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 housing-market-driven demand from Chinese households contributed $132 to $488 per ounce to the global price rally. The negative relationship between housing prices and gold demand also extends to other major economies.

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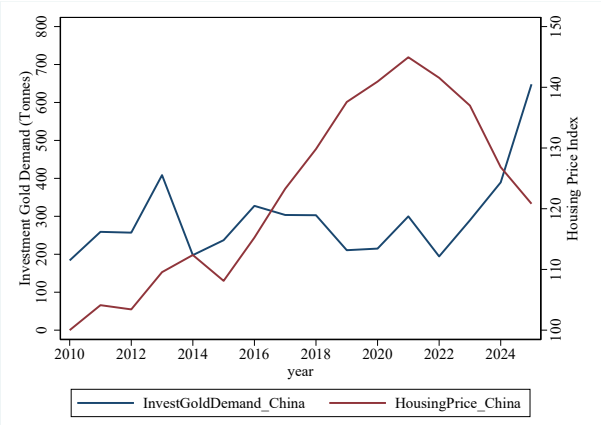
1. Introduction

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, tonnes) 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, tonnes) 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 tonnes per year before 2022 to over 600 tonnes 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 210.8 additional tonnes of gold investment demand nationwide over 2021–2025. Combined with the gold price-to-investment-demand elasticity estimated in the literature, which ranges from -0.3 to -1.1 (Immanuvel and Lazar, 2021), this implies that the housing-induced flight to gold contributed approximately \$74–\$270 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 18.7%, the estimated social amplification implies that peer effects multiply the baseline response by a factor of 1.79. Accounting for this social amplification, the total contribution of the Chinese housing channel to the global gold rally reaches approximately \$132–\$488 per ounce, or 5.5% to 20.2% of the total price increase.

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, Brazil, Singapore, South Korea, 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. 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

[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).

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 tonnes, whereas central bank purchases total only 363 tonnes 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 271.95 tonnes during 2016–2020 to 347.62 tonnes during 2021–2025, implying an increase of approximately 75.67 tonnes per year. In comparison, the PBC's annual gold purchases increase by 35.43 tonnes, from 37.20 tonnes to 72.63 tonnes over the same periods. Even allowing for the possibility that the PBC 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.

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 11.53% of China's total investment demand. This

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

volume is also comparable to the entire ETF channel: cumulative increases in China's gold ETF holdings amount to 186.95 tons, while cumulative net physical gold purchases through our bank total 200.32 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 con-

structed 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 2021. Housing returns decline sharply after 2021: the mean housing return changes from 0.069 pre-2021 to -0.007 post-2021, and the instrumented mean changes from 0.066 to -0.020. 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:

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

where $InvestVal_{n,t}$ is the dollar value of gold investment demand in country n in quarter t. The sample includes 21 countries between 2010Q1 and 2025Q3, the period for which the gold demand data are available. The coefficient on the interaction term is 3.082 (t-value = 25.17), indicating that China's quarterly gold demand increased by approximately $3.1 billion more than that of other countries after 2021. This magnitude is economically large: it is roughly 4.7 times the sample mean quarterly gold demand and about 1.7 standard deviations of the cross-country distribution. This finding is consistent with the shift in China's gold demand shown in Panel A of Figure 1, as well as the timing of the housing downturn highlighted in Panel B of Figure 1.

As a benchmark exercise, we also extend the main result of Jermann (2025) to this international setting. Jermann (2025) shows that the negative relationship between gold returns and changes in Treasury yields is concentrated in low-yield periods, when investors are more likely to enter the gold market. We examine the relationship between gold demand

and changes in Treasury yields using our country–quarter panel. As reported in Panel B of Table 2, changes in long-term interest rates are, on average, negatively correlated with gold demand, and this relationship is indeed stronger during low-yield periods. These findings suggest that the mechanism proposed by Jermann (2025) also applies in an international context.

