$), indicating that weaker housing-market performance is associated with higher gold purchases. When all variables are included jointly, the housing-return coefficient remains negative and highly significant (-5.384, $t = -11.00$).

Panel B further examines whether the housing-return relationship is driven solely by common time-series shocks by further including time fixed effects.[6] With both city and time fixed effects, the coefficient on lagged housing returns is -2.558 ($t = -6.03$) when entered alone and remains similar at -2.468 ($t = -5.81$) after controlling for GDP growth and gold-related attention. GDP growth is statistically insignificant, while attention is positively associated with gold purchases. Overall, Table 4 indicates that lagged housing returns are

[6]Because time fixed effects absorb variables that vary only at the time level, the specifications in Panel B do not separately report purely time-series variables such as stock market returns, changes in Treasury yields, aggregate gold returns, PBOC gold demand, and geopolitical risk.

both a robust predictor and the most powerful single explanatory variable for city-level gold demand in China.

4.3. City-Level Evidence on Housing Returns and Gold Demand: IV Approach

Although the baseline estimates indicate a robust negative association, housing returns may still contain local shocks that are correlated with gold demand. We therefore implement the sensitivity-based IV strategy following Guren et al. (2021). The idea of this IV is that aggregate housing market shocks affect cities differently depending on their historical sensitivity to national housing fluctuations. Interacting these aggregate shocks with predetermined city-level exposure generates plausibly exogenous variation in local housing returns. The details of this IV approach are described in Section 3.2. We restrict the sample to observations with sufficient pre-period data to estimate the exposure coefficient used to construct the instrument. The results are reported in Table 5.

[Insert Table 5 Around Here]

As shown in Column (1), the first stage is strong: the interaction between predetermined exposure and contemporaneous systematic housing returns predicts local housing returns with a coefficient of 0.505 ($t = 14.86$), and the corresponding F-statistic is 220.7. In the second stage, as reported in Column (2), the IV estimate of housing returns on gold purchases is -6.784 ($t = -3.15$). In terms of economic magnitude, the standard deviation of housing returns is 0.104 and that of *NetBuyValue* is 4.008. Therefore, a one-standard-deviation decline in housing returns increases city-level gold purchases by approximately 0.706 million RMB ($0.706 = 6.784 \times 0.104$), which corresponds to 17.6% of a standard deviation in gold demand ($17.6\% = 0.706/4.008$).

For comparison, the corresponding OLS estimate, reported in Column (3), equals -3.194 ($t = -5.24$). This implies that a one-standard-deviation decline in housing returns increases gold purchases by about 8.3% of a standard deviation ($8.3\% = 3.194 \times 0.104/4.008$). The larger IV magnitude relative to OLS is consistent with attenuation bias discussed in Section 3.2.

Results using alternative outcome measures yield similar patterns. For *NetBuy* measured in kilograms, the IV coefficient equals -17.992 ($t = -3.77$). In terms of economic magnitude, a one-standard-deviation decline in housing returns increases gold purchases by 1.871 kilograms ($1.871 = 17.992 \times 0.104$), corresponding to 18.5% of a standard deviation in gold quantity ($18.5\% = 1.871/10.121$). We also use the inverse hyperbolic sine transformation of *NetBuyValue* to mitigate the influence of extreme observations; the IV coefficient remains negative and statistically significant (-1.253, $t = -3.78$).

4.4. City-Level Evidence: DiD Analysis

To complement the IV estimation, we implement a difference-in-differences analysis based on the post-2021 housing downturn. The empirical design exploits the tightening of real estate financing conditions following the introduction of the "Three Red Lines" policy, which led to a sharp deterioration in China's housing market beginning in 2021. We classify cities according to their pre-determined exposure to aggregate housing fluctuations, measured by each city's pre-2021 housing elasticity. The specification then compares changes in gold demand after 2021 between cities with high exposure to housing-market shocks and those with lower exposure. The details of this DiD specification are described in Section 3.3.

We report the results in Table 6. Columns (1)–(3) present results using three measures of city-level gold demand. Column (1) uses $NetBuyValue$, defined as the real net value of gold purchases at the city–month level. Column (2) uses $NetBuy$, defined as the net quantity of gold purchased (in kilograms). Column (3) uses the inverse hyperbolic sine transformation of $NetBuyValue$. Across all specifications, the coefficient on *HighExposure* $\times$ *Post21* is positive and statistically significant, indicating that cities more exposed to housing-market shocks experience larger increases in gold purchases after 2021.

[Insert Table 6 Around Here]

We further present event-study estimates of dynamic treatment effects in Figure 5 Panel A. We use 2020 as the reference year. Coefficients in the pre-period fluctuate around zero and are statistically insignificant, suggesting no differential pre-trends between high- and

low-exposure cities. The coefficients become positive starting in 2021 and rise thereafter, indicating a persistent increase in gold purchases in cities more exposed to housing shocks.

[Insert Figure 5 Around Here]

4.5. Branch-Level Evidence: Within-City-Time Estimation

We next turn to the branch-level design, which is our most stringent specification. All regressions include branch fixed effects and city-by-month fixed effects, which absorb any time-varying shocks common to branches within the same city. We additionally control for time-varying branch characteristics, including average age, gender composition, log average assets under management, and log average wage.

We report IV results in Panel A of Table 7. The first stage estimate of the instrument is 0.295 ($t = 65.57$) and the F-statistic equals 4,299.8. In the second stage, the IV estimate equals -0.020 ($t = -2.80$) for *NetBuyValue*. In terms of economic magnitude, a one-standard-deviation decline in housing returns increases gold purchases by about 2.0% of a standard deviation in branch-level gold demand ($2.0\% = 0.020 \times 0.138/0.135$). Using gold quantities (*NetBuy*), the IV coefficient equals -0.020 ($t = -1.72$), implying that a one-standard-deviation decline in housing returns increases branch-level gold purchases by about 1.0% of a standard deviation in gold quantity ($1.0\% = 0.020 \times 0.138/0.279$).

[Insert Table 7 Around Here]

Panel B reports difference-in-differences results at the branch level. Branches in districts with higher exposure to systematic housing fluctuations generate significantly larger increases in gold demand following the housing downturn. Dynamic treatment effects are shown in Figure 5 Panel B. The coefficients prior to the shock are close to zero, suggesting no evidence of differential pre-trends. Overall, the branch-level IV and DiD results provide stronger within-city evidence that housing downturns causally increase household gold demand.

4.6. The Social Amplifier Effect

We next examine whether peer trading behavior amplifies the relationship between housing returns and gold purchases. Social interactions may propagate investment responses

within local financial networks: when investors observe peers earning positive returns from gold investments or actively purchasing gold, they may be more likely to imitate these behaviors. As a result, a housing shock that initially triggers gold purchases by some investors may spread within the branch through peer influence.

To capture this mechanism, we construct two branch-level peer variables. The first is $PeerReturn$, defined as the value-weighted cumulative return on gold holdings of investors within the same branch as of $t-1$, computed using investors' historical purchases and prevailing gold prices. The second measure is $PeerNetBuy$, defined as the lagged branch-level net gold purchases by peer investors.

Table 8 reports the results. Panel A uses total net gold purchases ($NetBuyValue$) as the dependent variable. Column (1) shows the baseline housing effect: housing returns are negatively related to gold purchases ($\beta = -0.004$, $t = -5.01$). This coefficient captures the direct substitution from housing to gold investment.

Column (2) introduces the interaction between housing returns and peer gold returns, where housing returns are instrumented. The interaction term is negative and highly significant ($\beta = -0.072$, $t = -8.83$), indicating that the housing–gold relationship becomes substantially stronger when peers have recently earned higher gold returns. The marginal effect of housing returns on gold purchases can be written as:

$$\text{Total effect} = \beta_{Housing} + \beta_{Interaction} \times PeerReturn. \tag{7}$$

Using the estimates in Column (2), the implied amplification multiplier relative to the housing effect is:

$$\text{Multiplier} = 1 + \frac{0.072}{0.029} \times PeerReturn. \tag{8}$$

In the pre-peak period, the mean value of $PeerReturn$ is 0.189. Substituting this value implies a multiplier of approximately 1.46, meaning that peer investment performance increases the magnitude of the housing-driven gold demand response by roughly 46 percent relative to the main effect. This result suggests that housing shocks initially affecting some investors propagate through local peer networks, leading to substantially larger aggregate gold demand responses.

Columns (3) and (4) provide complementary evidence using peer trading activity instead of peer returns. Lagged peer net purchases are strongly positively associated with branch-level gold demand, and the IV interaction between peer net buying and housing returns is again negative and highly significant. This suggests that both peer investment success and peer trading intensity contribute to amplifying the housing–gold substitution.

Panel B repeats the analysis using gold purchases by new investors ($NetBuyValue_New$) as the dependent variable, and the results are qualitatively similar.

Taken together, these findings suggest that peer trading acts as a social amplifier housing shocks initially affect a subset of investors but subsequently spread through local interaction channels, magnifying the aggregate response of gold demand.

[Insert Table 8 Around Here]

5. Aggregate Price Effects and Cross-Country Evidence

5.1. Aggregate Price Impacts: Back-of-the-Envelope Calculation

We conduct a back-of-the-envelope calculation to assess how much of the post-2021 increase in China's gold investment demand can be attributed to the housing downturn, and to evaluate the potential implications for global gold prices. The calculation has three steps. We first estimate a reduced-form price-impact elasticity for the gold market. We then estimate the cumulative increase in Chinese gold demand induced by the housing downturn. Finally, we combine these two objects to infer the implied price effect.

