Housing Cycles and Exchange Rates

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Exchange rates are stubbornly disconnected from macroeconomic fundamentals. This paper documents that the ratio of residential-to-nonresidential investment is a strong in-sample and out-of-sample for the dollar up to twelve quarters. The measure captures investment in the nontradable relative to tradable sector and drives dollar variations through relative price adjustments. The required dollar premium further varies as the expected fraction of nontradable output fluctuates, suggesting limited international risk sharing. Alternative explanations, including aggregate risk, capital flows, and time-varying market segmentation, find less empirical support. The predictability is robust to a host of additional checks and holds for other G10 currencies.

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The disconnect between macroeconomic fundamentals and exchange rates is the most stubborn puzzle in international finance (Meese and Rogoff, 1983). In particular, the predictability of exchange rates has been largely controversial for a few reasons. First, due to unstable in-sample results, weak out-of-sample performance, and limited international evidence, whether the predictability exists is debatable. Second, the literature disagrees on whether the predictability arises from risks or limits to arbitrage because existing predictors are mostly price or flow based. Third, many existing predictors are specific to currencies and do not provide a joint framework for understanding asset prices. This paper documents that a production-based measure, the ratio between residential and nonresidential investment (hereafter residential investment share) is a strong predictor of the dollar and its excess returns both in sample and out of sample. The predictive power is economically large and persistent.

The residential investment share measures "excess" investment in the nontradable relative to tradable sector.[1] While prices of tradables are determined globally, domestic prices of nontradables are only determined by domestic supply and demand. Therefore, output fluctuations in domestic nontradable sectors can generate stronger adjustments in the price of nontradables relative to tradables than tradable output fluctuations and further stronger adjustments in exchange rates. This is known as the relative price adjustment channel. Because higher residential investment share is associated with higher expected relative nontradable supply, we hypothesize that the share predicts dollar depreciation.

Empirically, the residential investment share strongly predicts the broad dollar index over the next quarter with R^2 of 6% from 1971:Q1 to 2016:Q4, implying a correlation of -0.24 between the share and future dollar variations. Over a two-year horizon, the residential investment share explains as high as 18% of dollar variations, implying a correlation of -0.4. In terms of magnitudes, one standard deviation increase in the share predicts 3.6% lower

[1] Burstein, Neves, and Rebelo (2004) documents that construction services are the largest component for nontradable investment expenditure.

dollar changes per annum over the next quarter and 2.7% over two years. The predictability is robust to controlling for predictors proposed in the literature, such as industrial production growth, inflation, and interest rate. In fact, our measure carries larger coefficients in magnitudes than all controls and higher R^2 than the controls combined.

For currency investors, dollar variations represent either currency excess returns or compensation for interest rate differentials through uncovered interest parity. The predictability that we uncover arises mostly from the former. One standard deviation increase in the share predicts 3.6% lower dollar excess returns per annum over the next quarter and 2.6% lower over the next two years, respectively, explaining almost all of the dollar predictability.

Why does the housing cycle predict dollar premium? The residential investment share captures the expected output share of the nontradable residential housing sector. Ma and Zhang (2019) establish the connection in a dynamic economy and document that the underlying risk is a factor significantly priced in the cross-section of returns within and across a wide range of asset classes. In the open economy, when the share is higher, nontradable shocks drive domestic aggregate output fluctuations more. Because the dollar responds more strongly to US nontradable output fluctuations as we uncover, the dollar now co-varies more negatively with US aggregate output. Assume that US output risks are not fully diversified internationally, but drive marginal utility variations of US investors. Then, the required risk premium becomes lower to hold the dollar, consistent with our evidence. Notice that the predictability stems solely from fluctuations in the expected fraction of nontradable output and does not require habit (Verdelhan, 2010), stochastic volatility (Colacito and Croce, 2011) or disaster risk (Farhi and Gabaix, 2015). As such, our channel provides a new source of time-varying currency premium so far unexplored in the literature.

The predictability and economic magnitudes are robust to alternative measures, dollar definitions, and samples ranging from non-overlapping data to different subsamples. Our results are also robust to the bootstrap correction addressing potential biases discussed in

Stambaugh (1985). These in-sample results are a contribution to the literature, because exchange rates have been notoriously difficult to predict, especially by economic fundamentals. Our evidence establishes a link between macroeconomy and exchange rates.

We further perform extensive out-of-sample tests to avoid potential data snooping bias. The forecasts using the residential investment share are more accurate than forecasts based on the historical mean. The findings are based on encompassing tests, out-of-sample $\overline{R}^2$, and investor utility gains from using the share to calculate portfolio weights. The results are not confined to any particular time period but are robust to whichever decade that we start the out-of-sample forecasts. These results are notable because Rossi (2013) finds little out-of-sample success for the dollar in her review article using predictors proposed in the literature.

To further guard against potential bias from focusing on US in-sample evidence, we turn to the international sample and study G10 currencies with available data. Over two years, the predictive coefficients are negative in 8 out of 9 currencies for currency changes and in all 9 currencies for currency premium. Both joint and average predictive coefficients are highly significant. The average coefficient across countries is comparable to baseline dollar estimates.

Economically, the share predicts time-varying dollar premium through time-varying expected fraction of nontradable output, or the "split". Alternatively, one can hypothesize that the measure proxies for aggregate economical or financial conditions and then predicts the dollar. We find that higher share is associated with higher growth, lower economic uncertainty, and lower equity and bond premium. These patterns suggest states with less volatile US pricing kernels and predict lower excess returns on the foreign currency or higher on the dollar, contradicting our empirical finding. Therefore, aggregate risks cannot explain the predictability. We further examine whether the predictability arises from limits to arbitrage in currency markets, proxied by CIP deviations and financial intermediary leverage, and find little supporting evidence.

This paper makes three major contributions. First, the paper proposes a new in-sample and even out-of-sample predictor of exchange rates. The predictability is a contribution to the literature where little predictability has been identified, going back to Meese and Rogoff (1983). Most existing predictors are based on prices, flows, or sentiments, as reviewed by Rossi (2013).[2] Our evidence directly links exchange rates and macroeconomic quantities.

Second, our paper connects housing markets to currency pricing. Real estate is mostly abstracted away in international asset pricing. This strikes us as an important gap in the literature. In the closed economy, Cochrane (1991) and Cochrane (1996) document pricing abilities of residential and nonresidential investments for equity based on time-series and cross-sectional evidence.[3] Our paper takes a first step at currency pricing by focusing on the nontradability of residential housing and measuring its share in the aggregate economy. A vast literature studies nontradables in international macroeconomics. Early contributions include Salter (1959) and Swan (1960). Baxter (1995) and Crucini (2008) review the literature more recently. Tian (2018) documents dollar predictability based on equity portfolios formed on tradability.

Third, we provide new evidence of market incompleteness. Existing studies propose various candidates for the missing link between economic fundamentals and asset pricing. Direct empirical evidence, however, is hard to come by. Farhi and Gabaix (2015) and Colacito, Croce, Gavazzoni, and Ready (2018) provide evidence on disaster and long-run risk. Bakshi, Cerrato, and Crosby (2017) and Zhang (2016) find support for incomplete markets. Our finding provides new evidence on market incompleteness. We leave it to future research to uncover the form of market incompleteness underlying our empirical finding.

In the rest of the paper, Section 1 describes the data and the measure of housing cycles.

[2]More recent contributions include Evans and Lyons (2002), Hau, Massa, and Peress (2009), Adrian, Etula, and Groen (2011), Chen and Tsang (2013), Lustig, Roussanov, and Verdelhan (2014), Dahlquist and Penasse (2017), Liu and Shaliastovich (2018) and Kremens and Martin (2019).

[3]In the international setting, Bernanke (2005), Gete (2009), Adam, Kuang, and Marcet (2012), Favilukis, Ludvigson, and Van Nieuwerburgh (2017), and Garriga, Manuelli, and Peralta-Alva (2019) study the interaction between current accounts, capital flows and housing cycles, but do not study currency pricing implications.

Section 2 develops our empirical hypothesis and tests the relation between housing cycles and the dollar. Section 3 presents out-of-sample and international evidence. Section 4 studies the economic mechanism empirically and assesses alternative explanations. Section 5 concludes.

1 Measuring Housing Cycle

This section explains the data and describes the housing cycle measure.

1.1 Data

Our quarterly sample spans the period 1971:Q1 to 2016:Q4 unless otherwise noted. The exchange rate and interest rate data are obtained from Datastream. The dollar index is computed as an equal-weighted average of the US dollar against a broad group of currencies, which consists of 19 advanced economies and 13 emerging markets. Advanced economies consist of Australia, Austria, Belgium, Canada, Denmark, the Euro area, France, Germany, Italy, Ireland, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. Emerging markets cover the Czech Republic, Hungary, India, Indonesia, Kuwait, Malaysia, Mexico, Philippines, Poland, Singapore, South Africa, South Korea, and Thailand. The G10 currencies include the Euro and currencies of Australia, Canada, Japan, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. The log dollar excess return, or dollar premium, is computed as the average of log change in foreign exchange rates (in US dollars) plus the US minus foreign interest rate differential. The trade-weighted dollar index is obtained from the Federal Research Board H.10 Release. It is a weighted average of the foreign exchange value of the US dollar against the currencies of a broad group of major US trading partners. Currency weights are based on annual data on international trade and are constant within a calendar year (see Loretan (2005) for details).

We obtain quarterly US private residential fixed investment (PRFI) and private nonresidential fixed investment (PNFI) from the national income and product accounts (NIPA) Table 1.1.5 (line 13) and Table 2.3.5 (line 15), respectively. We further supplement the investment data with new home mortgage loans and new other loans from the Federal Reserve Board Flow of Funds. The new home mortgage loans and total new loans issued by the financial sector are from Flow of Funds, Table F.218 Line 1 and Table F.214 Line 1, respectively. For G10 currency countries, the data on quarterly gross fixed capital formation and private nonresidential fixed capital formation are from OECD. Data for Switzerland is not available. The international data is in volume units due to data limitations.

Finally, the industrial production, unemployment rate, import, and export are from OECD Quarterly National Accounts. Data for gross output at aggregate and industry levels are from BEA. The macro uncertainty index is from Jurado, Ludvigson, and Ng (2015), the economic policy uncertainty index (EPU) is from Baker, Bloom, and Davis (2016), and CBOE Volatility Index (VIX) is from the Chicago Board Options Exchange (CBOE). Excess bond premium is from Gilchrist and Zakrajšek (2012). The interest and mortgage rates are the three-month T-bill and 30-Year fixed-rate mortgage rates, respectively. Both series are obtained from the FRED maintained by the St. Louis Fed. The CRSP value-weighted equity index is drawn from CRSP, and the BAA bond index series is from Barclays.