[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 computed as the log change in the house price index. $LowHousing$ is a dummy variable equal to one if the lagged year-over-year housing return in quarter t falls within the bottom 30% of the sample distribution. The results are reported in Panel C of Table 2. Lagged housing returns are negatively related to gold investment demand. In column (1), the coefficient on the lagged housing return is negative and statistically significant (31.938, t = 2.11). Column (2) further shows that this relationship becomes stronger when housing returns are low: the coefficient on the interaction term $LowHousing \times HouseYOY$ is negative and significant (97.859, t = 2.48). This pattern resembles the relationship between Treasury yields and gold returns documented for the U.S. market. Interestingly, the coefficients on changes in Treasury yields are statistically insignificant. One interpretation is that housing-market performance may serve as a salient benchmark for Chinese households, potentially more so than government bond yields. This interpretation is consistent with evidence that housing wealth constitutes a major component of Chinese household portfolios and that shocks to housing prices have meaningful effects on household behavior (e.g., Painter et al. (2022); Fang et al. (2022)). We view this housing-benchmark hypothesis as complementary to the interest-rate channel proposed by Jermann (2025).

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. 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 on day $t+1$ (Ret_{t+1}), 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+1}—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 (column (1)) and next-day AM-to-AM returns (column (3)). Moreover, the predictive relationship becomes stronger after 2021: the interaction term $Premium \times Post21$ is positive and statistically significant for both intraday and AM-to-AM returns (0.063 with $t = 2.69$; 0.093 with $t = 2.12$). In terms of economic magnitude, after 2021 a 1 percentage point increase in the premium predicts a 0.12 percentage point increase in next-day AM-to-AM London gold returns ($0.12\% = 1\% \times (0.024 + 0.093)$). Overall, these results suggest that demand spillovers from China to global gold prices.[4]

[Insert Table 3 Around Here]

[4]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.

4.2. City-Level Evidence: Baseline

We use the city-level gold transaction data to further examine the relationship between housing returns and gold investment demand in China. Specifically, we estimate a city–month panel regression of net gold purchases on lagged housing returns at the city level. The specification includes both city fixed effects and time fixed effects, which absorb common macroeconomic factors such as interest rates and inflation.[5] We additionally control for GDP growth and for changes in households' attention to gold, measured using the internet search volume of gold-related terms in each city-month. The results are reported in Table 4.

[Insert Table 4 Around Here]

Consistent with the aggregate-level analysis, the coefficient on lagged housing returns is negative and highly statistically significant across all specifications. In the baseline specification, the coefficient is -2.558 ($t = -6.03$), and it remains quantitatively similar at -2.468 ($t = -5.81$) after controlling for GDP growth and attention measures. In contrast, GDP growth is statistically insignificant in all specifications, while attention measures, although occasionally significant, do not display the same level of robustness.

Moreover, housing returns exhibit greater explanatory power than the other variables in explaining gold demand. Housing returns alone generate a within–fixed-effects R^2 of 0.63%, compared with 0.05% for GDP growth and 0.13% for attention. When all variables are included simultaneously, the R^2 increases to 0.77%, with most of the explanatory power attributable to housing returns. In unreported regressions without time fixed effects, we also find lagged housing returns has the highest R^2, compared to other well-documented determinants of gold demand such as changes in treasury yields and inflation. Overall, these results indicate that lagged housing returns have a robust and economically meaningful negative association with gold demand in China.

[5] In unreported regressions without time fixed effects, we also find that lagged housing returns exhibit the highest R^2 compared with other well-documented determinants of gold demand, such as changes in Treasury yields and inflation.

4.3. City-Level Evidence: IV Analysis

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 9 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. The interaction term is negative and highly significant ($\beta = -0.017$, $t = -8.54$), 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 baseline housing effect is:

$$\text{Multiplier} = 1 + \frac{0.017}{0.004} \times PeerReturn. \tag{8}$$

In the pre-2021 period, the mean value of $PeerReturn$ is 0.187. Substituting this value implies a multiplier of approximately 1.79, meaning that peer investment performance increases the magnitude of the housing-driven gold demand response by roughly 80 percent relative to the baseline 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 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 9 Around Here]

5. Aggregate Implications and Beyond China

5.1. Back-of-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.

Aggregate Demand Let $\Delta H = \overline{HousingRet}^{post} - \overline{HousingRet}^{pre}$ denote the change in average housing returns before and after 2021, and let β^{IV} denote the IV coefficient on *NetBuy* (in kilograms). The implied change in aggregate gold purchases within our bank during 2021–2025 is

$$\Delta Gold^{Bank} = \beta^{IV} \times \Delta H \times N_{city} \times N_{month}. \tag{9}$$

Using estimates in Table 1 Panel B, housing returns declined from 6.9% to −0.7%, implying $\Delta H = -0.076$. With $\beta^{IV} = -17.992$, $N_{city} = 296$, and $N_{month} = 60$, the implied increase in gold purchases within our bank equals 24.3 tons. Scaling to the national level using the bank's market share in gold investment demand during this period ($s = 11.53\%$) yields a national demand increase of $24.3/0.1153 = 210.8$ tons.