The accounting framework is as follows. Let P_{2021Q3} denote the London gold price at the end of 2021Q3, when China's housing market peaked, and let P_{2025} denote the corresponding price at the end of 2025. The left-hand side is the cumulative gold-price change from the housing-market peak to the end of 2025. Accordingly, the demand shock on the right-hand side is also measured cumulatively over the same period:

$$\frac{\Delta P(HousingYoY)}{P_{2021Q3}} \approx \lambda \times \frac{\Delta Q^{China}(HousingYoY)}{Q^{Global}}, \tag{9}$$

where $\Delta Q^{China}(HousingYoY)$ is the cumulative increase in Chinese gold investment demand induced by the housing downturn. The denominator, Q^{Global}, is the expected global gold supply. If ϵ denotes the relevant short-run elasticity, then

$$\lambda = \frac{1}{|\epsilon|}. \tag{10}$$

5.1.1. Estimating Elasticity

We estimate the price-impact parameter using a monthly time-series regression that relates gold returns to the housing-induced component of bank gold purchases. Specifically, we estimate

$$GoldRet_t = \alpha + \theta \widehat{NetBuy}_t^{Bank} + \rho_1 GoldRet_{t-1} + \rho_2 GoldRet_{t-2} + \delta \Delta CN10_t^{Real} + \varepsilon_t, \tag{11}$$

where $GoldRet_t$ is the monthly gold return, and $\widehat{NetBuy}_t^{Bank}$ is the component of bank gold demand predicted by the housing-return instrument. This is an IV-style price-impact regression. Rather than relating gold prices to total bank purchases, we use only the variation in bank gold purchases induced by housing returns. The identifying assumption is that Chinese housing returns affect global gold prices only through their effect on Chinese households' gold purchases, rather than through other channels. Under this exclusion restriction, the coefficient on $\widehat{NetBuy}_t^{Bank}$ captures the price response to an exogenous demand shift generated by the housing channel.

The first-stage relation comes from the city-level IV estimates in Table 5. In Panel B, using *NetBuy* in kilograms as the dependent variable, the IV coefficient is -17.992 ($t = -3.77$). Because the aggregate price-impact regression cannot absorb the city-level controls and fixed effects used in the panel estimates, we construct the first-stage demand component directly as the IV coefficient multiplied by housing returns ($\widehat{NetBuy}_{c,t}^{Bank} = -17.992 \times HousingRet_{c,t-1}$).

As shown in Table 9, the estimated coefficient is $\widehat{\theta} = 0.024$ (t=1.69). Let $s = NetBuy_t^{Bank}/Q_t^{China}$ to denote the market share of the bank, which equals 12.91% according to Section 2.2. Before the housing shock, monthly global gold supply averaged $Q^{Global} = 4{,}755.1/12 = 396.3$ tons, using the 2015–2020 average. As a result, the regression implies the following price-impact

mapping:

$$\frac{\Delta P}{P} = \widehat{\theta} \times NetBuy_t^{Bank} = \widehat{\theta} \times s \times Q_t^{China} = \left(\widehat{\theta} \times s \times Q_t^{Global}\right) \times \frac{Q_t^{China}}{Q_t^{Global}}. \tag{12}$$

The term in parentheses is the price-impact parameter for a demand shock expressed as a share of global supply:

$$\widehat{\lambda} = \widehat{\theta} \times s \times Q^{Global} = \widehat{\theta} \times 0.1291 \times 396.3 = 1.228 = \frac{1}{|\widehat{\epsilon}|}, \tag{13}$$

which implies $\widehat{\epsilon} = -1/\widehat{\lambda} = -0.814$. This estimate falls within the range of existing gold-demand elasticity estimates, which place the relevant elasticity between -0.3 and -1.1 (Immanuvel and Lazar, 2021).

5.1.2. Estimating Housing-Shock-Induced Chinese Demand

We next estimate the numerator in Eq. (9), $\Delta Q^{China}(HousingYoY)$. The calculation uses several inputs: the change in housing returns around the housing-market peak, the estimated effect of $HousingYoY$ on the monthly average $NetBuy$ of a city, number of cities and number of months post housing price peak. Intuitively, we first ask how much monthly gold purchases at our bank increased in an average city because housing returns declined after the peak. We then aggregate this city-level monthly effect across cities and months to obtain the cumulative change in gold demand within our bank. Specifically, we compute

$$\begin{aligned}\Delta Gold^{Bank}(HousingYoY) &= \beta^{IV} \times \Delta H \times N_{city} \times M_{post} \\ &= (-17.992) \times (-0.095) \times 296 \times 51 = 25{,}803 \text{ kg} = 25.8 \text{ tons}.\end{aligned} \tag{14}$$

Here, $\beta^{IV} = -17.992$ is the estimated effect of lagged year-over-year housing returns on monthly average city-level $NetBuy$ from Table 5 Panel B; $\Delta H = -0.095$ is the change in average housing returns after the 2021Q3 peak relative to the pre-period, from Table 1 Panel B; $N_{city} = 296$ is the number of cities; and $M_{post} = 51$ is the number of months from October 2021 through December 2025.

Scaling to the national level using the bank's market share in gold investment demand,

$s = 12.91\%$, yields

$$\Delta Q^{China}(HousingYoY) = \frac{\Delta Gold^{Bank}(HousingYoY)}{s} = \frac{25.8}{0.1291} = 199.8 \text{ tons.} \tag{15}$$

Using the current baseline inputs, this procedure implies a cumulative housing-downturn-induced increase of 199.8 tons. Public data indicate that China's annualized average gold investment demand increased from 258.8 tons in 2015–2021Q3 to 316.0 tons in 2021Q4–2025. Over the 51-month post-peak window, this implies a cumulative increase of 243.1 tons ($=(316.0 - 258.8)/12 \times 51$). The baseline estimate therefore suggests that the housing downturn accounts for approximately $199.8/243.1 = 82.2\%$ of the post-2021 increase in China's gold investment demand.

As shown in Section 5.7, peer interactions amplify the effect of housing shocks on gold demand. At the pre-2021 mean peer return, the estimated social amplification multiplier equals 1.46. Applying this multiplier to the baseline estimate implies an amplified housing-driven demand increase of 291.7 tons ($=199.8 \times 1.46$).

5.1.3. Implied Price Effect

Finally, we combine the estimated price impact with the housing-shock-induced demand increase. The estimate in Eq. (13) implies $\widehat{\lambda} = 1.228$. The baseline estimate of housing-induced Chinese demand is 199.8 tons, while the amplified estimate is 291.7 tons. We scale these quantities by expected global gold supply, $Q^{Global} = 4{,}755.1$ tons. Substituting these values into Eq. (9) gives

$$\widehat{P}(HousingYoY) = \widehat{\lambda} \times \frac{\Delta Q^{China}(HousingYoY)}{Q^{Global}} \times P_{2021Q3}, \tag{16}$$

where $\widehat{P}(HousingYoY)$ denotes the dollar price increase attributable to the housing-induced Chinese demand shock. Using $P_{2021Q3} = 1{,}789.4$ USD/oz, the baseline demand shock implies a price effect of

$$\widehat{P}(HousingYoY) = 1.228 \times \frac{199.8}{4{,}755.1} \times 1{,}789.4 = 92.3 \text{ USD/oz.}$$

The amplified demand shock implies

$$\widehat{P}_{amp}(HousingYoY) = 1.228 \times \frac{291.7}{4{,}755.1} \times 1{,}789.4 = 134.8 \text{ USD/oz}.$$

Relative to the 2021Q3 price of 1,789.4 USD/oz, these estimates correspond to price increases of 92.3/1,789.4 = 5.2% in the baseline calculation and 134.8/1,789.4 = 7.5% in the amplified calculation. The implied price effect is sensitive to the elasticity used to map demand shocks into prices. Note that these estimates are highly sensitive to the price elasticity used in the calculation. Using the elasticity range in Immanuvel and Lazar (2021), $\epsilon \in [-1.1, -0.3]$, implies a corresponding price-impact parameter between $1/1.1 = 0.909$ and $1/0.3 = 3.333$. Under this range, the baseline demand shock implies a price effect of approximately 68.3 to 250.5 USD/oz, or 3.8% to 14.0% of the 2021Q3 price. The amplified demand shock implies a larger price effect of approximately 99.8 to 365.9 USD/oz, or 5.6% to 20.4% of the 2021Q3 price. These ranges underscore that the implied price effect depends importantly on the assumed short-run elasticity of gold supply and demand.

5.2. Generalization Beyond China: Cross-Country Patterns

Finally, we examine whether the negative housing-gold relationship documented in China extends to other countries. The mechanism we propose is a portfolio reallocation decision: when expected returns to housing decline, households may shift savings toward alternative stores of value such as gold. If housing and gold play similar roles in household portfolios beyond China, the portfolio reallocation channel may also be present in other economies.

To investigate this possibility, we collect quarterly data for 18 countries and regions with complete information on investment gold demand and housing price indices from 2010Q1 to 2025Q4. For each country, we estimate the time-series relation between investment gold demand and lagged year-over-year housing returns. Both gold demand and housing returns are adjusted for local inflation. We control for quarterly changes in long-term government bond yields and lagged year-over-year stock market returns.