1.2 The Housing Cycle

We follow Cochrane (1991) and Backus, Kehoe, and Kydland (1992) to focus on the production economy. We measure investment in the nontradable relative to tradable sector as a proxy for the expected future relative output share. Therefore, what is important for our purpose is the tradability of the output instead of that of the capital. The residential housing investment is the measure of investment in the nontradable sector. The residential housing sector is nontradable and accounts for a sizeable fraction of household consumption (Piazzesi, Schneider, and Tuzel, 2007) and wealth (Lustig and Van Nieuwerburgh, 2005). Other sectors are classified as tradable. Our main measure, the residential investment share, is then calculated as the ratio of residential to nonresidential investment. We use the residential investment share and housing cycle interchangeably in the remaining texts.

Because of data limitation, we do not distinguish between tradability among nonresidential sectors and treat them as tradable. This simplification has limited quantitative significance for the following reasons. First, Burstein, Neves, and Rebelo (2004) document that construction services are the most important among all nontradable goods and service sectors in terms of investment expenditure. For nonresidential sectors, only the nonresidential commercial structure sector is completely nontradable. We construct an alternative measure adjusting for this sector in Section 2.3. Second, Burstein, Neves, and Rebelo (2004) document that nontradable service industries are less capital intensive and are hence less important in calculating investment shares. For example, the ratio of investment to sales is, on average, 0.4 for the personal care service industry, which is the least tradable service industry, and 3.0 for optical instruments and lens manufacturing, which are the most tradable (see Appendix B.1). Therefore, the residential investment share well captures excess investment in the nontradable relative to the tradable sector.

Figure 1 plots the residential investment, nonresidential investment and residential investment share, respectively. Both investments have grown significantly over the past four decades. The largest increase in residential investments is prior to the Global Financial Crisis, whereas comparable fluctuations have taken place historically as well. A large literature tries to uncover the drivers of housing cycles, ranging from user costs, financial liberalization, international capital flows to expectations (see Piazzesi and Schneider (2016) for an extensive review). We do not attempt to micro-found housing cycles in this paper but take the fluctuations as exogenous.

2 Predicting the Dollar

We now develop the empirical hypothesis on dollar predictability and then test the relation empirically.

2.1 Hypothesis Development

The dollar exchange rate is q and Δq denotes dollar depreciation. The residential investment share measures the relative investment in the nontradable sector, or the expected fraction of nontradable output. The share can link to exchange rate changes in a few ways.

First, housing investments drive the expected future supply of housing services and further supply of nontradables. The US price of nontradables is only determined by US demand and supply, whereas the price of tradables is determined globally. Then from US investors' point of view, the price of nontradables reacts more to domestic nontradable output shocks than that of tradables to domestic tradable output shocks. This is known as the relative price adjustment channel. Because the residential investment share indicates the relative future supply of nontradables, our first hypothesis follows.

H 1. *The residential investment share predicts dollar changes negatively.*

Second, when the residential investment share is high, the fraction of nontradables in the total output next period is expected to be high. Then, the total US output depends more on the nontradable sector. Because of the relative price adjustment effect, the dollar comoves more negatively with nontradable output variations than the tradable. Assume that US output and nontradable risks cannot be fully diversified internationally, the growth rate of marginal utilities now comoves with the nontradable output more and in turn, comoves with the dollar more. This time-varying comovement between the marginal utility growth and dollar leads to a time-varying dollar premium.

We can formulate this effect in an asset pricing framework. The dollar excess return is the log exchange rate changes adjusting for interest rate differentials

$$rx_{t+1} := \Delta q_{t+1} + r_t^* - r_t, \tag{1}$$

where r is the interest rate. All foreign counterparts are denoted by *. Denote the representative US investors' log stochastic discount factor (SDF) as m.

If US investors can invest without frictions in both US and foreign bonds, in absence of arbitrage, US investors' Euler equations need to hold for both:

$$\begin{aligned} E_t[\exp(m_{t+1} + r_{t+1})] &= 1, \\ E_t[\exp(m_{t+1} + r_{t+1}^* - \Delta q_{t+1})] &= 1. \end{aligned} \tag{2}$$

Then the expected log dollar excess return, or dollar premium, can be solved as

$$E_t rx_{t+1} - \frac{1}{2}\sigma_t^2(\Delta q_{t+1}) = cov_t(m_{t+1}, -\Delta q_{t+1}). \tag{3}$$

$-\Delta q$ denotes foreign currency appreciation. Our second hypothesis is that the covariance varies as the residential investment share fluctuates, generating a time-varying dollar premium.

H 2. *The residential investment share predicts dollar premium negatively.*

2.2 Dollar Changes and Excess Returns

Now we predict dollar variations with the residential investment share (hypothesis H1). The baseline dollar index is the equal-weighted US dollar index against a basket of currencies that include both advanced economies and emerging markets. We focus on US variables as predictors following Lustig, Roussanov, and Verdelhan (2014).[4] Figure 2 plots the share with log dollar index changes over the next two years. The residential investment share exhibits a negative correlation with future dollar index changes as low as -0.41, consistent with H1.[5] The correlation is in sharp contrast with the lack of correlation between exchange rates and macroeconomic variables documented in the literature.

Formally, the predictability regression is specified as follows:

$$\frac{4}{h}\sum_{s=t+1}^{t+h}\Delta q_s = \alpha_0 + \beta I_{HKt} + \varepsilon_{t+h}, \tag{4}$$

where $\frac{4}{h}\sum_{s=t+1}^{t+h}\Delta q_s$ denotes annualized log dollar index changes over the following h quarters in percentage points. I_{HKt} is the residential investment share at time t. The variable is normalized to have zero mean and unit variance, so β can be interpreted as percentage changes in the dollar when the share increases by one standard deviation. To account for the overlapping data structure, we report both Newey and West (1987a) and Hodrick (1992) standard errors.

Table 1 presents the regression results. Panel A shows that the residential investment share significantly predicts the nominal dollar index changes from one quarter to twelve quarters. One standard deviation increase in the share predicts 3.56% lower dollar changes per annum over the next quarter with 5.86% R^2. The implied correlation between the share and dollar changes is -0.24. The explanatory power, measured by R^2, strengthens over longer horizons and peaks at the 8-quarter horizon. For the 8-quarter horizon, our measure predicts 2.72% lower dollar changes per annum. The explanatory power is as high as 17.8%, implying a correlation of -0.41 between our measure and dollar changes over the next two years.

[4]If foreign variables for individual countries are largely independent, it is innocuous to focus on US variables. If foreign variables comove, measuring US variables ignores the exposure of the US to global cycle and biases the coefficients toward zero.

[5]The correlation between the residential investment share and future dollar premium changes over the next one year and -0.38 and the plot is included in the Appendix.

The pattern that we document is not just a nominal phenomenon. Panel B presents results with the real dollar index. Results are similar, and if anything, stronger than the nominal. One standard deviation increase in the residential investment share predicts 3.92% lower dollar changes per annum over the next quarter with 6.52% R^2. The coefficient is -3.04%, and the R^2 is 18.69% for the 8-quarter horizon. All point estimates are greater in magnitudes than nominal dollar results.

Next, we test our hypothesis H2 about dollar premium. It is helpful to relate the dollar premium to dollar changes before the empirical test. The dollar excess return is defined in equation (1). Then the dollar changes can be written as

$$\Delta q_{t+1} = rx_{t+1} + r_t - r_t^*. \tag{5}$$

In words, from currency investors' perspective, dollar changes are either excess returns rx or merely compensation for the interest differential $r_t^* - r_t$, which is the uncovered interest parity (UIP). These are the only two sources for exchange rate predictability.

Panel C presents the results with dollar excess returns. The residential investment share consistently predicts dollar premium negatively across all horizons. Over one quarter, a one standard deviation increase in the share predicts 3.55% decrease in the annualized dollar premium. The coefficient is almost the same as the coefficient from the dollar regression. The pattern is similar for the longer horizons. For the 8-quarter horizon, our measure predicts 2.61% decrease in the dollar premium, explaining most of the coefficient, 2.72%, for dollar index changes. In short, the dollar predictability documented above almost entirely comes from the time-varying dollar premium for investors.

One natural question is, does the housing cycle provide new information in addition to existing predictors? It is well documented that exchange rates are notoriously difficult to predict, especially in the medium to long horizons. We control for the limited set of predictors proposed in the literature and run the following multivariate regression:

$$\frac{4}{h}\sum_{s=t+1}^{t+h}\Delta\log(dollar_s) = \alpha_0 + \beta I_{HKt} + \gamma\mathbf{X}_t + \varepsilon_{t+h}, \tag{6}$$

where $\frac{4}{h}\sum_{s=t+1}^{t+h}\Delta\log(dollar_s)$ denotes the annualized log dollar index changes Δq or the annualized dollar excess returns rx in the following h quarters in percentage points. $\mathbf{X}$ is a vector of controls that include the industrial production (IP) growth, inflation, three-month T-bill rate, and the current level of the dependent variable. All predictors are standardized to have zero mean and unit variance to make the coefficients comparable.

Table 2 presents the results. We report only Hodrick (1992) standard errors to conserve space. Both the statistical significance and economic magnitudes are similar to univariate ones. For nominal dollar index changes, a one standard deviation increase in the residential investment share predicts a 3.23% decrease in dollar changes over the next quarter, which compares well with a 3.56% decrease from the univariate regression. The explanatory power increases from 5.86% in the univariate analysis to merely 10.33% with all controls. Over the 8-quarter horizon, the coefficient strengthens from −2.72% in the univariate regression to −3.37% with controls, and the explanatory power increases from 17.80% to 33.12%, again less than double. Results are consistent, and the message is similar as explained above for the real dollar index and dollar excess returns.[6]

All controls are business cycle or financial indicators that are mostly sector-neutral. In terms of coefficients, inflation and the risk-free rate predict dollar changes or excess returns positively, consistent with existing evidence from the literature. All control coefficients are smaller in magnitudes than that of the residential investment share, suggesting that the share predicts larger dollar movements than all controls. Further, the statistical significance

[6]The forward discount is arguably a better measure of interest rates, but the forward data is only available from 1983 onward. The regression controlling for the average forward discount over the subsample is in the Appendix, and results are similar.

is weak. We only see some significance for inflation from four quarters onwards in the multivariate setting. IP growth predicts dollar positively, though insignificant, suggesting that the dollar does not provide risk sharing to aggregate US output risks as standard international risk sharing predicts. Results suggest that the strong predictability of the share arises more from the relative price adjustment channel than risk sharing for sector-neutral aggregate risks. We further control for other predictors that have been proposed or potential drivers of housing cycles, such as the excess bond premium, term spread, credit-to-GDP ratio, broker-dealer leverage, and real dollar level, individually and jointly in the Appendix. Our finding is robust, and few controls are significant as the literature finds.

In sum, we find that the residential investment share is the strongest predictor for the dollar in the past five decades, even comparing to the price-based predictors. The share captures relative investment in the nontradable relative to tradable sector, and the relative price adjustment effect drives the predictability. Further analysis shows that the dollar predictability almost entirely comes from the dollar premium.