Public data indicate that China's annual average gold investment demand increased from 266.14 tons in 2015–2020 to 347.63 tons in 2021–2025, implying a cumulative increase of $(347.63-266.14)\times 5 = 407.45$ tons. The baseline estimate therefore suggests that the housing

downturn accounts for approximately $210.8/407.45 = 51.7\%$ of the post-2021 increase in China's gold investment demand.

Considering Social Amplifier 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 1.79. Applying this multiplier to the baseline estimate implies an amplified housing-driven demand increase of $210.8 \times 1.79 = 377.3$ tons, corresponding to approximately $377.3/407.45 = 92.6\%$ of the post-2021 increase in China's gold investment demand.

Price Impact Gold supply is widely regarded as highly inelastic in the short run. Global gold production increased by only about 5 percent between 2020 and 2025, reflecting the slow adjustment of mining capacity. Over the same period, however, the London gold price rose from 1,891 USD per ounce at the end of 2020 to approximately 4,307 USD, corresponding to an increase of about 128 percent. This large divergence between relatively stable supply and sharply rising prices suggests that changes in investment demand can have substantial effects on equilibrium prices.

Motivated by this observation, we assess the potential price implications of the housing-driven demand shock documented in this paper. Our baseline estimate implies that the housing downturn increased China's gold investment demand by 210.8 tons, while incorporating the social amplification mechanism discussed in Section 5.7 raises the estimate to 377.3 tons. Relative to annual global gold production of 4,878.58 tons, these magnitudes correspond to demand shocks of roughly 4.3 percent and 7.7 percent, respectively.

Following the literature, let

$$\epsilon = \frac{\partial \ln P}{\partial \ln Q} \tag{10}$$

denote the gold price–to–investment-demand elasticity. Under a constant-elasticity approximation, the implied price response satisfies

$$\frac{\Delta P}{P} \approx \frac{\Delta Q/Q}{|\epsilon|}. \tag{11}$$

Existing estimates place this elasticity between −0.3 and −1.1 (Immanuvel and Lazar, 2021). Applying these values implies price increases of 3.9% to 14.3% in the baseline case and 7.0% to 25.8% when social amplification is incorporated. Using the London AM gold price at the end of 2020 (1,891 USD per ounce), these magnitudes correspond to price increases of approximately 74–270 USD/oz in the baseline scenario and 132.4–488 USD/oz after accounting for social amplification.

These calculations are only illustrative. Nevertheless, they suggest that the post-2021 housing downturn in China may have been large enough not only to shift household portfolios toward gold, but also to exert economically meaningful upward pressure on global gold prices.

5.2. Generalization Beyond China: Cross-Country Patterns

To benchmark external validity, we next summarize how the housing–gold relation varies across countries. Table 10 reports country-by-country correlations between quarterly investment gold demand ($InvestVal$) and year-on-year housing returns ($HouseYOY$) over 2010Q1–2025Q3.

[Please Insert Table 10 Around Here]

Consistent with the housing-benchmark interpretation, the correlation is negative not only for China (−0.547) but also for the United States (−0.218). Several other large economies in our sample display negative correlations as well, including Brazil (−0.173), Singapore (−0.136), South Korea (−0.052), Canada (−0.043), and the United Kingdom (−0.026).

In contrast, India, a major gold-demand country, exhibits a positive correlation (0.373). This cross-country heterogeneity cautions against a one-size-fits-all interpretation: the mapping from housing-market conditions to gold demand likely depends on country-specific institutions and the composition of gold demand (e.g., investment versus consumption motives). We view these patterns as descriptive evidence that complements the more formal within-country designs in earlier subsections.

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, Brazil, Singapore, South Korea, 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.