[Please Insert Table 10 Around Here]

Table 10 reports the results. Countries are ranked by the t-statistic on lagged housing returns. Consistent with the evidence from China, we find a significantly negative association between housing returns and gold demand in several major economies, including the United Kingdom, Canada, Singapore, and the United States. This suggests that households in these economies may respond to housing-market fluctuations in ways similar to those observed in China. At the same time, three countries exhibit significantly positive coefficients, a pattern more consistent with a wealth effect in which housing appreciation increases households' demand for gold. For the remaining countries, the estimated relationship is statistically indistinguishable from zero.

Overall, the evidence suggests that the negative housing-gold link extends beyond China, although substantial cross-country heterogeneity remains. While the relationship is far from universal, the results indicate that the interaction between housing-market conditions and household gold demand is not solely a China-specific phenomenon.

6. Conclusion

This paper documents a novel mechanism through which housing shocks can influence gold demand and spill over to global prices. Focusing on 2015-2025 China, We show that the residential housing market collapse triggered a large-scale reallocation of household wealth into gold. Using transaction-level data from a major state-owned bank, we find that cities and neighborhoods experiencing larger housing downturns saw significantly higher gold purchases, and that social interactions amplified this response. Quantitatively, we estimate that this flight-to-gold contributed roughly \$210–\$490 per ounce, or 11–26% of the global gold price increase, demonstrating that household portfolio reallocations can transmit localized shocks into international prices.

These patterns are not unique to China. Using country-level data, we document similar negative correlations between housing returns and gold investment demand in major economies, including the United States, Singapore, Canada, and the United Kingdom. More broadly, our findings speak to the evolving role of gold in the global safe-asset landscape. While our empirical setting centers on housing shocks, the mechanism we document reflects

a more general process of portfolio reallocation toward alternative stores of value when perceived risks to existing wealth increase. In an environment where traditional safe assets, such as U.S. Treasuries and the U.S. dollar, face declining hedging capacity, gold may increasingly serve as an alternative safe asset for households and investors worldwide.

References

Allen, F., Qian, J., Shan, C., Zhu, J. L., 2024. Dissecting the long-term performance of the Chinese stock market. The Journal of Finance 79, 993–1054.

Baele, L., Bekaert, G., Inghelbrecht, K., Wei, M., 2020. Flights to safety. The Review of Financial Studies 33, 689–746.

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., 2018. The economic effects of social networks: Evidence from the housing market. Journal of Political Economy 126, 2224–2276.

Barberis, N., Greenwood, R., Jin, L., Shleifer, A., 2018. Extrapolation and bubbles. Journal of Financial Economics 129, 203–227.

Barro, R. J., Misra, S., 2016. Gold returns. The Economic Journal 126, 1293–1317.

Basak, S., Pavlova, A., 2016. A model of financialization of commodities. The Journal of Finance 71, 1511–1556.

Baur, D. G., Lucey, B. M., 2010. Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financial Review 45, 217–229.

Baur, D. G., McDermott, T. K., 2010. Is gold a safe haven? International evidence. Journal of Banking & Finance 34, 1886–1898.

Caballero, R. J., Krishnamurthy, A., 2008. Collective risk management in a flight to quality episode. The Journal of Finance 63, 2195–2230.

Caldara, D., Iacoviello, M., 2022. Measuring geopolitical risk. American Economic Review 112, 1194–1225.

Chen, K., Du, H., Ma, C., 2024. The spillover effects of real estate. Working Paper.

Chen, Z., Jiang, Z., Lustig, H., Van Nieuwerburgh, S., Xia, M. Z., 2025. Exorbitant privilege gained and lost: Fiscal implications. Journal of Political Economy 133, 3713–3761.

Cheng, I.-H., Xiong, W., 2014. Financialization of commodity markets. Annu. Rev. Financ. Econ. 6, 419–441.

Chetty, R., Sándor, L., Szeidl, A., 2017. The effect of housing on portfolio choice. The Journal of Finance 72, 1171–1212.

Cocco, J. F., 2005. Portfolio choice in the presence of housing. The Review of Financial Studies 18, 535–567.

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. The Journal of Finance 66, 1461–1499.

Duffie, D., 2023. Resilience redux in the u.s. treasury market. In: *Jackson Hole Economic Policy Symposium*, Federal Reserve Bank of Kansas City.

Erb, C. B., Harvey, C. R., 2013. The golden dilemma. Financial Analysts Journal 69, 10–42.

Erb, C. B., Harvey, C. R., 2024. Is there still a golden dilemma? SSRN Electronic Journal Available at SSRN.

Erb, C. B., Harvey, C. R., 2025. Understanding gold. SSRN Electronic Journal Available at SSRN.

Fang, H., Wang, L., Yang, Y., 2022. Housing wealth and online consumer behavior: Evidence from xiong'an new area in china. NBER Working Paper 30465, National Bureau of Economic Research.

Fang, X., Liu, Y., Roussanov, N., 2026. Getting to the core: Inflation risks within and across asset classes. The Review of Financial Studies 39, 702–743.

Greenwood, R., Shleifer, A., 2014. Expectations of returns and expected returns. The Review of Financial Studies 27, 714–746.

Guren, A. M., McKay, A., Nakamura, E., Steinsson, J., 2021. Housing wealth effects: The long view. The Review of Economic Studies 88, 669–707.

Harrison, J. M., Kreps, D. M., 1978. Speculative investor behavior in a stock market with heterogeneous expectations. The Quarterly Journal of Economics 92, 323–336.

He, Z., Krishnamurthy, A., Milbradt, K., 2016. What makes u.s. government bonds safe assets? American Economic Review 106, 519–523.

Hong, H., Kubik, J. D., Stein, J. C., 2004. Social interaction and stock-market participation. The Journal of Finance 59, 137–163.

Hu, G. X., Jin, Z., Pan, J., 2023. The stock-bond correlation: A tale of two days in the u.s. treasury market. SSRN Electronic Journal Available at SSRN.

Huang, D., Kilic, M., 2019. Gold, platinum, and expected stock returns. Journal of Financial Economics 132, 50–75.

Immanuvel, S. M., Lazar, D., 2021. Elasticities of gold demand: An empirical analysis using cointegration and error correction model. Arthaniti: Journal of Economic Theory and Practice 20, 131–142.

Jermann, U. J., 2025. Gold's value as an investment. The Review of Financial Studies 38, 422–456.

Jiang, Z., Krishnamurthy, A., Lustig, H., 2021. Foreign safe asset demand and the dollar exchange rate. Journal of Finance 76, 1049–1089.

Jiang, Z., Krishnamurthy, A., Lustig, H., Richmond, R., 2025. Dollar erosion: Understanding the loss of reserve currency status. SSRN Electronic Journal Available at SSRN.

Kuchler, T., Stroebel, J., 2021. Social finance. Annual Review of Financial Economics 13, 37–55.

Painter, G., Yang, X., Zhong, N., 2022. Housing Wealth as Precautionary Saving: Evidence from Urban China. Journal of Financial and Quantitative Analysis 57, 761–789.

Rogelberg, S., 2025. Goldman sachs says the demand for gold is not just hype, and predicts the u.s. could still see a repeat of a nixon-era spike. Fortune .

Scheinkman, J. A., Xiong, W., 2003. Overconfidence and speculative bubbles. Journal of Political Economy 111, 1183–1220.

Shue, K., 2013. Executive networks and firm policies: Evidence from the random assignment of MBA peers. The Review of Financial Studies 26, 1401–1442.

Singleton, K. J., 2014. Investor flows and the 2008 boom/bust in oil prices. Management Science 60, 300–318.

World Gold Council, 2024. Gold demand trends full year 2024. World Gold Council Research.

Xie, Y., Jin, Y., 2015. Household wealth in China. Chinese Sociological Review 47, 203–229.