2.3 Alternative Measures

This section considers alternative measures of the dollar and housing cycles, respectively. First, we decompose the broad dollar index into the index against the advanced economy and emerging market currencies, respectively. Panel A, Table 3 reports the predictive results. Only 1-quarter and 8-quarter results are included to be concise. For the 8-quarter horizon, a one standard deviation increase in the residential investment share predicts a 2.74% decrease in dollar changes against advanced economy currencies and 2.42% against emerging market currencies per annum. Both coefficients are highly significant. The R^2 is 13.72% against advanced economy currencies and 18.72% against emerging market currencies, both comparable to the baseline.

In the baseline, we use the equal-weighted dollar index to avoid using weights that change over time or are based on a specific year. However, larger economies play more important roles in the global economy in general. We now use the trade-weighted dollar index. Panel A, Table 3 reports the results. Coefficients and R^2s are comparable to baseline results with the equal-weighted dollar index. Over the 8-quarter horizon, a one standard deviation increase in the residential investment share predicts 2.37% decrease in dollar index changes per annum, with 15.54% R^2, similar to 2.72% and 17.80% in the baseline.

Next, we construct various alternative measures of the housing cycle. Our main measure classifies the residential sector as the nontradable sector and all other sectors as tradable. Among nonresidential sectors, the nonresidential commercial structure sector (industry IO code 230101) is also nontradable. We now classify the nonresidential commercial structure sector and construct an alternative measure. Investments in this sector account for 8% of the total nonresidential investment. This adjustment has a small quantitative impact. The alternative series has a correlation of 0.95 with our main measure. Panel B, Table 3 reports the predictive results. Over the 8-quarter horizon, a one standard deviation in the share predicts a 2.83% decrease in dollar changes per annum with R^2 of 18.75% and 3.01% decrease in dollar premium with R^2 of 19.19%. Both coefficients and R^2s are slightly larger in magnitudes than the baseline.

The investment rate or asset growth is often used as the measure of capital investment rate. The variable is typically calculated as the ratio of new investments to existing capital. Because capital is slow-moving and the capital stock is not directly observable, our main measure focuses on new investments to avoid look-ahead bias. However, because depreciation rates of residential and nonresidential capital are different, the corresponding investment rates in these two sectors can follow different dynamics. We now explicitly account for the depreciation rates and construct estimates of existing capital stock using a perpetual inventory model (Cochrane, 1991):

$$\begin{aligned} IH_t &= \frac{I_{Ht}}{I_{Ht-1}} \frac{IH_{t-1}}{1-\rho+IH_{t-1}}, \\ IK_t &= \frac{I_{Kt}}{I_{Kt-1}} \frac{IK_{t-1}}{1-\rho+IK_{t-1}}. \end{aligned} \tag{7}$$

The initial value of investment rates IH_t and IK_t are set to the steady-state levels, i.e., the depreciation rate ρ_i, $i = H, K$, plus the average investment growth rate, $IH_0 = \rho_H + E(I_{Ht}/I_{Ht-1}) - 1$ and $IK_0 = \rho_K + E(I_{Kt}/I_{Kt-1}) - 1$. The depreciation rate for residential investment is set to 0.285% per quarter, the BEA depreciation estimate for new private residential structures. The depreciation rate for nonresidential investment is set to 1.425% per quarter, the BEA depreciation estimate for new private nonresidential investment, including structures and equipment. The time series of investment rates are derived recursively accordingly. Then the relative investment rate of the nontradable sector is calculated as IH_t/IK_t. We call IH_t/IK_t the investment rate ratio.

The top panel of Figure 3 plots this alternative measure. The lower panel plots the residential and nonresidential investment rates, respectively. In contrast to the nominal investment series, both investment rate series are stationary. Panel B, Table 3 reports the predictive results. The investment rate ratio explains 5% and 18.2% of dollar variations over the next quarter and eight quarters, respectively. The ratio explains 3.93% and 11.53% of dollar premium variations over the same horizons. All coefficients are highly significant, and the economic magnitude is comparable to the baseline.

To capture the broad activity of the residential versus other sectors, we further gauge different aspects of investment and production by measuring relative employment and financing. The employment ratio is calculated as the ratio of total construction employees to the total employees net of construction workers. Because of data limitations, the total construction includes various construction activities, ranging from constructions in nontradable residential housing and nontradable nonresidential commercial structures to constructions in the tradable manufacturing industries. This measure is a rough proxy for the relative employment in the nontradable sector. The loan ratio is calculated as the ratio of new home mortgage loans to other new loans issued by financial sectors. The underlying drivers of housing cycles have been heatedly debated. Financial liberalization is considered to be a key driver of the housing boom prior to the Global Financial Crisis. For example, Cheng, Raina, and Xiong (2014) highlight temporary changes in mortgage lending standards.

Panel B, Table 3 presents the predictive results. Over the 8-quarter horizon, for the employment ratio, the R^2 is 11.46% for dollar changes and 8.71% for dollar premium. For the loan ratio, the R^2 is 10.14% for dollar changes and 11.82% for dollar premium. The explanatory power is similar but slightly smaller than in the baseline, providing support to the output based channel that we propose. In short, the relative investment in the nontradable sector strongly predicts dollar changes and dollar premium. The result is robust to various alternative definitions and measurements.

2.4 Alternative Estimation and Samples

This section now examines the robustness under different estimation methods and sample periods. The baseline specification uses the overlapping data structure to make use of all available data and improve the test power. Stambaugh (1985) shows that in standard time-series predictive regressions, when returns of various holding periods are regressed on a variable measured at the end of the last period, the regression coefficient is subject to an upward small-sample bias, if the innovations of the predictor are negatively correlated with contemporaneous returns. To address this issue, we follow the Nelson and Kim (1993) randomization method that adjusts for the autocorrelation of the predictor (see details in Appendix A). Panel A, Table 4 reports the bias-adjusted estimates and the associated randomized p-value. Overall, the adjustment is quantitatively small. Over the 8-quarter horizon, the coefficients are -2.59% per annum for dollar changes and -2.51% for dollar premium, comparing with -2.72% and -2.61% in the baseline.

To further gauge the economic magnitudes and explanatory power for long-horizon predictability, we now conduct the analysis with non-overlapping data. Panel B, Table 4 reports the results. At the 8-quarter horizon, a one standard deviation increase in the residential investment share predicts a 2.74% decrease in dollar changes and a 2.56% decrease in dollar premium, comparing well with 2.72% and 3.04% in the baseline with overlapping data. The R^2s are 17.96% and 12.15%, respectively, comparable to 17.80% and 14.82% in the baseline.

Finally, we examine the results' sensitivity to various sample periods. Exchange rates are determined by a nexus of various economic forces. The importance of different economic channels can potentially vary across economic periods or regimes, and one would expect the predictability to be time-varying. However, a good predictor should not be driven by a single time period. We first exclude the Global Financial Crisis from 2007 to 2009. Panel B shows that the R^2 is 16.20% and 10.22% for dollar changes and dollar premium, respectively, slightly lower than 17.80% and 14.82% in the baseline. The change suggests that the mortgage meltdown and sharp decline of residential investments before the crisis timely predict dollar appreciation during the Global Financial Crisis. Furthermore, we look at the subsample performance by considering an investor who begins using the predictor at the beginning of different decades. The predictability that she experiences shows some time variation across decades but overall consistent. For the 8-quarter horizon, the predictive coefficients are largely stable and vary from -2.02% to -2.53% for dollar changes and from -2.51% to -2.70% for dollar excess returns. The R^2 varies from 13.87% to 25.44% for dollar changes and from 11.85% to 25.51% for dollar excess returns. Overall, the predictive power is robust to whatever decade we use as the sample start and is not driven by a particular decade.

3 Out-of-Sample and International Evidence

Section 2 documents that the residential investment share is a strong and robust in-sample macroeconomic predictor for the dollar. This is a notable finding and contribution to the literature in which little robust predictability is identified. At the same time, a growing literature emphasizes potential data-snooping concerns of relying only on in-sample evidence. To address the concern, Section 3.1 conducts out-of-sample tests for the dollar and Section 3.2 assesses its economic significance. Section 3.3 turns to other G10 currencies.

3.1 Out-of-Sample Evidence

Out-of-sample performance has been the weakness of many predictors in various contexts. Welch and Goyal (2007) shows that many, if not all, traditional equity return predictors have large negative out-of-sample $\bar{R}^2$ and results are sensitive to the choice of evaluation periods. Rossi (2013) summarizes that almost no predictors from economic models exhibit positive predictability out-of-sample for the dollar, with the exception of Clark and West (2006) at longer horizons.

We use only the data available up to time t and run the predictive regression of the dollar on lagged residential investment shares as in the univariate regression. The out-of-sample forecast is constructed for the next quarter using past sample estimates and current values of our measure. The out-of-sample $\bar{R}^2$ is calculated as $\bar{R}^2 = 1 - \Sigma_t(\hat{r}_{t+1|t} - r_{t+1})^2 / \Sigma_t(\bar{r}_t - r_{t+1})^2$, where $\hat{r}_{t+1|t}$ is the dollar forecast with the share using data up until t, and $\bar{r}_t$ is the historical average until t, or the forecast of a moving average model. The forecast horizon spans one quarter to three years as in the in-sample tests. We require at least five years of minimum burnin period, or the initial estimation sample, for all horizons.

Panel A, Table 5 presents $\bar{R}^2$ for our measure and the associated test statistics (Clark and West, 2007). For the broad nominal dollar index, $\bar{R}^2$ is 2.75% for the 1-quarter horizon and increases to 9.06% over 8 quarters. The out-of-sample $\bar{R}^2$ is significant at 5% level or higher for all horizons. For dollar excess returns, the $\bar{R}^2$ is 2.76% at the 1-quarter horizon and increases to 6.31% over the 8-quarter horizon. The $\bar{R}^2$ is significant at the five-percent level or higher from the one-quarter to two-year horizon. Therefore, the share consistently outperforms the historical mean model across various horizons in predicting the dollar.

In order to rule out any particular period driving out-of-sample results, we now use different initial estimation and evaluation periods. First, we exclude the measure and returns from 2007 to 2009, the Global Financial Crisis period. Panel B shows that over the 8-quarter horizon, $\bar{R}^2$ is 17.69% for dollar changes and 11.09% for dollar premium, higher than the numbers including the crisis period. The results suggest that our model fails to predict the dollar movements during the crisis out of sample. This is in contrast to the robust in-sample performance during the crisis period. Economically, during the crisis period, there was a strong flight to safety into the dollar which could have been a more important driver of dollar appreciation than the relative price adjustment. Statistically, the residential investment share reaches historical highs during prior to the financial crisis (see Figure 1), and the recursive estimates of with smaller historical fluctuations fail to extrapolate correctly into the more volatile financial crisis period.