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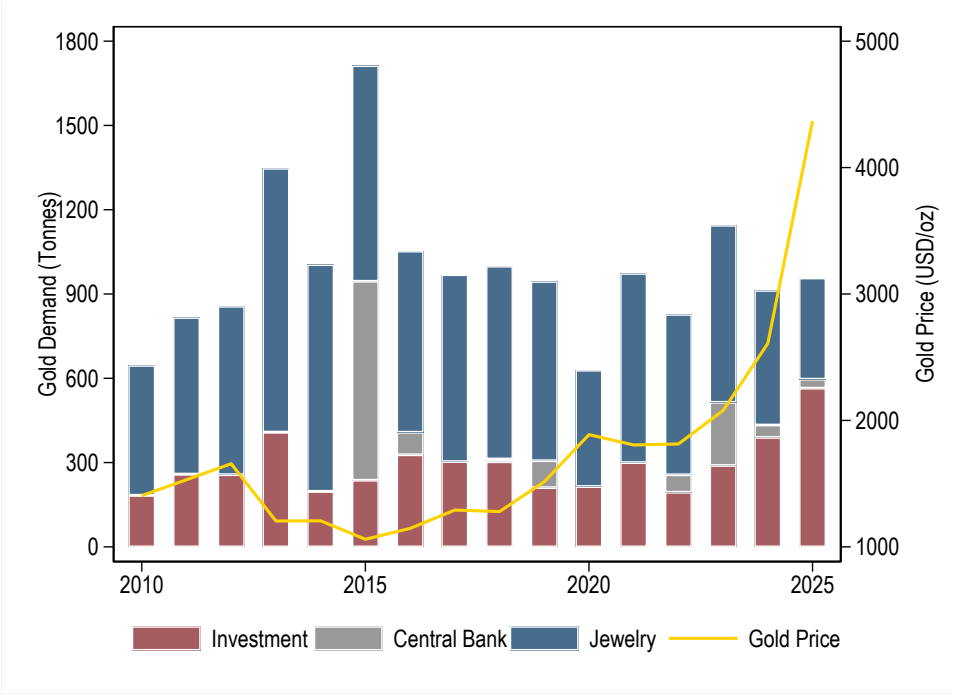
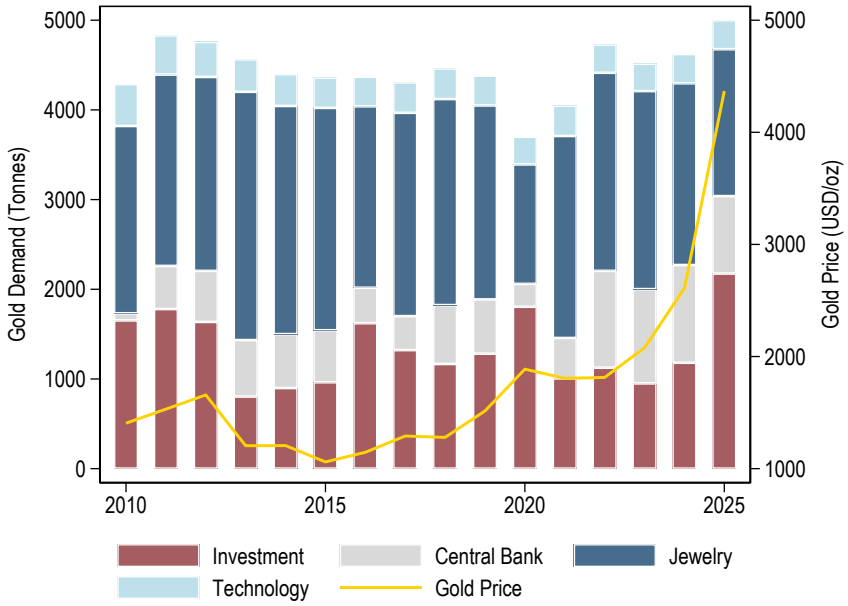
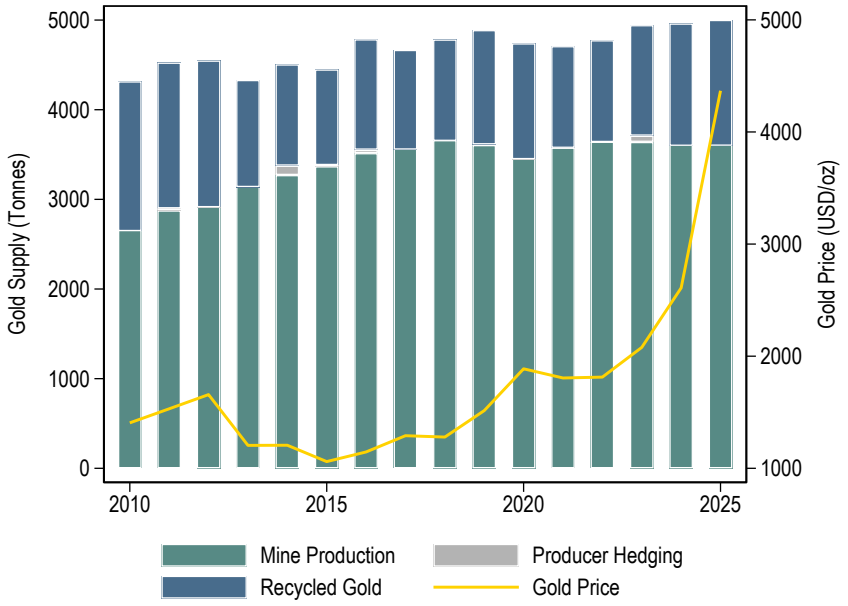