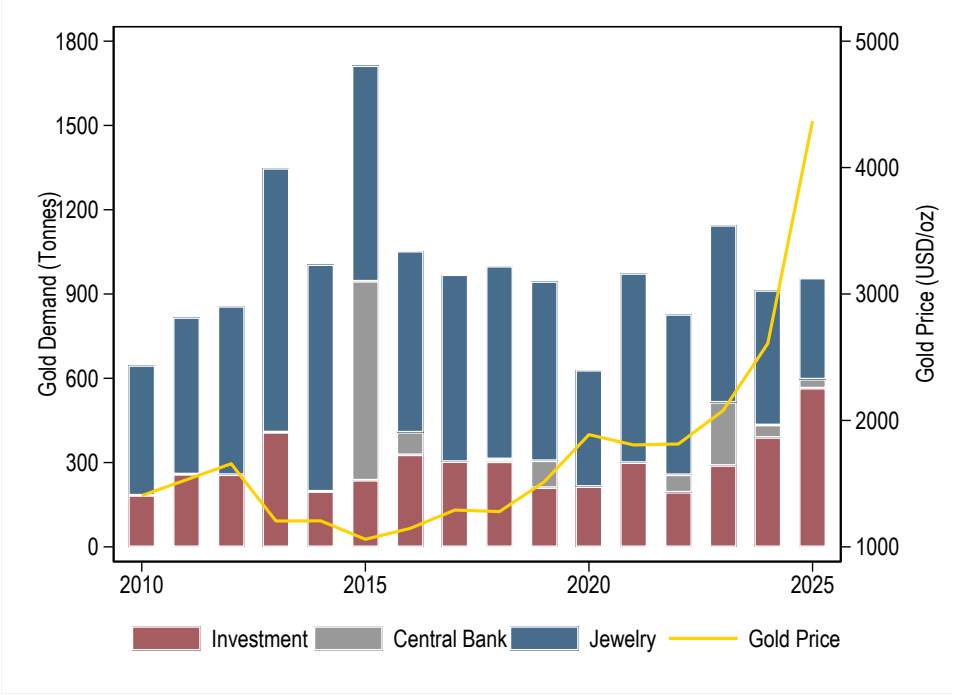
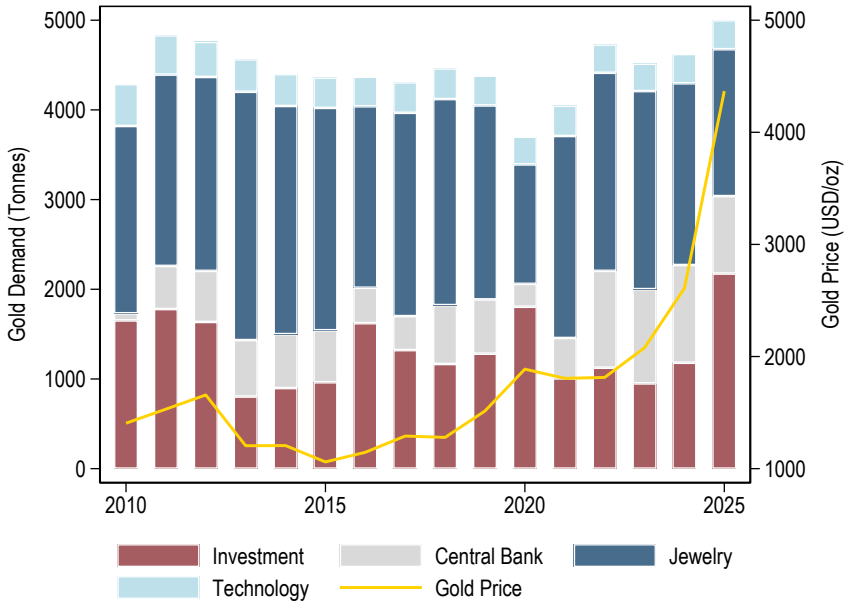
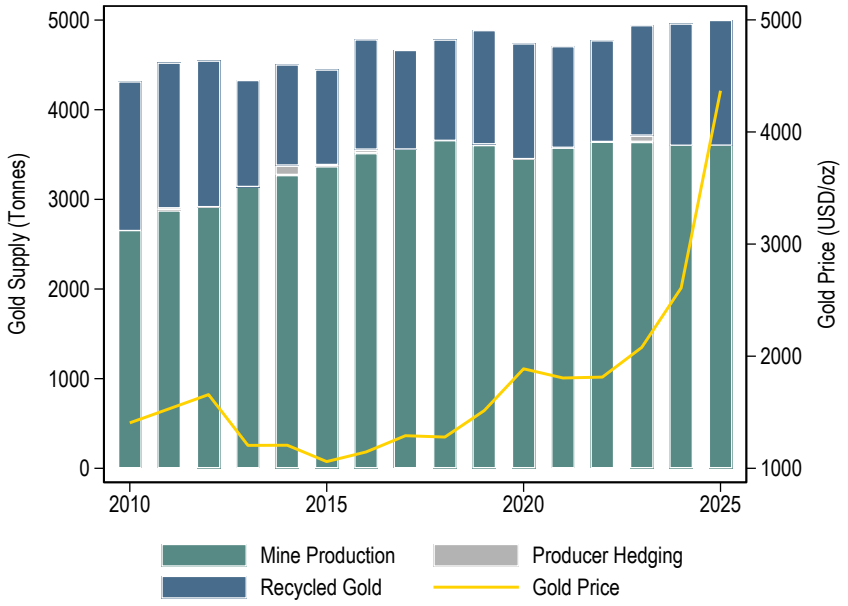


Fig. 2. China Gold Demand by Type

This figure plots annual China gold demand (tonnes) by category reported by the World Gold Council. Each bar stacks jewelry demand, investment demand, and central bank demand for each year from 2010 to 2025; segment lengths correspond to category-specific quantities.



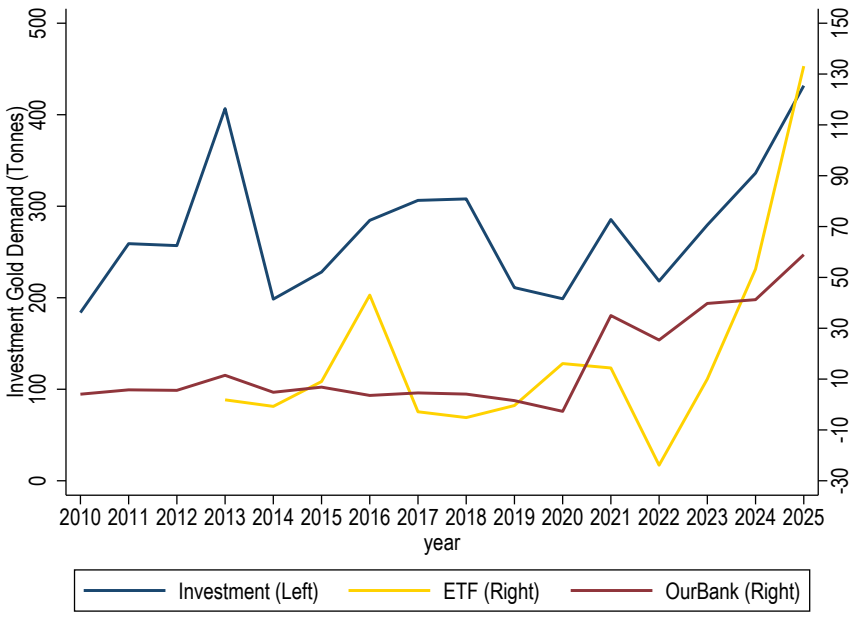
Panel A. Gold Demand By Type



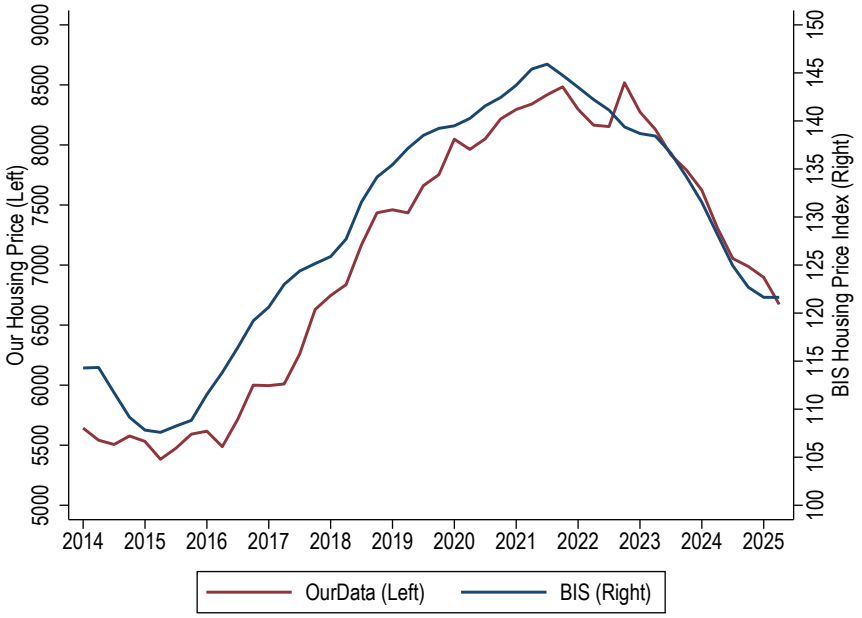
Panel B. Gold Supply By Type

Fig. 3. Global Gold Demand and Supply by Type

This figure plots annual global gold demand and supply (tonnes) by category reported by the World Gold Council. In Panel A, Each bar stacks jewelry demand, technology demand, investment demand, and central bank demand for each year from 2010 to 2025; segment lengths correspond to category-specific quantities. The line is the nominal London AM Price at the end of the year. In Panel B, Each bar stacks mine production, net producer hedging and recycled gold supply for each year from 2010 to 2025; segment lengths correspond to category-specific quantities. The line is the nominal London AM Price at the end of the year.