Second, we now start our out-of-sample exercise at the beginning of different decades. The minimum burnin sample or initial estimation periods are set to 1971Q1 until the last quarter prior to the beginning of evaluation periods. The estimation is done recursively, and estimation windows extend with the progress of evaluation periods. Panel B shows that our measure consistently outperforms the historical mean model, irrespective of in whichever decade we start the out-of-sample test.

One potential concern of using macroeconomic series is that the series are revised periodically. We conduct additional robustness using the real-time data from historical vintages in the Internet Appendix and find robust out-of-sample performance. We further conduct out-of-sample results for the alternative measures, including employment ratios and loan ratios, in the Internet Appendix. Results are consistent with the baseline out-of-sample results.

3.2 Economic Significance

Next, we assess the economic significance of the predictive ability by conducting an asset allocation exercise in the spirit of Campbell and Thompson (2007). We consider a mean-variance investor who allocates her investment between US T-bills and the equal-weighted basket of foreign T-bills. For the h-quarter investment horizon, the investor rebalances every h quarters. At each rebalancing point t, the investor optimally constructs a portfolio with the following weight

$$\omega_t = \frac{1}{\gamma}\frac{\hat{r}_{t+1|t}}{\hat{\sigma^2}_{t+1|t}}$$

for US T-bills and $1-\omega_t$ for foreign T-bills. γ is the investor's risk aversion which is set to 3, $\hat{r}_{t+1|t}$ is the dollar excess return forecast with the residential investment share using data up until t, and $\hat{\sigma^2}_{t+1|t}$ is a variance forecast of dollar currency excess returns from a 40-quarter moving average model. The foreign excess return equals the minus dollar excess return. To avoid extreme portfolio weights, we impose a leverage constraint that restricts the weights to between -0.5 and 1.5. The investor's utility level can be calculated as the certainty equivalent return (CER):

$$\text{CER} = Er_{pt} - 0.5\gamma\sigma^2\left(r_{pt}\right),$$

where r_{pt} is the realized portfolio return over the evaluation period. The utility gain (ΔCER) is then the difference between the investor's utility levels when she forecasts using the share and when she forecasts using only historical means. Because the estimation is done recursively using data only up to the time t, the utility gain is out-of-sample. The number is further annualized and can be interpreted as annual management fees that the investor is willing to pay to a hedge fund that uses the share as the predictor.

Panel C of Table 5 reports the numbers. If the investor begins to invest in the hedge fund from the beginning of the sample, she achieves an annualized utility gain of as high as 4.63% with quarterly rebalancing and 3.78% with annual rebalancing. Further analysis shows that if the investor begins to invest at the beginning of different decades, she will achieve sizeable utility gain irrespective of when she joined. In conclusion, we find robust out-of-sample predictability of the residential share for the US dollar. The predictive power is robust to excluding the Global Financial Crisis, different estimation periods, and evaluation periods. The economic gains generated for the investor are sizable and also stable over different evaluation periods.

3.3 International Evidence

In order to further guard against data snooping bias and to serve as an out-of-sample test of the in-sample dollar predictability, we now test the predictability using other currencies. The test assets are G10 currency indices. Each currency index is constructed as the equal-weighted average against the board basket of other currencies. As such, the indices are dollar neutral. Swiss Franc is not included because the Swiss residential investment data is not available. We calculate the residential investment share as the ratio of gross-minus-nonresidential fixed capital formation to the private nonresidential fixed capital formation. Because nominal amounts are not available, the volume series is adopted. Because of the measure's definition change, the dollar is included again for comparison. Figure 4 plots the detrended series for each countries. The fluctuations exhibit very different patterns across countries, suggesting limited global comovement.

To assess the predictive power of domestic residential investment share for exchange rates, our goal is to simultaneously estimate nine predictive regression equations of the form,

$$\frac{4}{h}\sum_{s=t+1}^{t+h}\log\left(\Delta \mathrm{y}_{is}\right)=\alpha+\beta I_{HKit}+\gamma\mathbf{X}_{it}+\varepsilon_{ih},\quad i=1,...,9, \tag{8}$$

where i indexes country, $\frac{4}{h}\sum_{s=t+1}^{t+h}\log\left(\Delta \mathrm{y}_{it}\right)$ is the annualized cumulative currency change or excess return from $t+1$ to $t+h$, I_{HKit} is the residential investment share for country i at time t and X are controls. There are multiple ways to estimate this system of equations. A natural estimation methodology would be to run nine separate regressions. This, however, makes joint hypothesis testing difficult and is not efficient. Instead, we adopt a GMM estimation with Newey-West standard errors that allows for both cross-correlation and autocorrelation. In fact, Newey-West estimates on a panel allow for cross-correlations not only contemporaneously, but also a lead-lag structure in cross-correlations.[7]

For GMM estimation of the system of equations (8), there are 18 moment conditions,

$$\begin{aligned}\frac{1}{T}\sum_{t=1}^{T}\varepsilon_{it+h}&=0,\qquad i=1,...,9,\\ \frac{1}{T}\sum_{t=1}^{T}I_{IKit}\varepsilon_{it+h}&=0,\qquad i=1,...,9.\end{aligned} \tag{9}$$

In this system, we have 18 moment equations to estimate 18 parameters, so the system has no overidentifying restrictions. Table 6 reports the results with the same set of controls as in Table 2. Panel A reports predictive results for exchange rate changes. 7 out of 9 currencies carry negative coefficients over the one-quarter horizon, and 8 carry negative coefficients over the 8-quarter horizon. We conduct two sets of Wald tests. In the first set of tests, we test whether the average predictive coefficient is zero, specifically, $\frac{1}{9}\sum_i\beta_i=0$. The

[7]See Cochrane (2001). The Bartlett estimate, as in Newey and West (1987b), estimates the spectral density matrix as $\hat{S}=\sum_{j=-k}^{k}\left(\frac{k-|j|}{k}\frac{1}{T}\sum_{t=1}^{T}(u_t u_{t-j}')\right)$, where $u_t=[u_{it},...,u_{Nt}]'$. u_t is a vector of errors in period t for the N moment conditions in the GMM system.

second test examines whether coefficients jointly equal to zero, $\beta_1 = \beta_2 = ... = \beta_9 = 0$. The bottom of Panel A shows that both hypotheses are rejected for all horizons and particularly strong for the longer horizon. Excluding the US dollar in the joint and average test delivers similar results as well. The average coefficients are comparable with the dollar estimates in the baseline. For example, the average coefficient is -2.74% over the 8-quarter horizon, and the corresponding dollar estimate in the baseline is -3.11%. The univariate results are comparable and included in the Appendix.

Panel B reports results for excess returns. Strikingly, all point estimates are negative across countries and horizons. Again, the bottom of Panel B shows that both sets of Wald tests are rejected. The average coefficient is -2.97% for the 1-quarter horizon with a 95% confidence interval of $[-4.85\%, -1.09\%]$, and -1.63% for the 8-quarter horizon with a 95% confidence interval of $[-2.06\%, -1.20\%]$. Joint coefficient tests are rejected at the five-percent significance level at the 1-quarter horizon and are rejected at the one-percent significance or higher from the 4-quarter horizon onwards. In sum, the evidence shows the residential investment share is not only a strong in-sample predictor for the dollar but also exhibits out-of-sample predictability for the dollar and holds for G10 currencies.

4 The Source of Predictability

The empirical evidence up until now has established that the housing cycle is a strong and robust in-sample and out-of-sample predictor of exchange rates. This section provides empirical evidence of our proposed economic channels and examines alternative explanations. Because the predictability mostly comes through the risk premium channel, this section also emphasizes the risk premium.

4.1 Relative Price Adjustments

This subsection examines the source of predictability for the dollar and dollar premium, respectively. First, Section 2.1 hypothesizes that the price of nontradables decreases relative to that of tradables following high relative investment in the nontradable sector. Then the dollar depreciates. We test the relative price adjustments directly. We use PPI as the measure of the tradable price index, use CPI as the composite price index, and construct the nontradable price index following Betts and Kehoe (2006).[8]

Panel A, Table 7 reports the results of regressing relative price changes on lagged residential investment shares. Over the 8-quarter horizon, one standard deviation increase of the share predicts a 2.23% decrease in the price of nontradables relative to that of tradables. To tease out the potential international risk sharing due to aggregate economy fluctuations, we further control for total investment and industrial production. Industrial production predicts relative price adjustment within two quarters, whereas the gross investment shows no significance. The coefficients for the share remain largely unchanged and increase in magnitudes over longer horizons. The evidence is consistent with our hypothesis that nontradable output shocks have a much larger impact on relative prices than the tradable. In short, the dollar provides hedging against US output risks, especially nontradable risks.

Second, Section 2.1 hypothesizes that the time-varying dollar premium is driven by the time-varying exposure of domestic output to the nontradable sector. The exposure varies with the residential investment share or the expected fraction of nontradable output. To test the hypothesis, we estimate the exposure of domestic output to the nontradable sector by regressing aggregate gross output growth on nontradable gross output growth. Panel B,

[8] We assume the composite good basket is a Cobb-Douglas function of two goods, P_t can be decomposed as follows:

$$P_t = \left(P_t^T\right)^\alpha \left(P_t^{NT}\right)^{1-\alpha}, \tag{10}$$

where P_t denote the price deflator or index for the composite good basket, and P_t^T and P_t^{NT} are price indices for tradables and nontradables, respectively. The parameter α is calculated as the share of real gross output in the nontradable goods sector and equals about 2/3 over the sample.

Table 7 shows that when the share is below the median, a one percent increase in nontradable output growth in the next year is associated with a 0.68% increase in aggregate output growth over the same period of time. The exposure increases to 0.90% when the share is above the median, consistent with our hypothesis. Results are similar when the output growth is measured over two years. The exposure is 0.92% when the share is above the median, again higher than the exposure, 0.64%, when the share below the median.

4.2 Aggregate Economy

Now we consider a few alternative explanations. In our proposed channel, the dollar premium is time-varying because the expected output ratio between tradable and nontradable sectors varies. In other words, the residential investment share captures the split between tradables and nontradables. It is possible that the predictability arises because the share proxies for aggregate risk, aggregate economy, or overall financial market conditions instead. This section now examines the link between the share and aggregate economy. The next section studies financial markets.

Notice that we have controlled for aggregate variables in previous sections, including industrial production, inflation, interest rates, and further extensive proxies such as EBP, term spread, credit-to-GDP ratio, etc. Nevertheless, empirical controls can be noisy and incomplete. Could the relation between housing cycles and aggregate economy generate the predictability documented? Under complete markets, the expected dollar premium reflects the relative riskiness of US and foreign SDFs:

$$E_t rx_{t+1} = \frac{1}{2}\sigma_t^2(m^*_{t+1}) - \frac{1}{2}\sigma_t^2(m_{t+1}). \tag{11}$$

In words, the dollar premium is higher when the US marginal utilities are less risky. If the housing cycle predicts lower a dollar premium through the aggregate risk channel, the housing cycle needs to predict higher domestic risks.