Fig. 2. China Gold Demand by Type

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.



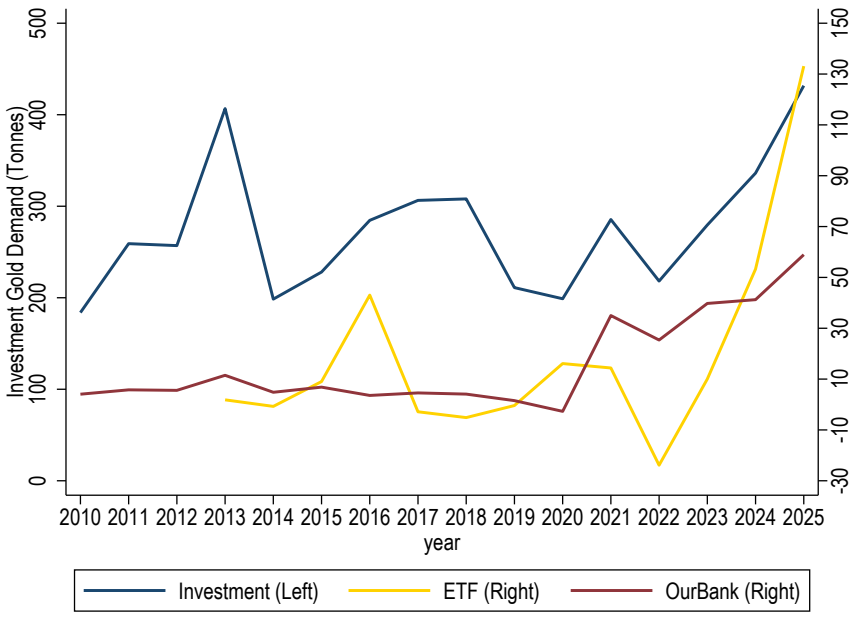
Panel A. Gold Demand By Type



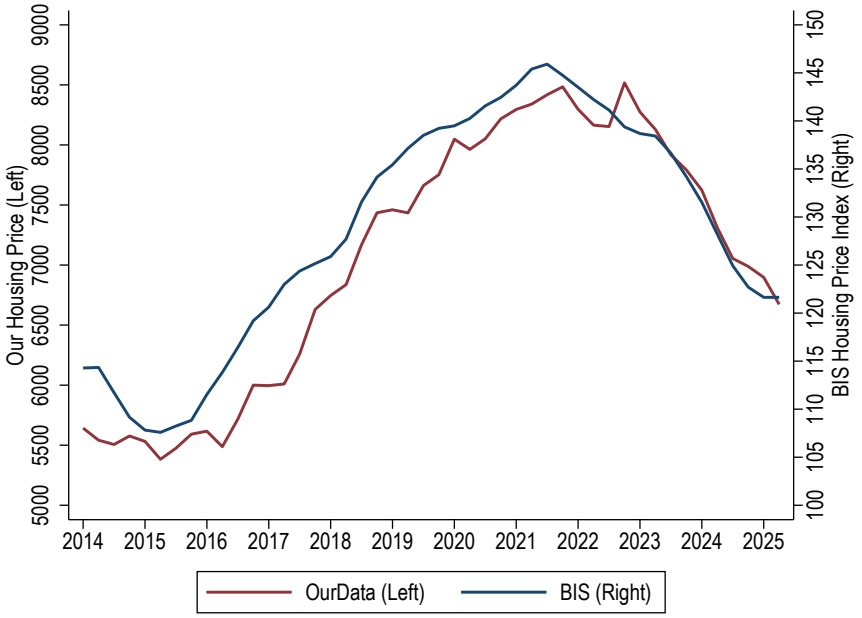
Panel B. Gold Supply By Type

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.



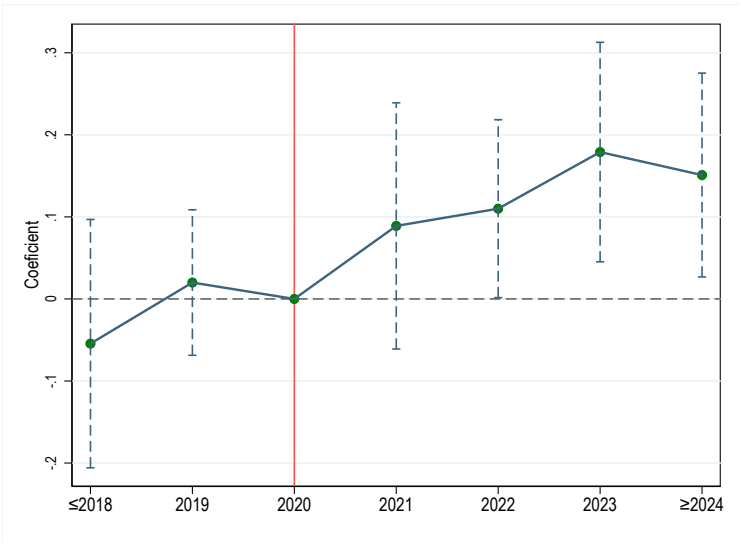
Panel A. Gold Data Comparison



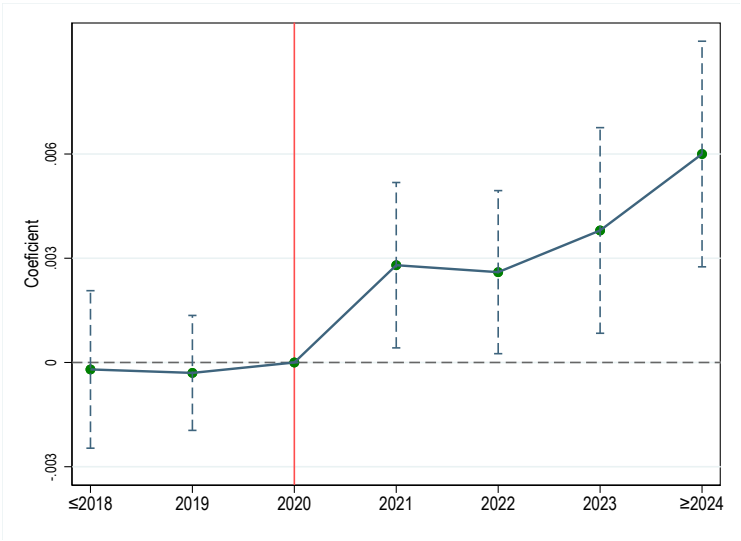
Panel B. Housing Prices Data Comparison

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

Table 1 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 2021. 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 2021 vs. Post 2021

	Pre2021	Post2021	Diff	T-Stat
HousingRet_l1	0.069	-0.007	0.076	62.562
HousingRet_iv_l1	0.066	-0.020	0.086	100.208
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: The impact of housing returns on gold demand

Table 2 studies the relationship between housing market conditions and gold investment demand using a country–quarter panel of 21 countries from 2010Q1 to 2025Q3. Variable definitions are provided in Appendix Table A1. Panels A–B report international evidence using country and year-quarter fixed effects; reported t-statistics are based on standard errors clustered at the country level. Panel C focuses on China and reports Newey–West adjusted t-statistics. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: International Evidence: Housing Bust in China and Gold Demand