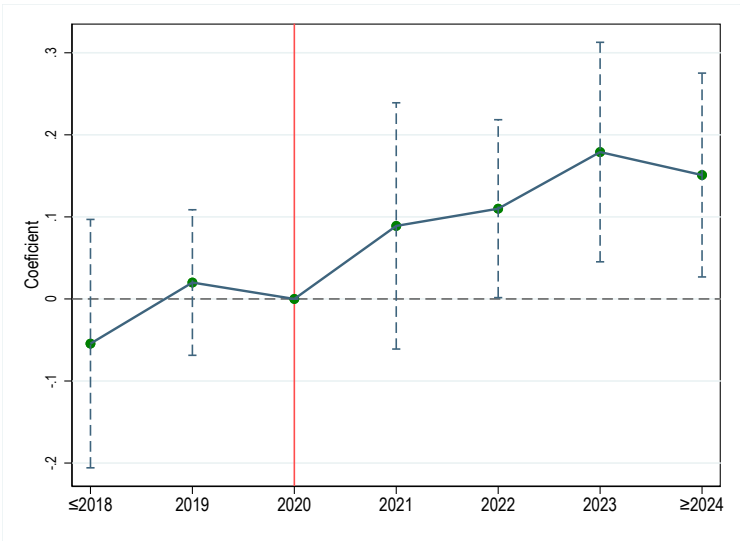
Panel A. Gold Data Comparison



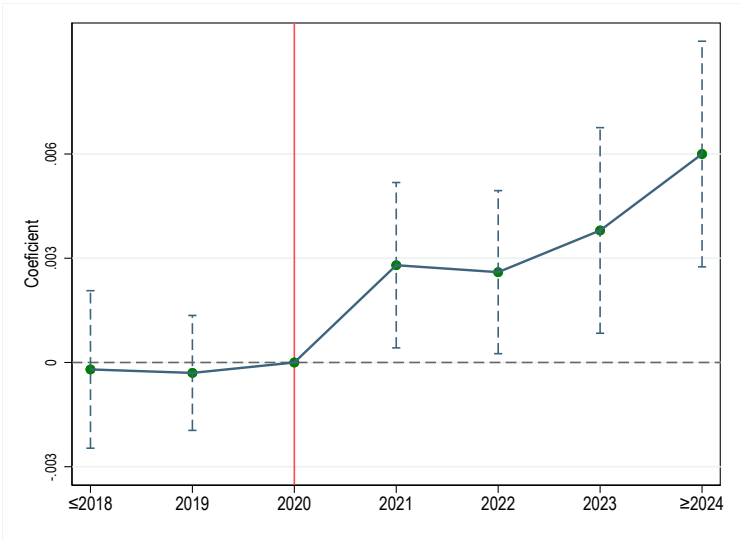
Panel B. Housing Prices Data Comparison

Fig. 4. External Validation of Gold Demand and Housing Price Data

This figure compares internal bank data with external benchmark series to validate data quality. Panel A plots annual Chinese gold demand from World Gold Council, including total household gold demand and its components—investment demand, consumption demand, and ETF demand—alongside gold demand observed in the bank's internal data (China Construction Bank). Panel B compares the bank's internal housing price series with the nominal residential property price index for China obtained from the Bank for International Settlements (BIS). The internal housing price series is constructed using the average appraisal value of residential properties within the bank's mortgage portfolio. The BIS index is downloaded from the FRED.



Panel A. City-Level



Panel B. Branch Level

Fig. 5. Dynamic Effects
This figure plots event-time coefficients from the following specification:

$$Y_{b,t} = \sum_{k \neq 2020} \beta_k \left(HighExposure_b \times 1\{Year_t = k\} \right) + \Gamma X_{b,t} + FE + \varepsilon_{b,t},$$

where $HighExposure_b$ equals one if a branch's housing elasticity is in the top quartile of the sample distribution, and zero otherwise. The omitted category is the year 2020, which serves as the reference period. α_b denotes branch fixed effects, and $\delta_{c,t}$ denotes city-time fixed effects. $X_{b,t}$ includes branch-level controls. Panel A uses *NetBuyValue* as the dependent variable, defined as the real net gold purchase value (in constant 2014 RMB, million) at the city–yearmonth level. The specification includes city fixed effects and time fixed effects. Panel B uses *NetBuyValue*, defined as the real net gold purchase value at the branch–yearmonth level. The specification includes branch fixed effects and city-by-time fixed effects. The vertical red line indicates 2020 (the reference year immediately prior to housing price peak). The vertical bars represent 95% confidence intervals based on standard errors clustered at the branch level. All continuous variables are winsorized at top and bottom 2.5%. All variables are defined in Appendix A.

Table 1: Summary statistics

This table presents summary statistics of the main variables at the city–yearmonth level. Panel A reports city–yearmonth level variables constructed by aggregating internal administrative gold trading records to the city level (296 cities, January 2015 to June 2025). Panel B compares the average values of selected variables before and after 2021Q3, when the China's housing prices peaked. Panel C presents within-time comparisons between cities with low and high housing elasticity (top quartile). All continuous variables are winsorized at top and bottom 2.5%. City-level variables are defined in Appendix A.

Panel A: City–year-month level variables

	N	Mean	STD	P25	P50	P75
NetBuy (in kg)	28025	5.060	10.121	0.080	1.148	5.358
NetBuyValue (in million)	28025	1.978	4.008	0.013	0.363	2.077
#Trader	28025	78.773	209.369	8.000	24.000	71.000
AvgDeal (in kg)	28025	0.088	0.287	0.010	0.058	0.125
AvgDealValue (in thousand)	28025	35.471	119.461	2.362	20.765	56.348
HousingRet	28025	0.036	0.104	-0.036	0.021	0.091
HousingRet_IV	27677	0.023	0.083	-0.025	0.003	0.050
HousingElasticity	27677	1.006	0.921	0.460	1.011	1.534
GDPGrowth	28025	0.063	0.025	0.045	0.068	0.081
DeltaLogAtt	28025	0.096	0.324	-0.130	0.060	0.293

Panel B: Pre Housing Peak vs. Post Housing Peak

	PrePeak	PostPeak	Diff	T-Stat
HousingRet_l1	0.063	-0.021	0.084	70.291
HousingRet_iv_l1	0.060	-0.035	0.095	114.340
NetBuyValue	0.762	4.116	-3.354	-49.078
NetBuy	2.808	9.256	-6.448	-38.078
NetBuyNumber	40.228	69.750	-29.522	-23.830
GDPGrowth	0.064	0.056	0.008	24.160
DeltaLogAtt	0.068	0.180	-0.112	-27.321

Panel C: Cities with Low vs. High Housing Elasticity

	Low Elasticity	High Elasticity	Diff	T-Stat
HousingElasticity	0.091	1.959	-1.868	-151.066
HousingRet_iv	0.010	0.046	-0.036	-34.056
HousingRet	0.030	0.043	-0.013	-9.786
NetBuyValue	2.244	2.206	0.038	0.584
NetBuy	5.751	5.492	0.259	1.581
NetBuyNumber	52.388	53.826	-1.437	-1.174
GDPGrowth	0.058	0.063	-0.005	-14.569
DeltaLogAtt	0.123	0.111	0.012	2.967

Table 2: Housing Market Conditions and China's Gold Demand

This table reports the relationship between housing market conditions and gold investment demand. Panel A presents country-quarter regressions using 19 countries from 2010Q1 to 2025Q4. The dependent variable, $InvestVal$, is the IHS-transformed quarterly inflation-adjusted value of bars-and-coins gold demand (USD billions). $China$ is a dummy equal to one for China. $Post21$ is a dummy equal to one for quarters after 2021Q3. We control for quarterly changes in the 10-year government bond yield ($\Delta Treasury$) and lagged year-over-year stock market returns ($MKTYOY$). t-statistics are computed using standard errors clustered at the country level. Panel B reports the results of time-series regressions of gold demand on housing returns using data from China. $HouseYoY$ is the lagged quarterly year-over-year housing return. $LowHousing$ is an indicator equal to one if the housing price index falls within the bottom quartile of the sample distribution. Newey–West adjusted t-statistics are reported. Variable definitions are provided in Appendix Table A1. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: China's Gold Demand Relative to Other Countries After 2021

	(1)	(2)
	InvestVal	
$China \times Post21$	0.388***	0.386***
	(11.50)	(11.65)
$\Delta Treasury$		-1.846**
		(-2.63)
$MKTYOY$		0.016
		(0.21)
Country FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	1,118	1,118
Adj. R^2	0.883	0.883

Panel B: Housing Returns and Gold Demand in China

	(1)	(2)
	InvestVal	
$HouseYOY$	-4.602**	-3.506**
	(-2.60)	(-2.38)
$LowHousing$		-0.524*
		(-1.71)
$LowHousing \times HouseYOY$		-11.671**
		(-2.28)
$\Delta Treasury$	5.172	5.864
	(1.04)	(1.22)
$MKTYOY$	0.351	0.186
	(1.21)	(0.73)
Observations	64	64
Adj. R^2	0.252	0.277

Table 3: China Gold Price Premium and Future London Gold Returns

This table examines whether the price premium between Shanghai and London gold markets predicts subsequent London gold returns. The sample consists of daily observations from January 3, 2003 to June 30, 2025, indexed by London trading day t. The premium and return series are winsorized at the top and bottom 1%. $Premium_t$ is defined as the log difference between the London AM gold fixing price (10:30 London time) on day t and the Shanghai PM gold fixing price (15:00 China Standard Time, approximately 07:00 London time) on the same calendar day, measured at the beginning of day t. $Ret_t^{Intraday}$ is the London intraday return on day t, computed as the log difference between the London PM fixing price (15:00 London time) and the London AM fixing price (10:30 London time). Ret_t is the AM-to-AM return over day t, defined as the log difference between the London AM fixing price on day $t+1$ and the London AM fixing price on day t. $PostPeak$ equals one for observations in or after October 2021 and zero otherwise; this cutoff follows BIS residential property price data, in which China's national house price index peaks in 2021Q3. All specifications include lagged return controls Ret_{t-1} and Ret_{t-2} and $\Delta Treasury$, defined as the daily change in TIPS return. The reported t-statistics in parentheses are computed using Newey–West standard errors with 21 lags. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) $Ret_t^{Intraday}$	(2) $Ret_t^{Intraday}$	(3) Ret_t	(4) Ret_t
$Premium_t$	0.030***	0.016	0.049***	0.029
	(2.90)	(1.27)	(2.82)	(1.44)
$PostPeak_t$		-0.000		-0.000
		(-1.51)		(-0.62)
$Premium_t \times PostPeak_t$		0.057**		0.068*
		(2.47)		(1.70)
Ret_{t-1}	0.012	0.010	-0.016	-0.019
	(1.25)	(1.08)	(-1.15)	(-1.30)
Ret_{t-2}	0.022***	0.021***	-0.021	-0.023
	(2.86)	(2.75)	(-1.50)	(-1.59)
$\Delta Treasury$	-0.020***	-0.020***	-0.047***	-0.047***
	(-10.17)	(-10.15)	(-12.16)	(-12.19)
Constant	-0.000***	-0.000***	0.000*	0.000*
	(-4.20)	(-3.47)	(1.81)	(1.89)
Observations	5,563	5,563	5,607	5,607