Table 8 examines the plausibility of this condition. Panel A shows that housing booms are positively correlated with higher industrial production growth (0.30). The share is negatively correlated with various uncertainty measures, −0.19 with macro uncertainty, −0.54 with the economic policy uncertainty, and −0.20 with expected equity volatility (VIX). Although the current account balance is procyclical, the net import positively correlates with the share (0.23), or in other words, the current account balance deteriorates during housing booms.[9] The reason is that our measure differs from traditional sector-neutral business cycle indicators and captures the "excess" investment in the nontradable relative to tradable sector. Next, interest rates are often considered to be candidate drivers of housing cycles and also sources of exchange rate fluctuations. Contemporaneously, the correlations between the share and both interest and mortgage rates are positive though insignificant.

In terms of asset prices, higher residential investment share is associated with a lower risk premium in various markets. Term spread, default spread, and excess bond premium (EBP) are measures of bond risk premium. Correlations of the share with these variables are −0.21, −0.33, and −0.30, respectively. Finally, Panel B shows that the measure predicts persistently lower returns for the CRSP value-weighted equity index over the next two to three years and lower returns for the BAA-rated corporate bond index from one quarter to three years. The measure also predicts lower future dollar volatility across various horizons. As such, higher share corresponds to states with less volatile SDFs, instead of riskier states as equation (11) requires.

In sum, the residential investment share corresponds to states with higher growth, lower uncertainty, lower risk premium and volatility, or in other words, states with less volatile SDFs. However, the measure predicts dollar premium negatively and foreign currency pre-

[9] The predictability is still strong and significant, especially at longer-horizons, after controlling for the current account balance.

mium positively, inconsistent with predictions of complete markets. The evidence instead supports incomplete markets. We adopt the formulation of Backus, Foresi, and Telmer (2001) in Appendix C and show that the predictability requires the wedge to complete markets to be time-varying and heteroskedastic.

4.3 Time-varying Market Segmentation

This section now examines the relation between the measure and aggregate financial market conditions and related alternative explanations. The channel that we propose builds on time-varying risk premium under incomplete markets. We assume that no arbitrage holds in currency markets. Alternatively, currency markets can be segmented from time to time. The segmentation can arise due to potentially irrational demand or limits to arbitrage in currency markets. For example, Bernanke (2005) remarks that international capital flows played an important role in US current account deficit accumulation and housing booms prior to the Global Financial Crisis. We evaluate whether the capital flow jointly drives housing cycles and exchange rates.

Panel A, Figure 5 shows that the housing boom in the early 2000s indeed corresponds to large debt inflow into the US, though the foreign direct investment (FDI) shows much less comovement. Overall, the capital flow was small compared to GDP before taking off in the 1990s. Now we assess whether the capital flow can explain the predictability, at least in more recent periods. We first regress the residential investment share I_{HK} on international capital flows X and decompose the share into the component related to capital flows and the residual:

$$I_{HKt} = \alpha_0 + \underbrace{\beta X_t}_{I_{HK}\text{ Fitted}} + \underbrace{\varepsilon_t}_{I_{HK}\text{ Residual}} \tag{12}$$

Then, we predict dollar excess returns with both fitted and residual components. We conduct the analysis for debt flows and FDI, respectively. Panel A, Table 9 presents the results.

Despite the comovement between debt flows and housing cycles, the predictability arises only from the residual, which are not correlated to debt flows. The fitted component of FDI shows some predictive power for dollar premium for one quarter. But the long-horizon predictability only comes from the residual again. The pattern looks similar in the full sample as well as the post-1990 sample. In short, the evidence on capital flows jointly driving housing cycles and exchange rates is weak.

Finally, we consider limits to arbitrage in the currency market. It is possible that our measure predicts currency premium because the measure predicts arbitrage opportunities instead of risk premium in currency markets. In particular, the demise of Lehman Brothers vividly illustrates that housing booms can lead to excess risk-taking behavior of financial institutions. We use two proxies of financial stress in the currency market, the covered interest parity (CIP) deviation (Du and Schreger, 2016) and the broker-dealer leverage (Adrian, Etula, and Muir, 2014). Panel B, Figure 5 shows that the housing boom leads the spike in CIP deviation and broker-dealer leverage around the Global Financial Crisis, but does not show much comovement in other episodes. Formally, we regress dollar excess returns on the lagged share and the interaction of financial stress measures with the lagged share. In Panel B, Table 9, we find very weak evidence that the predictability is stronger during periods of financial stress.

In conclusion, we find supporting evidence that the residential investment share predicts relative price adjustments and provides time-varying hedge to aggregate output shocks, further leading to the time-varying dollar premium. Our finding is inconsistent with the hypothesis that our measure proxies for the aggregate economy and further predicts currency premium. We find some mixed evidence for time-varying market segmentation following housing booms, which can potentially lead to time-varying currency premium.

5 Conclusion

This paper proposes the residential investment share as a strong in-sample and out-of-sample predictor of the dollar. The evidence is robust to a host of robustness checks and holds for other G10 currencies. Higher residential investment share predicts future dollar depreciation over the next one to twelve quarters, and the predictability is stronger than economy-wide aggregate predictors. The reason is that the measure captures investment in the nontradable relative to nontradable sector, which drives stronger relative price adjustments.

The predictable dollar fluctuations are mostly risk premium for investors. The residential investment share is associated with expected future nontradable output share. As the share fluctuates, the loading of future domestic aggregate output on nontradable output shocks varies. If US output risks are not fully diversified, the expected dollar premium further varies.

These findings establish a link between fundamentals and exchange rates under incomplete markets. Our finding is inconsistent with the alternative interpretation that the measure proxies for the aggregate economy or aggregate risks. Specifically, the procyclical measure is associated with lower equity and bond premium, but higher foreign currency premium, inconsistent with complete markets. We also find little support for other alternative explanations, such as capital flows and limits to arbitrage in currency markets. We leave it to future research to uncover the type of market incompleteness that can jointly generate the predictability and match the stylized facts in international finance.

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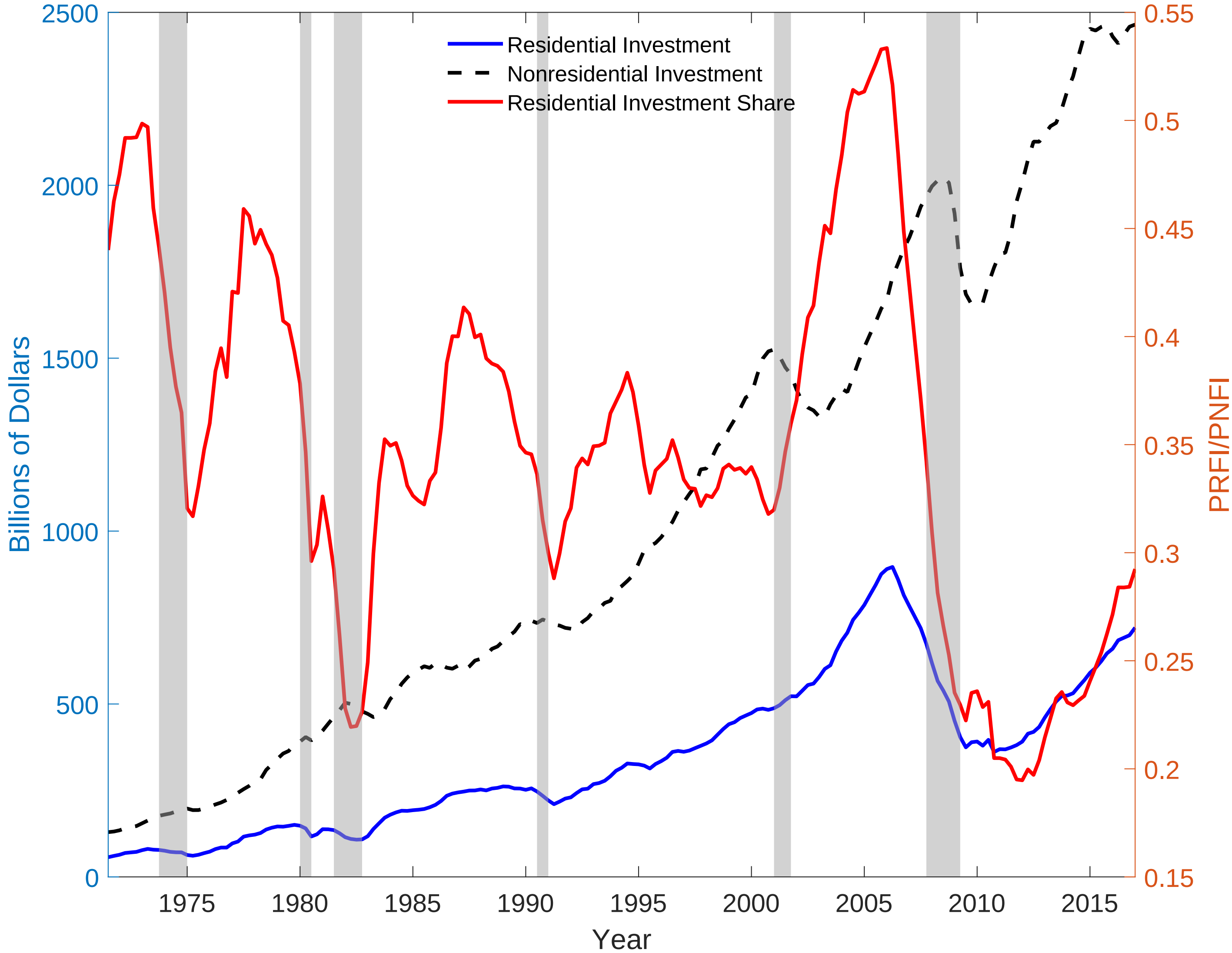
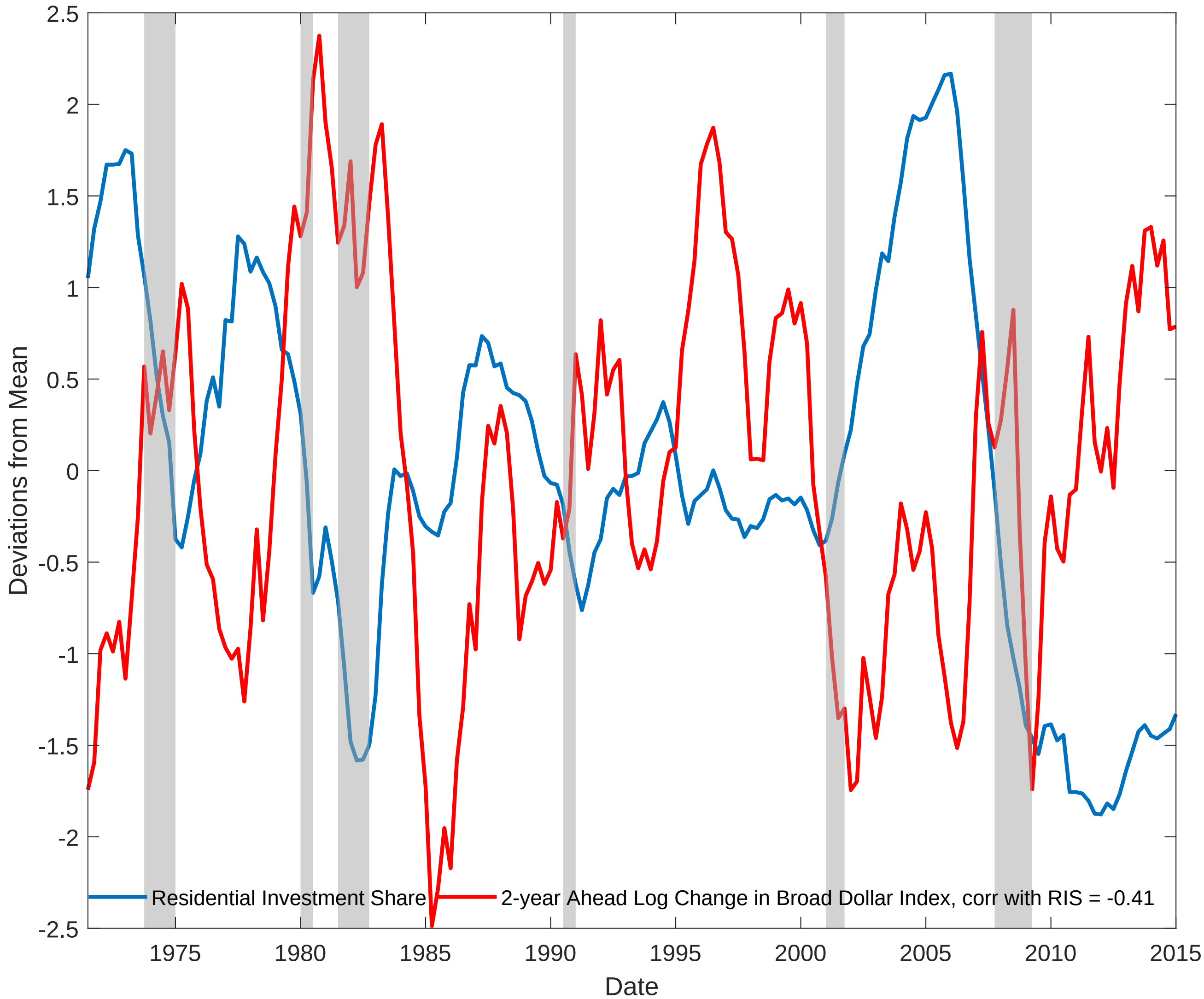
Figure 1: **Investment and Residential Investment Share**