	(1)	(2)
	InvestVal	
$China \times Post21$	2.938***	3.082***
	(24.44)	(25.17)
$\Delta Treasury$		-0.054***
		(-4.29)
$GDPYOY$		4.752**
		(2.19)
Country FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	1,201	1,201
Adj. R^2	0.356	0.359

Panel B: Treasury has stronger negative impacts on gold demand when interest rate is low

	(1)	(2)
	InvestVal	
$\Delta Treasury_q$	-0.056***	0.042***
	(-4.62)	(3.55)
$LowTreasury \times \Delta Treasury_q$		-0.172***
		(-4.75)
$LowTreasury$		0.035
		(0.30)
Country FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	1,220	1,220
R^2	0.376	0.377
Adj. R^2	0.330	0.330

Panel C: Housing Returns and Gold Demand in China

	(1)	(2)
	InvestVal	
$HouseYOY$	-31.938**	-15.884*
	(-2.11)	(-1.74)
$LowHousing$		-3.300**
		(-2.44)
$LowHousing \times HouseYOY$		-97.859**
		(-2.48)
$\Delta Treasury_q$	-0.687	23.087
	(-0.03)	(0.96)
$GDPYOY$	6.866	5.668
	(0.98)	(0.86)
Observations	62	62
Adj. R^2	0.269	0.416

Table 3: 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. $Ret_t^{Intraday}$ 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+1} is the AM-to-AM return, defined as the log difference between the London AM fixing price on day $t+1$ and the London AM fixing price on day t. $Post21$ equals one for observations from 2021 onward and zero otherwise. All specifications include lagged return controls Ret_t, Ret_{t-1}, and Ret_{t-2}. 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+1}	(4) Ret_{t+1}
$Premium_t$	0.030***	0.013	0.048**	0.024
	(2.75)	(1.04)	(2.42)	(0.99)
$Premium_t \times Post21_t$		0.063***		0.093**
		(2.69)		(2.12)
$Post21_t$		-0.000**		-0.001*
		(-2.03)		(-1.70)
Ret_t	0.020**	0.018*	0.007	0.004
	(2.08)	(1.88)	(0.45)	(0.26)
Ret_{t-1}	0.022***	0.021***	-0.013	-0.015
	(2.74)	(2.61)	(-0.85)	(-0.96)
Ret_{t-2}	0.010	0.009	0.013	0.012
	(1.03)	(0.92)	(0.81)	(0.73)
Observations	5,563	5,563	5,607	5,607

Table 4: Horse Race

Table 4 presents horse-race regressions examining the relative explanatory power of housing market conditions and alternative city-level fundamentals for gold net purchases. In Panel A, the dependent variable is *NetBuyValue*, defined as the real net gold purchase value (in constant 2014 RMB, million) at the city–yearmonth level. The main explanatory variables include lagged real housing returns, GDP growth, and gold-related search attention scaled by population. The specifications progressively include these variables to assess their relative importance in explaining variation in city-level gold demand. Panel B reports robustness tests using *NetBuy* (measured in kilograms) as the dependent variable. Panel C further reports robustness tests using the inverse hyperbolic sine transformation of net purchases, *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. The reported t-statistics (without parentheses in the table) 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)	(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

Panel B: 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 C: 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

Table 5: Instrumental Variable Estimates

Table 5 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: Difference-in-differences: Housing Exposure and City-level Gold Purchases

Table 6 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: IV and DiD

Table 7 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: DiD

	(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 9: Peer Trading and the Effect of Housing Returns

Table 8 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 peers 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. 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***	0.008***		
	(24.43)	(25.16)		
$PeerNetBuy_{t-1}$			0.091***	0.089***
			(55.41)	(54.77)
$PeerReturn_{t-1} \times HousingRet_{t-1}$		-0.017***		
		(-8.54)		
$PeerNetBuy_{t-1} \times HousingRet_{t-1}$				-0.122***
				(-11.14)
$HousingRet_{t-1}$	-0.004***	-0.004***	-0.001*	-0.000
	(-5.01)	(-5.03)	(-1.72)	(-0.47)
Controls	YES	YES	YES	YES
Branch FE	YES	YES	YES	YES
City-Time FE	YES	YES	YES	YES
R^2	0.18%	1.22%	0.20%	1.26%
N	899518	899518	899518	899518