Table 4: Housing Returns versus Alternative Determinants of Gold Demand

This table presents horse-race regressions examining the relative explanatory power of housing market conditions and alternative city-level fundamentals for gold net purchases. The dependent variable is *NetBuyValue*, defined as the real net gold purchase value (in constant 2014 RMB, million) at the city–yearmonth level. Panel A includes lagged real housing returns, GDP growth, gold-related search attention scaled by population, changes in Treasury yields, gold returns, PBOC gold demand, stock-market returns, and geopolitical risk. Panel B reports the baseline horse-race specifications. The sample period is from January 2015 to June 2025. All continuous variables are winsorized at the top and bottom 2.5%. All variables are defined in Appendix A. The reported t-statistics (in parentheses) are based on standard errors clustered at the city level. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Horse-Race Regressions without Time Fixed Effects

	Macroeconomics and Major Asset Performance					Behavioral and Speculative Variables			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					NetBuyValue				
HousingRet_l1	-8.685***								-5.384***
	(-13.09)								(-11.00)
GDPGrowth		-34.767***							-15.120***
		(-9.92)							(-5.98)
StockMktRet_l1			-0.759***						-1.308***
			(-2.67)						(-4.48)
GPR_l1				0.017***					0.006***
				(18.92)					(9.56)
$\Delta Treasury$					-0.208***				-0.549***
					(-8.38)				(-15.80)
DeltaLogAtt						1.339***			0.322***
						(12.94)			(4.47)
GoldRetYoY_l1							4.814***		2.275***
							(16.48)		(10.86)
DemandPBOC_l1								0.066***	0.021***
								(20.90)	(9.07)
City FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	NO	NO	NO	NO	NO
R^2	5.97%	5.76%	3.33%	0.02%	0.09%	1.56%	3.12%	2.28%	13.95%
N	28025	28025	28025	28025	28025	28025	28025	28025	28025

Panel B: Horse-Race Regressions with Time Fixed Effects

	(1)	(2)	(3)	(4)
		NetBuyValue		
HousingRet_l1	-2.558***			-2.468***
	(-6.03)			(-5.81)
GDPGrowth		-4.239		-3.191
		(-1.26)		(-0.98)
DeltaLogAtt			0.461***	0.426***
			(5.56)	(5.23)
City FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
R^2	0.63%	0.05%	0.13%	0.77%
N	28025	28025	28025	28025

Table 5: Housing Returns and Gold Demand: Instrumental Variable Estimates

This table reports instrumental variable estimates of the effect of housing returns on gold purchases. Following Guren et al. (2023), the instrument is constructed as the interaction between city-specific housing elasticity—estimated using pre-determined expanding-window regressions—and the contemporaneous systematic housing return. Panel A presents the main results. The dependent variable is *NetBuyValue*, defined as the real net gold purchase value (in constant 2014 RMB, million). Columns (1) and (2) report OLS and second-stage IV estimates, respectively, and column (3) reports the corresponding first-stage regression. The key explanatory variable is the lagged real housing return. Control variables include GDP YoY Growth and change in gold-related attention. Panel B replaces the dependent variable with alternative measures of gold demand, including *NetBuy* (in kg) and *IHS(NetBuyValue)*. Fixed effects are as indicated in the table. All continuous variables are winsorized at top and bottom 2.5%. All variables are defined in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the city level. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Baseline results

	(1)	(2)	(3)
	IV		OLS
	HousingRet_l1	*NetBuyValue*	*NetBuyValue*
Exposure×*SystematicHousingRet_l1*	0.505***		
	(14.86)		
HousingRet_l1		-6.784***	-3.194***
		(-3.15)	(-5.24)
F-stat	220.73		
Controls	YES	YES	YES
City FE	YES	YES	YES
Time FE	YES	YES	YES
R^2	14.18%	0.43%	0.62%
N	27677	27677	27677

Panel B: Alternative Dependent Variables

	NetBuy		*IHS(NetBuyValue)*	
	(1)	(2)	(3)	(4)
	IV	OLS	IV	OLS
HousingRet_l1	-17.992***	-6.496***	-1.253***	-0.360***
	(-3.77)	(-4.66)	(-3.78)	(-2.81)
Controls	YES	YES	YES	YES
Branch FE	YES	YES	YES	YES
City-Time FE	YES	YES	YES	YES
R^2	0.25%	0.36%	0.20%	0.13%
N	27677	27677	27677	27677

Table 6: Housing Downturns and Gold Demand

This table reports difference-in-differences estimates of the effect of housing exposure on city-level gold purchases. *Post21* equals one for observations from 2021 onward, following the introduction of the "Three Red Lines" housing policy, and zero otherwise. *HighExposure* equals one if a city's *HousingElasticity* prior to 2021 is in the top quartile of the sample distribution and zero otherwise. The coefficient of interest is *HighExposure* × *Post21*. All continuous variables are winsorized at top and bottom 2.5%. All variables are defined in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the city level. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *NetBuyValue*	(2) *NetBuy*	(3) *IHS(NetBuyValue)*
HighExposure×*Post21*	0.150***	0.357***	0.164*
	(2.76)	(2.66)	(1.77)
Controls	YES	YES	YES
City FE	YES	YES	YES
Time FE	YES	YES	YES
R^2	0.37%	0.30%	0.20%
N	27677	27677	27677

Table 7: Branch-level Evidence: Housing Returns and Gold Demand

This table reports branch-level evidence using instrumental variable (IV) and difference-in-differences (DiD) designs controlling for city-by-time fixed effects. Panel A presents the IV results. The dependent variable in columns (1) and (2) is *NetBuyValue*, defined as the real net gold purchase value (in constant 2014 RMB, million) at the branch–yearmonth level. Column (1) reports the OLS estimate, column (2) reports the second-stage IV estimate, and column (3) reports the corresponding first-stage regression where the dependent variable is the lagged real housing return. The instrument follows Guren et al. (2023) and is constructed as the interaction between branch-specific housing elasticity—estimated using pre-determined expanding-window regressions—and the contemporaneous systematic housing return. Control variables include branch-level customer demographics (average age and gender composition) and financial characteristics (log assets under management and log wage). Panel B reports branch-level DiD estimates that exploit differential exposure to housing shocks. The dependent variables include *NetBuyValue*, *NetBuy*, and *NetBuyNumber*. *HighExposure* equals one if a branch's *HousingElasticity* prior to 2021 is in the top quartile of the sample distribution and zero otherwise. All specifications include branch fixed effects and city-time fixed effects. The sample consists of 899,518 branch–month observations from June 2017 to June 2025. All continuous variables are winsorized at the top and bottom 2.5%. All variables are defined in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the branch level. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Branch-level IV and OLS results

	(1)	(2)	(3)	(4)	(5)
		IV		OLS	
	HousingRet_l1	*NetBuyValue*	*NetBuy*	*NetBuyValue*	*NetBuy*
Instrument	0.2899***				
	(64.35)				
HousingRet_l1		-0.0280***	-0.0205**	-0.0044**	-0.0072*
		(-3.42)	(-2.30)	(-2.20)	(-1.69)
Age	-0.0013***	0.0024***	0.0031***	0.0024***	0.0031***
	(-3.21)	(9.19)	(13.80)	(2.84)	(3.69)
Male	0.0788***	-0.2794***	-0.3444***	-0.2817***	-0.3458***
	(3.97)	(-27.17)	(-33.21)	(-5.72)	(-6.88)
ln(AUM)	-0.0066***	0.0255***	0.0299***	0.0257***	0.0300***
	(-2.78)	(16.25)	(22.78)	(5.45)	(6.46)
ln(Wage)	-0.0071***	0.0104***	0.0138***	0.0106***	0.0140***
	(-3.66)	(6.83)	(10.21)	(4.08)	(5.06)
F-stat	4140.4				
Branch FE	YES	YES	YES	YES	YES
City-Time FE	YES	YES	YES	YES	YES
R^2	8.05%	0.11%	0.21%	0.11%	0.21%
N	899518	899518	899518	899518	899518

Panel B: Branch-level DiD Results

	(1) *NetBuyValue*	(2) *NetBuy*	(3) *NetBuyNumber*
HighExposure×*Post21*	0.005***	0.007***	0.059**
	(4.10)	(2.85)	(2.42)
Controls	YES	YES	YES
Branch FE	YES	YES	YES
City-Time FE	YES	YES	YES
R^2	0.30%	0.24%	0.43%
N	899518	899518	899518