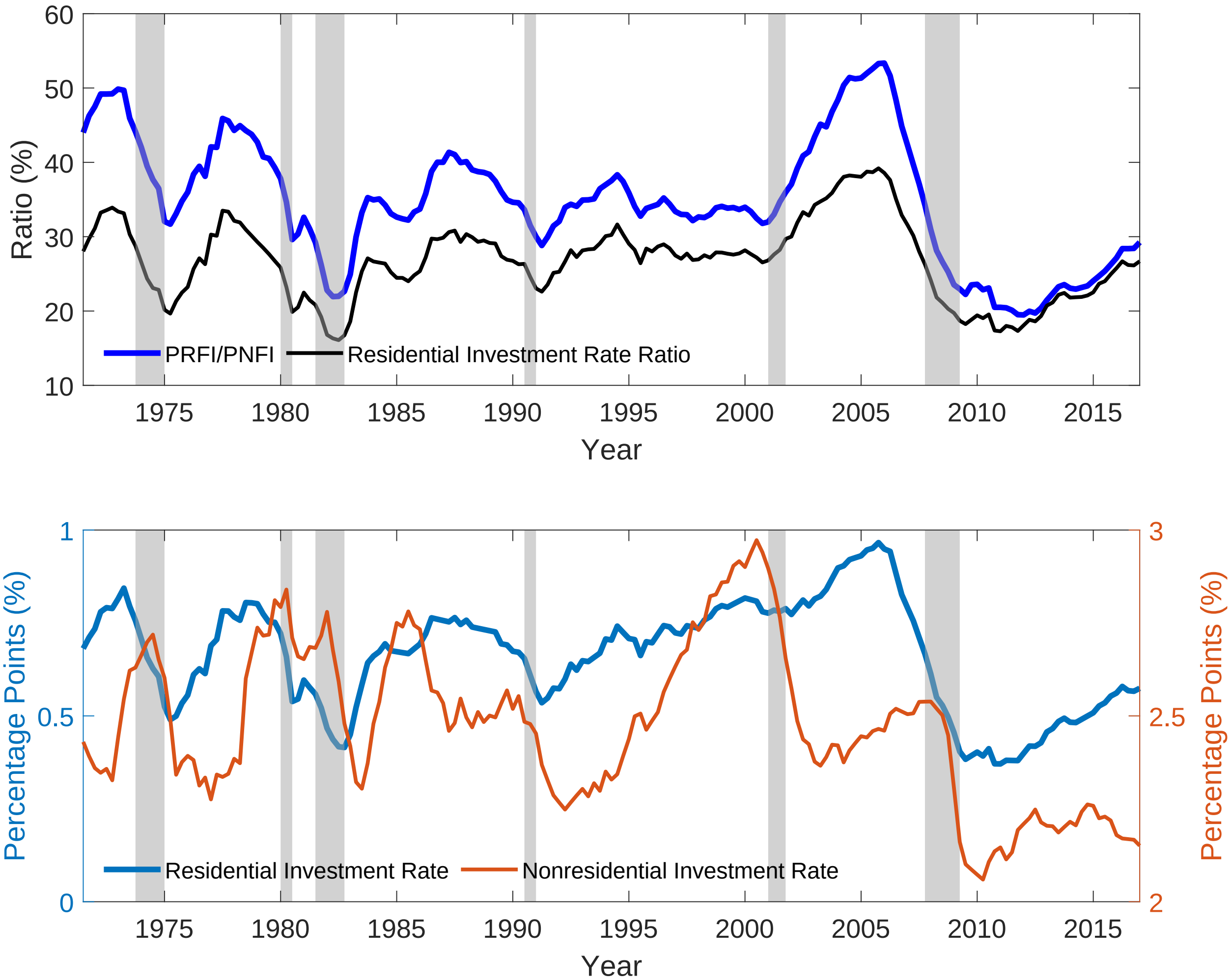
The figure plots the quarterly time-series of residential investment share (PRFI/PNFI), private residential fixed investment (PRFI) and private nonresidential fixed investment (PNFI). Both PRFI and PNFI are obtained from BEA. Shaded areas correspond to NBER recession dates. The sample spans the period 1971:Q2 to 2016:Q4.

Figure 2: **Housing Cycle and Dollar**



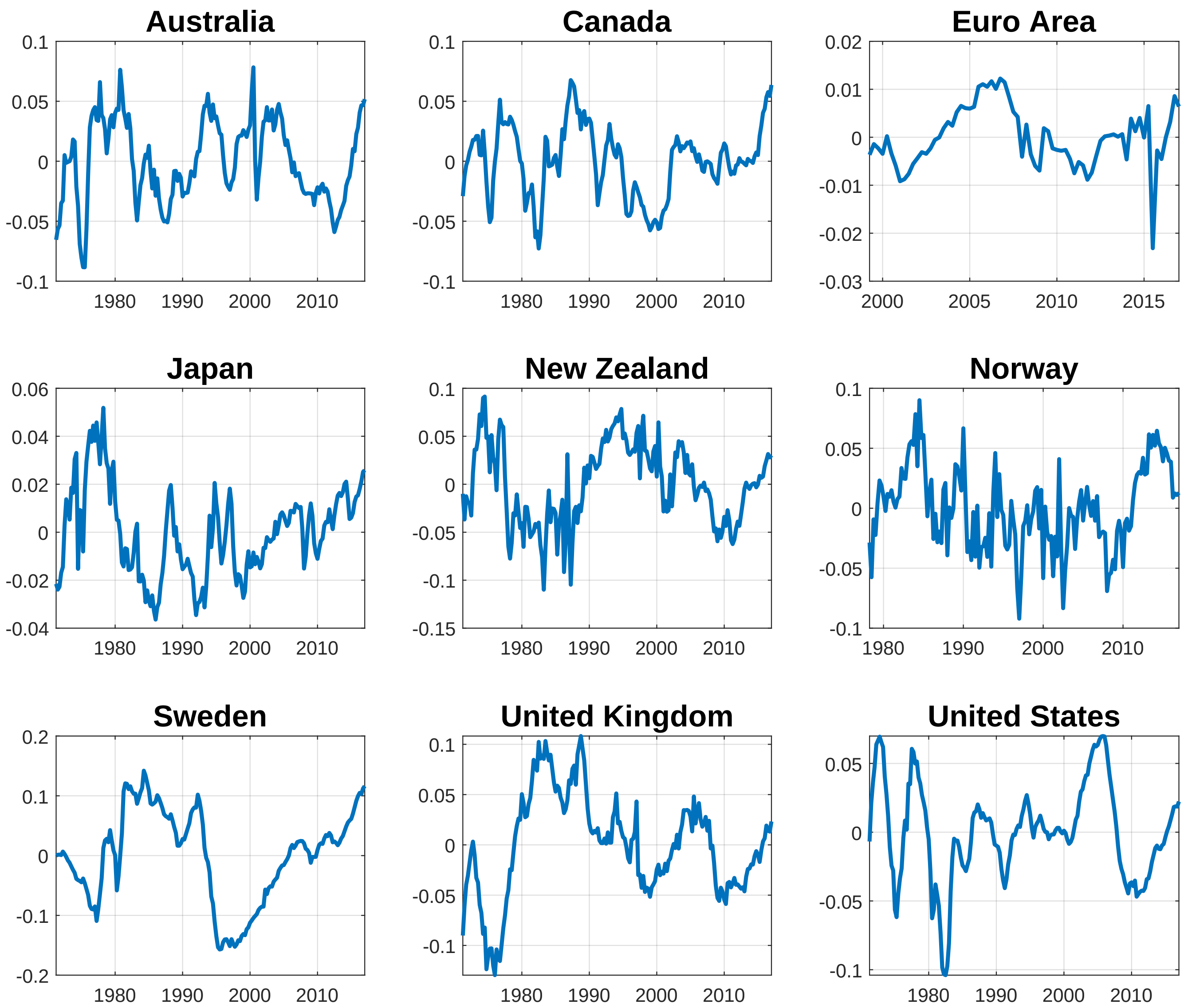
The figure plots the time-series of the standardized residential investment share and two-year ahead log changes in the broad dollar index. The dollar Index is computed as an equal weighted average value of the US dollar against a broad group of currencies which consists of 19 advanced economies and 13 emerging markets. Shaded areas correspond to NBER recession dates. The sample spans the period 1971:Q1 to 2016:Q4.