Panel B: Dependent variable $NetBuyValue_New$

	(1)	(2)	(3)	(4)
		$NetBuyValue_New$		
$PeerReturn_{t-1}$	0.005***	0.006***		
	(22.52)	(23.37)		
$PeerNetBuy_{t-1}$			0.061***	0.060***
			(50.73)	(50.03)
$PeerReturn_{t-1} \times HousingRet_{t-1}$		-0.014***		
		(-9.73)		
$PeerNetBuy_{t-1} \times HousingRet_{t-1}$				-0.091***
				(-11.32)
$HousingRet_{t-1}$	-0.003***	-0.003***	-0.001	-0.000
	(-5.11)	(-5.10)	(-1.54)	(-0.72)
Controls	YES	YES	YES	YES
Branch FE	YES	YES	YES	YES
City-Time FE	YES	YES	YES	YES
R^2	0.16%	0.96%	0.18%	1.26%
N	899518	899518	899518	899518

Table 10: Cross-country analysis

This table reports country-by-country correlations between quarterly investment gold demand (*InvestVal*) and year-on-year housing returns (*HouseYOY*) using country–quarter data from 2010Q1 to 2025Q3.

Region	Corr(*InvestVal*, *HouseYOY*)
China	-0.547
US	-0.218
Brazil	-0.173
Singapore	-0.136
South Korea	-0.052
Canada	-0.043
UK	-0.026
Hong Kong, China	0.053
Malaysia	0.128
Italy	0.138
Indonesia	0.139
Switzerland	0.179
Japan	0.195
France	0.236
India	0.373
Russia	0.456
Austria	0.461
Australia	0.549
Turkey	0.616
Germany	0.731

Appendix A. Variable Definitions

A.1. Macro-Level Variable Definitions

Table A1: Macro-Level Variable Definitions

Variable	Definition
InvestVol	Quarterly investment 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 investment gold demand value (USD, 10 billion), computed as *InvestVol* times *GoldPrice* and scaled. Demand volumes are from the World Gold Council and gold prices are from Bloomberg.
JewVal	Quarterly jewelry gold demand value (USD, 10 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.
$\Delta Treasury_q$	Quarter-to-quarter change in the 10-year U.S. Treasury yield (decimal), from Bloomberg.
GDPYOY	Quarterly year-on-year GDP growth, $(GDP_q - GDP_{q-4})/GDP_{q-4}$ (decimal).
HouseYOY	Year-on-year housing return computed as the log change in the real house price index: $\log(HPI_q^{real}) - \log(HPI_{q-4}^{real})$, where HPI_q^{real} is the quarterly real HPI from FRED.

Variable	Definition
$Premium_t$	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, from Bloomberg.
$Ret_{t+1}^{Intraday}$	London intraday return on day $t+1$, computed as log(London PM fixing price) minus log(London AM fixing price), from Bloomberg.
Ret_{t+1}	London AM-to-AM return from day t to $t+1$, 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.
$AvgDealValue$ (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.

Variable	Definition
$HousingRet_IV$	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.
$GDPYoY$	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.
$\Delta LogAtt$	Year-over-year Change in log Gold-related search attention.

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.

Variable	Definition
$NetBuy$ (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.
$HouingElasticity$	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.

Variable	Definition
$AvgLiq$	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 21 countries from 2010Q1 to 2025Q3. Gold demand series are from the World Gold Council and gold prices used to construct value measures are from Bloomberg. $\Delta Treasury_q$ is the quarter-to-quarter change in the 10-year U.S. Treasury yield (decimal) from Bloomberg. $GDPYOY$ is quarterly year-on-year GDP growth (decimal). $HouseYOY$ 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	1131	0.661	1.831	0.012	0.106	0.689
JewValue	1131	1.029	2.329	0.115	0.203	0.468
CentralBankValue	1131	0.109	0.866	0.000	0.000	0.000
InvestVol	1131	12.556	32.974	0.298	2.103	14.289
JewVol	1131	20.610	45.975	2.413	4.020	9.663
CentralBankVol	1131	2.156	20.111	0.000	0.000	0.000
$\Delta Treasury_q$	1131	-0.002	0.759	-0.005	0.000	0.004
GDPYOY	1131	0.027	0.041	0.011	0.026	0.047
HouseYOY	1131	0.047	0.091	0.012	0.036	0.068