Table 8: Peer Trading and the Housing Return–Gold Demand Relation

This table examines whether peer trading activity amplifies the effect of housing returns on branch-level gold purchases. The key explanatory variables are lagged peer gold return ($PeerReturn_{t-1}$) and lagged peer net gold purchases ($PeerNetBuy_{t-1}$), as well as their interactions with lagged housing returns. Peer measures are constructed based on trading activity of past investors within the same branch. Specifically, $PeerReturn_{t-1}$ captures the lagged value-weighted average gold return realized by all peer purchases in the branch, and $PeerNetBuy_{t-1}$ captures the lagged net gold purchases of peers in $t-1$. Panel A uses $NetBuyValue$ as the dependent variable. Panel B uses $NetBuyValue_New$ as the dependent variable, defined as the real net gold purchase value attributable to new investors at the branch–yearmonth level. Columns (1) and (3) report baseline specifications, while columns (2) and (4) report IV estimates for the interaction specifications. All specifications include branch-level controls, branch fixed effects, and city-time fixed effects. The sample consists of 899,518 branch–month observations from June 2017 to June 2025. The t-statistics reported in parentheses are based on standard errors clustered at the branch level. All continuous variables are winsorized at top and bottom 2.5%. All variables are defined in Appendix A. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Dependent variable $NetBuyValue$

	(1)	(2)	(3)	(4)
		$NetBuyValue$		
$PeerReturn_{t-1}$	0.007***	0.010***		
	(24.43)	(23.02)		
$PeerNetBuy_{t-1}$			0.091***	0.107***
			(55.41)	(52.77)
$PeerReturn_{t-1} \times HousingRet_{t-1}$		-0.072***		
		(-8.83)		
$PeerNetBuy_{t-1} \times HousingRet_{t-1}$				-0.775***
				(-11.32)
$HousingRet_{t-1}$	-0.004***	-0.029***	-0.001*	-0.022***
	(-5.01)	(-8.10)	(-1.72)	(-6.92)
Controls	YES	YES	YES	YES
Branch FE	YES	YES	YES	YES
City-Time FE	YES	YES	YES	YES
R^2	0.18%	0.23%	0.20%	1.32%
N	899518	899518	899518	899518

Panel B: Dependent variable $NetBuyValue_New$

	(1)	(2)	(3)	(4)
		$NetBuyValue_New$		
$PeerReturn_{t-1}$	0.005***	0.008***		
	(22.52)	(4.48)		
$PeerNetBuy_{t-1}$			0.061***	0.074***
			(50.73)	(48.83)
$PeerReturn_{t-1} \times HousingRet_{t-1}$		-0.060***		
		(-10.96)		
$PeerNetBuy_{t-1} \times HousingRet_{t-1}$				-0.600***
				(-17.74)
$HousingRet_{t-1}$	-0.003***	-0.024***	-0.001	-0.019***
	(-5.11)	(-8.59)	(-1.54)	(-7.71)
Controls	YES	YES	YES	YES
Branch FE	YES	YES	YES	YES
City-Time FE	YES	YES	YES	YES
R^2	0.16%	0.23%	0.18%	1.32%
N	899518	899518	899518	899518

Table 9: Gold Returns and Housing-Induced Bank Demand

This table reports a monthly time-series regression of gold returns on the housing-induced component of bank gold purchases. The dependent variable is the monthly gold return. $\widehat{NetBuy}^{Bank}$ is predicted bank gold demand, in kilograms, using the housing return instrument. Newey–West adjusted t-statistics are reported.

	GoldRet
$\widehat{NetBuy}^{Bank}$	0.024*
	(1.69)
GoldRet_l1	0.264***
	(3.95)
GoldRet_l2	-0.106
	(-1.16)
$\Delta CN10^{Real}$	-0.002
	(-0.33)
Constant	0.013***
	(2.69)
R^2	9.40%
N	126

Table 10: Housing Returns and Gold Demand: Cross-country Evidence

This table reports country-level time-series estimates of the relation between investment gold demand and housing returns for 18 countries and regions. The dependent variable is the IHS-transformed value of bars-and-coins gold demand. The key independent variable, $HousingYoY$, is the lagged year-over-year housing return. Control variables include changes in the 10-year government bond yield and lagged year-over-year stock market returns. Countries are ranked by the t-statistic on $HousingYoY$. β_{House} denotes the coefficient on $HousingYoY$, and t_{House} denotes its Newey-West adjusted t-statistic. The sample period spans 2010Q1-2025Q4.

Region	β_{House}	t_{House}	Adj. R^2
UK	-0.748	-4.013	0.140
Canada	-0.373	-2.877	0.236
Singapore	-0.243	-2.736	0.097
US	-1.206	-2.001	0.059
Hong Kong	-0.031	-0.753	0.025
Mexico	-0.034	-0.432	0.014
South Korea	0.050	0.108	-0.049
Brazil	0.006	0.341	0.006
Malaysia	0.088	0.581	-0.020
Japan	1.340	0.650	0.043
Austria	0.140	0.733	0.176
Indonesia	1.855	1.269	0.078
France	0.295	1.437	0.021
Germany	1.951	1.517	0.208
India	4.313	1.896	0.121
Turkey	0.990	2.504	0.085
Switzerland	4.008	3.261	0.244
Australia	0.551	4.752	0.320

Appendix A. Variable Definitions

A.1. Macro-Level Variable Definitions

Table A1: Macro-Level Variable Definitions

Variable	Definition
InvestVol	Quarterly bars-and-coins gold demand volume (tonnes) at the country–quarter level, from the World Gold Council.
JewVol	Quarterly jewelry gold demand volume (tonnes) at the country–quarter level, from the World Gold Council.
TechVol	Quarterly technology gold demand volume (tonnes) at the country–quarter level, from the World Gold Council.
CentralBankVol	Quarterly central bank gold demand volume (tonnes) at the country–quarter level, from the World Gold Council.
GoldPrice	Quarterly average daily gold price (USD/oz), from Bloomberg, used to construct value measures from demand volumes.
InvestVal	Quarterly bars-and-coins gold demand value (USD, billions), calculated as investment demand volume multiplied by the average quarterly gold price and deflated by the country's consumer price index (CPI). Investment demand volumes are obtained from the World Gold Council, and gold prices are from Bloomberg.
JewVal	Quarterly jewelry gold demand value (USD, billion), computed as *JewVol* times *GoldPrice* and scaled. Demand volumes are from the World Gold Council and gold prices are from Bloomberg.
TechVal	Quarterly technology gold demand value (USD, 10 billion), computed as *TechVol* times *GoldPrice* and scaled. Demand volumes are from the World Gold Council and gold prices are from Bloomberg.
CentralBankVal	Quarterly central bank gold demand value (USD, 10 billion), computed as *CentralBankVol* times *GoldPrice* and scaled. Demand volumes are from the World Gold Council and gold prices are from Bloomberg.
$\Delta Treasury$	Quarter-over-quarter change in the 10-year Government bond yield, from Bloomberg.
MKTYOY	Quarterly year-over-year GDP stock market returns.

Variable	Definition
$HouseYOY$	Year-over-year housing return, computed as the log change in the real house price index: $(HPI_q^{real} - HPI_{q-4}^{real})/HPI_{q-4}^{real}$, where HPI_q^{real} is the quarterly real HPI from FRED.
$Premium_t$	Shanghai–London price premium, defined as the log difference between the London AM gold fixing price (10:30 London time) and the Shanghai PM gold fixing price (15:00 China Standard Time, approximately 07:00 London time) on the same calendar day, measured at the beginning of day t, from Bloomberg.
$Ret_t^{Intraday}$	London intraday return on day t, computed as log(London PM fixing price) minus log(London AM fixing price), from Bloomberg.
Ret_t	London AM-to-AM return over day t, defined as log(London AM fixing price$_{t+1}$) minus log(London AM fixing price$_t$), from Bloomberg.

A.2. City-Level Variables

Table A2: City-Level Variable Definitions

Variable	Definition
$NetBuyValue$ (in million)	Real net gold purchase value at the city–year-month level. It is defined as total gold purchase value minus total gold sale value aggregated across all investors within a city in a given month. The variable is deflated to constant 2014 RMB using the CPI and expressed in million RMB.
$NetBuy$ (in kg)	Net gold purchase quantity at the city–year-month level. It is calculated as total kilograms of gold bought minus kilograms sold across all investors within the city during the month.
$\#Trader$	Total number of gold traders at the city–year-month level. It equals the sum of investors who buy gold and investors who sell gold during the month.
$AvgDeal$ (in kg)	Average gold transaction size at the city–year-month level. It is computed as the average quantity of gold traded per transaction during the month, measured in kilograms.

Variable	Definition
$AvgDealValue$ (in thousand)	Average transaction value at the city–year-month level. It is calculated as the average monetary value per gold transaction during the month and is expressed in thousand RMB.
$HousingRet$	Real year-over-year housing price return at the city–year-month level. It is constructed as the nominal housing price return provided by the bank minus the contemporaneous year-over-year CPI inflation rate.
$HousingRet_l1$	One-month lag of city-level real year-over-year housing price return.
$HousingRet_IV$	Instrument for city-level real housing return constructed as the product of the estimated city housing elasticity and the contemporaneous systematic housing return.
$HousingElasticity$	Housing return elasticity at the city–year-month level. For each city c and month t, we construct an expanding-window sample using observations from January 2015 through $t-1$. We estimate a time-series regression of real city-level housing returns on the systematic housing return and a constant. The regression requires at least 12 monthly observations. The estimated coefficient on the systematic housing return is defined as the city housing elasticity.
$GDPGrowth$	Year-over-year GDP growth rate at the city–year-month level. It is measured as the annual percentage change in gross domestic product of the city.
$Attention$	Gold-related search attention at the city–year-month level. Attention is measured as the raw monthly search volume for gold-related keywords from Baidu Index.
$DeltaLogAtt$	Year-over-year change in log gold-related search attention.
$\Delta Treasury$	Change in Treasury yields over the corresponding month.
$GoldRetYoY$	Year-over-year gold return.
$DemandPBOC$	Monthly gold demand by the People's Bank of China.
$StockMktRet_l1$	One-month lag of stock market return.
GPR_l1	One-month lag of the geopolitical risk index, from Caldara and Iacoviello (2022).