Figure 3: **Investment Rates and Investment Rate Ratio**



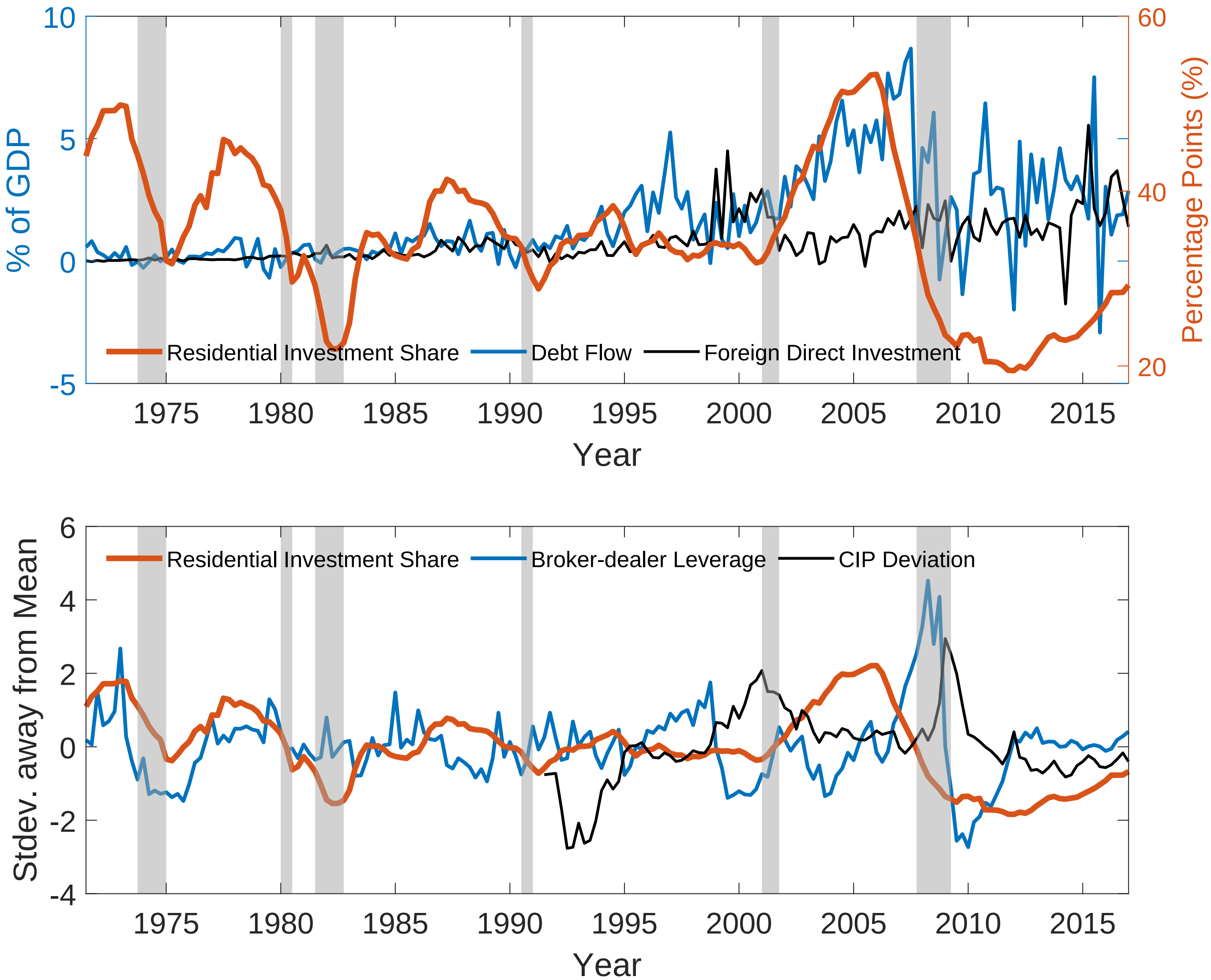
The top panel of the figure plots the quarterly time-series of the residential investment share (PNFI/PRFI) and investment rate ratios, and the bottom panel plots the residential and nonresidential investment rates. The investment rate ratio equals the ratio of residential and nonresidential investment rates. The residential and nonresidential investment rates are derived from via a perpetual inventory model. The sample spans the period 1971:Q2 to 2016:Q4.

Figure 4: **Residential Investment Shares By Country**



The figure plots the time series of the detrended residential investment share for each country. The residential investment share is computed as the ratio of the residential fixed capital formation to nonresidential and government fixed capital formation. The residential capital formation is defined as the gross fixed capital formation net of the nonresidential and government fixed capital formation. The quarterly data spans the period 1971:Q1 to 2016:Q4.

Figure 5: **Housing Cycles, Capital Flows, and Limit to Arbitrage**



The figure plots the time-series of the residential investment share, US debt flow from the rest of the world (scaled by GDP), foreign direct investment (scaled by GDP), five-year government bond CIP deviation, and HP-detrended broker-dealer leverage. The debt flow from the rest of the world is from the Flow of Funds (F.133, Line 22). The FDI is from the Flow of Funds (F.133, Line 34). Data on the five-year government bond CIP deviation is from Du and Schreger (2016), and broker-dealer leverage is calculated based on Adrian, Etula, and Muir (2014). Series in the bottom panel are standardized to have zero mean and unit variance. Shaded areas correspond to NBER recession dates. The sample spans the period 1971:Q1 to 2016:Q4.

Table 1: **Univariate Predictive Regressions**

$\frac{4}{h}\sum_{s=t+1}^{t+h}\Delta\log(dollar_s)=\alpha_0+\beta\mathrm{I}_{HKt}+\varepsilon_{t+h}$					
h	1	2	4	8	12
	Panel A: **Nominal Dollar Index**				
β	**−3.56**	**−3.51**	**−3.25**	**−2.72**	**−2.00**
t(NW)	[−3.16]	[−3.53]	[−3.81]	[−3.57]	[−3.14]
t(H)	(−3.37)	(−3.48)	(−3.34)	(−2.80)	(−2.09)
R^2 (%)	5.86	9.27	14.61	17.80	14.19
	Panel B: **Real Dollar Index**				
β	**−3.92**	**−3.86**	**−3.62**	**−3.04**	**−2.20**
t(NW)	[−3.27]	[−3.62]	[−3.87]	[−3.42]	[−2.78]
t(H)	(−3.56)	(−3.62)	(−3.47)	(−2.84)	(−2.03)
R^2 (%)	6.52	10.07	15.72	18.69	13.80
	Panel C: **Dollar Excess Return**				
β	**−3.55**	**−3.48**	**−3.19**	**−2.61**	−1.92
t(NW)	[−3.12]	[−3.43]	[−3.65]	[−3.57]	[−3.26]
t(H)	(−3.28)	(−3.33)	(−3.10)	(−2.47)	(−1.82)
R^2 (%)	5.60	8.65	13.07	14.82	11.43

This table reports results of the univariate forecasting regressions of dollar on the residential investment share. Coefficients are scaled to be interpreted as percentage changes in annual dollar changes or returns associated with one standard deviation increase in the predictor. The Dollar Index is computed as an equal weighted average of US dollar against a broad group of currencies which consists of 19 advanced economies and 13 emerging markets. The dollar excess return is computed as the average of log change in foreign exchange rates (in dollars) plus the US minus foreign interest rate differential. Newey-West(1987) and Hodrick(1992) t-statistics with lags that equal to the number of overlapping windows are reported in the parenthesis. Constants are omitted from the table. Bold numbers indicate significance at five percent level or higher. The sample spans the period 1971:Q1 to 2016:Q4.

Table 2: **Multivariate Predictive Regressions**

$\frac{4}{h}\sum_{s=t+1}^{t+h}\Delta\log(dollar_s) = \alpha_0 + \beta \mathrm{I}_{HKt} + \gamma \mathbf{X}_t + \varepsilon_{t+h}$					
h	1	2	4	8	12
	Panel A: **Nominal Dollar Index**				
I_{HKt}	**−3.23**	**−3.94**	**−3.97**	**−3.37**	**−2.55**
	(−2.81)	(−3.73)	(−4.14)	(−3.80)	(−2.97)
IP	0.05	0.34	0.88	0.97	0.64
	(0.05)	(0.36)	(1.17)	(1.64)	(1.29)
CPI	0.25	2.01	**2.20**	**2.09**	**2.00**
	(0.18)	(1.69)	(2.17)	(2.33)	(2.38)
R^f	1.45	0.69	0.81	0.68	0.49
	(1.06)	(0.56)	(0.73)	(0.66)	(0.49)
R^2 (%)	10.33	14.09	24.89	33.12	32.73
	Panel B: **Real Dollar Index**				
I_{HKt}	**−3.37**	**−4.23**	**−4.39**	**−3.70**	**−2.76**
	(−2.85)	(−3.84)	(−4.33)	(−3.89)	(−2.91)
IP	−0.43	0.25	0.96	0.99	0.66
	(−0.38)	(0.26)	(1.23)	(1.59)	(1.23)
CPI	0.81	2.32	**2.24**	**2.21**	**2.20**
	(0.57)	(1.84)	(2.06)	(2.26)	(2.34)
R^f	1.44	0.93	1.33	1.19	0.93
	(1.02)	(0.72)	(1.13)	(1.06)	(0.83)
R^2 (%)	12.84	16.60	27.91	37.17	36.06
	Panel C: **Dollar Excess Return**				
I_{HKt}	**−3.07**	**−3.75**	**−3.72**	**−3.11**	**−2.37**
	(−2.62)	(−3.42)	(−3.60)	(−3.03)	(−2.30)
IP	0.14	0.37	0.83	0.96	0.69
	(0.12)	(0.38)	(1.03)	(1.44)	(1.19)
CPI	0.18	1.97	**2.21**	**2.11**	1.92
	(0.13)	(1.59)	(2.03)	(2.04)	(1.91)
R^f	0.93	0.06	0.05	−0.22	−0.44
	(0.67)	(0.05)	(0.04)	(−0.18)	(−0.36)
R^2 (%)	10.02	12.06	19.90	24.28	20.57

This table reports results of the forecasting regressions of dollar on the residential investment share with control variables. Coefficients are scaled to be interpreted as percentage changes in annual dollar changes or returns associated with one standard deviation increase in the predictors. The Dollar Index is computed as an equal weighted average of US dollar against a broad group of currencies which consists of 19 advanced economies and 13 emerging markets. The dollar excess return is computed as the average of log change in foreign exchange rates (in dollars) plus the US minus foreign interest rate differential. Hodrick(1992) t-statistics with lags that equal to the number of overlapping windows are reported in the parenthesis. Constants are omitted from the table. Bold numbers indicate significance at five percent level or higher. The sample spans the period 1971:Q1 to 2016:Q4.