A.3. Branch-Level Variables

Table A3: Branch-Level Variable Definitions

Variable	Definition
$NetBuyValue$ (in million)	Real net gold purchase value at the branch–year-month level. It is defined as total gold purchase value minus total gold sale value aggregated across all investors within a branch in a given month. The variable is deflated to constant 2014 RMB using the CPI and expressed in million RMB.
$NetBuyValueNew$ (in million)	Real net gold purchase value attributable to new gold investors at the branch–year-month level. New investors are those who initiate gold investment in the given month. It is defined as their total gold purchases minus total gold sales and is deflated to constant 2014 RMB using the CPI.
$NetBuy$ (in kg)	Net gold purchase quantity at the branch–year-month level. It is calculated as total kilograms of gold bought minus kilograms sold across all investors within the branch during the month.
$NetBuyNew$ (in kg)	Net gold purchase quantity attributable to new gold investors at the branch–year-month level. It is defined as kilograms bought minus kilograms sold among investors who initiate gold investment in that month.
$NetBuyNumber$	Net number of gold investors at the branch–year-month level. It equals the number of investors with positive net gold purchases minus the number of investors with net gold sales during the month.
$NetBuyNumber_New$	Net number of new gold investors at the branch–year-month level. It equals the number of newly participating investors with positive net purchases minus newly participating investors with net sales during the month.
$PeerReturn$	Value-weighted cumulative return on gold holdings at the branch–year-month level. The measure aggregates investors' historical gold purchases within the branch and computes the mark-to-market return up to the current month using prevailing gold prices.
$HousingRet$	Real year-over-year housing price return in the geographic area corresponding to the branch. It is constructed as the nominal housing price return provided by the bank minus the contemporaneous year-over-year CPI inflation rate.

Variable	Definition
$HouingElasticity$	Housing return elasticity at the branch–year-month level. For each branch b and month t, we construct an expanding-window sample using observations from January 2015 through $t-1$ for that branch. We estimate a time-series regression of real branch-level housing returns on the systematic housing return and a constant. The regression requires at least 12 monthly observations. The estimated coefficient on HousingRetSystem is defined as the branch housing elasticity.
$HousingRet_IV$	Instrument for branch-level real housing return constructed as the product of the estimated branch housing elasticity and the contemporaneous systematic housing return.
$AvgAUM$	Average assets under management per customer at the branch–year-month level. It is computed as the mean total financial assets held by customers in the bank in a given month for a given branch.
$AvgLiq$	Average liquid assets per customer at the branch–year-month level. It is measured as the mean balance of demand deposits held by customers in the bank during the month.
$AvgAge$	Average customer age at the branch–year-month level.
$Male$	Fraction of male customers at the branch–year-month level.
$Wage$	Average monthly wage income per customer at the branch–year-month level.

Appendix B. Additional Tables

Table B1: Branch-level summary statistics

This appendix table presents summary statistics of the main branch-level variables. Panel A reports branch–year-month level variables constructed by aggregating internal administrative gold trading records to the branch level. Panel B compares the average values of selected variables before and after 2021. Panel C presents within city–time comparisons between treatment branches and control branches. Gold trading and housing variables are defined in Appendix A.

Panel A: Branch-level variables

	N	Mean	STD	P25	P50	P75
NetBuy (in kg)	899518	0.105	0.279	0.000	0.000	0.050
NetBuyNew (in kg)	899518	0.086	0.217	0.000	0.000	0.050
NetBuyValue (in million)	899518	0.050	0.135	0.000	0.000	0.021
NetBuyValueNew (in million)	899518	0.041	0.103	0.000	0.000	0.023
NetBuyNumber	899518	1.005	2.044	0.000	0.000	1.000
NetBuyNumber_New	899518	0.815	1.560	0.000	0.000	1.000
PeerReturn	899518	0.227	0.557	0.000	0.000	0.168
HousingRet	899518	0.031	0.138	-0.063	0.011	0.102
HouingElasticity	899518	1.297	1.600	0.354	1.122	2.015
HousingRet_IV	899518	0.035	0.134	-0.041	0.002	0.082
AvgAUM	899518	102623.626	152928.964	69133.413	90334.479	119462.978
AvgAge	899518	45.992	3.961	43.377	45.922	48.521
Male	899518	0.501	0.058	0.463	0.497	0.536
Wage	899518	6602.996	3628.179	5106.696	6068.715	7301.580
AvgMortgageBalance	899518	476040.000	244699.000	312889.000	412021.000	567116.000
IfHousing	899518	0.098	0.060	0.061	0.086	0.118
SecondHouse/AllHouse	899518	0.209	0.110	0.125	0.201	0.277
HousingOccupation	899518	0.101	0.049	0.070	0.094	0.122

Panel B: Pre 2021 vs. Post 2021

	Pre2021	Post2021	Diff	T
HousingRet	0.087	-0.034	0.121	391.820
HousingRet_IV	0.097	-0.038	0.135	445.326
PeerReturn	0.211	0.247	-0.036	-55.625
NetBuy	0.054	0.164	-0.110	-229.300
NetBuyNew	0.047	0.131	-0.084	-219.757
NetBuyValue	0.020	0.085	-0.065	-264.376
NetBuyValue_New	0.018	0.067	-0.050	-261.237
NetBuyNumber	0.647	1.420	-0.773	-185.924
NetBuyNumber_New	0.508	1.723	-1.215	-201.567

Panel C: Within City–Time Comparisons of Treat Branches and Control Branches

	Control	Treat	Diff	T-Value
HousingRet	-0.001	0.003	-0.004	-19.800
HousingElasticity	-0.192	0.592	-0.783	-259.791
HousingRet_IV	-0.008	0.023	-0.031	-149.163
AvgAUM	221.080	-683.664	904.744	2.130
AvgLiq	29.053	-89.841	118.893	2.434
AvgAge	0.061	-0.188	0.249	31.206
Male	0.000	0.001	-0.002	-12.584
Wage	8.886	-27.469	36.354	3.850

Table B2: Country-level summary statistics

This appendix table reports country–quarter summary statistics for the macro-level variables used in the cross-country analyses. The sample consists of 19 countries from 2010Q1 to 2025Q4. Gold demand series are from the World Gold Council and gold prices used to construct value measures are from Bloomberg. $\Delta Treasury$ is the quarter-to-quarter change in the 10-year U.S. Treasury yield (decimal) from Bloomberg. $MKTYOY$ is the quarterly year-over-year stock market return. $HouseYOY$ is the year-on-year log change in the real HPI from FRED. All variables are defined in Appendix Table A1.

	N	Mean	SD	p25	p50	p75
InvestValue	1118	0.655	1.343	0.042	0.170	0.649
JewValue	1118	1.104	2.479	0.127	0.208	0.473
CentralBankValue	1118	0.116	0.881	-0.000	0.000	0.000
InvestVol	1118	11.842	20.825	0.833	3.168	12.310
JewVol	1118	21.206	46.586	2.569	4.103	9.552
CentralBankVol	1118	2.223	20.256	-0.000	0.000	0.000
$\Delta Treasury$	1118	-0.000	0.009	-0.004	-0.000	0.004
MKTYOY	1118	0.101	0.182	-0.017	0.088	0.196
HouseYOY	1118	-0.013	0.069	-0.043	-0.009	0.024

Table B3: Horse Race Robustness

This appendix table reports robustness tests for the horse-race regressions in Table 4. Panel A uses *NetBuy* (measured in kilograms) as the dependent variable. Panel B uses *IHS(NetBuyValue)* as the dependent variable. All specifications include city fixed effects and time fixed effects. The sample period is from January 2015 to June 2025. All continuous variables are winsorized at the top and bottom 2.5%. All variables are defined in Appendix A.

Panel A: Robustness: Use *NetBuy* (in kg)

	(1)	(2)	(3)	(4)
		NetBuy		
HousingRet_l1	-5.422***			-5.246***
	(-5.43)			(-5.23)
GDPGrowth		-10.452		-8.123
		(-1.35)		(-1.07)
DeltaLogAtt			0.646***	0.574**
			(2.82)	(2.53)
City FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
R^2	0.43%	0.05%	0.04%	0.48%
N	28025	28025	28025	28025

Panel B: Robustness: Use *IHS(NetBuyValue)*

	(1)	(2)	(3)	(4)
		IHS(NetBuyValue)		
HousingRet_l1	-0.030***			-0.030***
	-2.92			-2.82
GDPGrowth		-0.013		-0.007
		-0.69		-0.49
DeltaLogAtt			0.009	0.007
			1.08	0.94
City FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
R^2	0.12%	0.01%	0.01%	0.13%
N	28025	28025	28025	28025