Table 3: **Alternative Measures**

$\frac{4}{h}\sum_{s=t+1}^{t+h} \log\left(dollar_s\right) = \alpha_0 + \beta \mathrm{I}_{HKt} + \varepsilon_{t+h}$						
h	1-quarter			2-year		
	Panel A: **Alternative Dollar Measures**					
	β	t(H)	R^2 (%)	β	t(H)	R^2 (%)
Advanced Economies	**−3.66**	(−2.96)	4.60	**−2.74**	(−2.39)	13.72
Emerging Markets	**−3.00**	(−3.26)	5.52	**−2.42**	(−2.92)	18.72
Trade-weighted	**−3.09**	(−3.26)	5.71	**−2.37**	(−2.52)	15.54
	Panel B: **Alternative Housing Cycles**					
	Nominal Dollar Index					
Include Com. Structure	**−3.44**	(−3.24)	5.47	**−2.83**	(−2.87)	18.75
Investment Rate Ratio	**−3.28**	(−3.09)	5.00	**−2.71**	(−2.88)	18.20
Employment Ratio	**−2.72**	(−2.54)	3.43	**−2.16**	(−2.14)	11.46
Loan Ratio	**−2.77**	(−2.59)	3.56	**−2.04**	(−3.14)	10.19
	Excess Return					
Include Com. Structure	**−3.65**	(−3.38)	5.91	**−3.01**	(−2.89)	19.19
Investment Rate Ratio	**−2.97**	(−2.73)	3.93	**−2.26**	(−2.15)	11.53
Employment Ratio	**−2.24**	(−2.04)	2.22	−1.98	(−1.80)	8.71
Loan Ratio	**−2.99**	(−2.74)	3.97	**−2.31**	(−3.41)	11.87

This table reports results of the predictive regressions of log dollar changes on various predictors. "Include Com. Structure" includes investment in nonresidential commercial structure sector as nontradable investment in calculating the investment share. The investment rate ratio equals the ratio of residential and nonresidential investment rates, derived from via a perpetual inventory model. The loan ratio is the ratio of new home mortgage loans to other new loans. The employment ratio is the ratio of total construction employees to other workers. Hodrick(1992) t-statistics with lags that equal to the number of overlapping windows are reported in the parenthesis. Bold numbers indicate significance at five percent or higher level. The sample spans the period 1971:Q1 to 2016:Q4.

Table 4: **Alternative Estimation and Sample**

$$\frac{4}{h}\sum_{s=t+1}^{t+h}\log\left(dollar_s\right)=\alpha_0+\beta \mathrm{I}_{HKt}+\varepsilon_{t+h}$$

h	1-quarter			2-year		
	Panel A: **Randomization Adjustment**					
	β_{OLS}	β_{NK}	p_{NK}	β_{OLS}	β_{NK}	p_{NK}
Dollar	−3.56	−3.45	0.98	−2.72	−2.59	0.99
Excess Return	−3.55	−3.42	0.97	−2.61	−2.51	0.99
	Panel B: **Alternative Sample Periods**					
	Nominal Dollar Index					
	β	t(H)	R^2 (%)	β	t(H)	R^2 (%)
Non-overlapping	**−3.56**	(−3.37)	5.86	**−2.74**	(−2.97)	17.96
Excluding GFC	**−3.12**	(−2.95)	4.74	**−2.70**	(−2.57)	16.20
1980Q1-2016Q4	**−3.04**	(−2.44)	3.96	**−2.53**	(−2.17)	13.87
1990Q1-2016Q4	**−2.48**	(−1.98)	3.50	**−2.02**	(−1.97)	15.26
2000Q1-2016Q4	−2.34	(−1.81)	4.59	**−2.05**	(−2.36)	25.44
	Dollar Excess Return					
Non-overlapping	**−3.55**	(−3.28)	5.59	**−2.56**	(−1.96)	12.15
Excluding GFC	**−2.93**	(−2.08)	3.33	−2.55	(−1.72)	10.22
1980Q1-2016Q4	**−3.48**	(−2.49)	4.44	−2.51	(−1.84)	11.85
1990Q1-2016Q4	**−3.50**	(−2.58)	5.79	−2.65	(−1.92)	16.13
2000Q1-2016Q4	**−3.42**	(−2.48)	8.29	**−2.70**	(−2.14)	25.51

This table reports alternative estimations for the predictive regression of dollar on the residential investment share. Reported predictive coefficients are scaled to be interpreted as the percentage change in expected annual dollar changes or returns for one standard deviation increase in the predictor. Panel A presents results from the Nelson and Kim (1993) randomization distribution adjusting for the Stambaugh (1989) bias. Panel B presents results for alternative sample periods. Bold numbers indicate significance at five percent or higher level. The sample spans the period 1971:Q1 to 2016:Q4 unless otherwise noted.

Table 5: **Out-of-sample Evidence**

$\frac{4}{h}\sum_{s=t+1}^{t+h} \Delta \log(dollar_s) = \alpha_0 + \beta \mathrm{I}_{HKt} + \varepsilon_{t+h}$					
h	1	2	4	8	12
	Panel A: **Out-of-Sample** R^2				
	Nominal Dollar Index				
In-sample $R^2(\%)$	5.86	9.27	14.61	17.79	14.19
Out-of-sample $R^2(\%)$	2.75	3.19	4.02	9.06	0.65
CW p-value	0.00	0.00	0.00	0.01	0.05
	Dollar Excess Return				
In-sample $R^2(\%)$	5.59	8.65	13.07	14.82	11.43
Out-of-sample $R^2(\%)$	2.76	2.69	1.66	6.31	1.15
CW p-value	0.00	0.00	0.00	0.01	0.06
	Panel B: **Alternative Windows**				
	Nominal Dollar Index				
Excluding GFC	6.43	10.15	11.21	17.69	6.38
1980Q1-2016Q4	6.24	9.37	9.94	19.30	8.95
1990Q1-2016Q4	3.54	5.91	5.37	16.56	24.23
2000Q1-2016Q4	1.86	4.53	0.99	10.49	24.21
	Dollar Excess Return				
Excluding GFC	5.98	8.52	6.95	11.09	2.87
1980Q1-2016Q4	5.93	8.14	6.47	13.27	4.56
1990Q1-2016Q4	4.61	7.04	6.03	10.53	11.93
2000Q1-2016Q4	3.93	7.28	4.42	9.60	17.30
	Panel C: **Utility Gain (%)**				
Full sample	4.63	4.62	3.78	1.61	0.00
Excluding GFC	5.40	5.20	4.38	2.07	0.65
1980Q1-2016Q4	4.46	4.56	3.39	1.51	−0.11
1990Q1-2016Q4	3.64	3.75	2.74	1.59	1.41
2000Q1-2016Q4	3.98	4.21	3.44	1.17	1.46

Panel A and B report out-of-sample R-squared and the associated Clark-West (2007) p-values, calculated using a recursive estimation with 5-year minimum burnin period and the rest of the sample as the evaluation period. Panel C reports the certainty-equivalent utility gain for the mean-variance investor who allocates investments between foreign and US T-bills using the predictive model compared to using historical mean benchmark model only. Excluding GFC excludes the Global Financial Crisis periods of 2007 to 2009 from the both burnin and evaluation sample. Alternative evaluation windows use various evaluation periods and all historical data up to that point as minimum burnin period.

Table 6: **International Evidence**

	Panel A: **Exchange Rates**				
h	1	2	4	8	12
AUS	0.83	0.01	0.33	0.48	0.52
	(0.31)	(0.00)	(0.18)	(0.35)	(0.48)
CAN	−2.05	−1.99	−2.12	−2.35	−1.08
	(−0.89)	(−1.10)	(−1.50)	(−2.16)	(−1.23)
EUR	−0.23	0.14	0.09	−0.20	−0.38
	(−0.22)	(0.18)	(0.14)	(−0.39)	(−1.02)
GBR	−5.90	−5.29	−4.56	−5.29	−4.66
	(−1.68)	(−1.81)	(−1.67)	(−2.10)	(−1.95)
JPN	−3.28	−3.54	−2.87	−2.42	−4.06
	(−1.24)	(−1.75)	(−3.28)	(−3.49)	(−1.66)
NOR	−0.90	−0.45	−0.65	−1.21	−1.15
	(−0.72)	(−0.48)	(−0.92)	(−2.46)	(−2.94)
NZL	0.03	0.20	0.12	−0.11	0.01
	(0.01)	(0.10)	(0.07)	(−0.08)	(0.01)
SWE	−1.23	−1.67	−2.45	−2.10	−1.62
	(−0.93)	(−1.43)	(−2.34)	(−2.49)	(−2.35)
USA	−4.75	−4.18	−4.61	−3.69	−3.04
	(−2.80)	(−2.80)	(−4.53)	(−3.99)	(−1.96)
	Average β				
G10	−2.28	−2.42	−2.84	−2.71	−1.72
[95% CI]	[−4.16, −0.39]	[−3.77, −1.08]	[−3.87, −1.82]	[−3.33, −2.08]	[−2.23, −1.20]
Ex US	−1.97	−2.08	−2.59	−2.56	−1.55
[95% CI]	[−4.13, 0.20]	[−3.54, −0.61]	[−3.67, −1.50]	[−3.23, −1.89]	[−2.14, −0.96]
	Joint χ^2				
G10	12.28	19.86	37.84	130.11	75.59
[p-value]	[0.09]	[0.02]	[0.00]	[0.00]	[0.00]
Ex US	8.34	13.93	31.48	125.58	62.48
[p-value]	[0.20]	[0.08]	[0.00]	[0.00]	[0.00]

Table 6 continues on the next page

Panel B: **Excess Returns**					
h	1	2	4	8	12
AUS	−2.23	−3.17	−2.39	−1.77	−1.70
	(−0.83)	(−1.44)	(−1.34)	(−1.30)	(−1.39)
CAN	−3.46	−3.47	−3.24	−2.88	−0.98
	(−1.44)	(−1.81)	(−2.16)	(−2.35)	(−0.87)
EUR	−0.90	−0.19	−0.09	−0.04	−0.06
	(−0.80)	(−0.22)	(−0.13)	(−0.07)	(−0.14)
GBR	−6.32	−5.75	−4.73	−5.09	−3.92
	(−1.78)	(−1.91)	(−1.65)	(−1.86)	(−1.48)
JPN	−2.67	−2.86	−2.66	−2.15	−2.55
	(−1.11)	(−1.55)	(−2.86)	(−2.73)	(−0.90)
NOR	−0.16	−0.19	−0.10	−0.44	−0.32
	(−0.13)	(−0.20)	(−0.13)	(−0.82)	(−0.74)
NZL	−2.40	−1.94	−1.70	−1.32	−0.76
	(−0.87)	(−0.97)	(−1.06)	(−1.05)	(−0.68)
SWE	−0.09	−0.38	−1.03	−0.57	−0.02
	(−0.07)	(−0.31)	(−0.96)	(−0.63)	(−0.03)
USA	−3.51	−3.69	−4.51	−3.53	−2.98
	(−2.03)	(−3.10)	(−4.15)	(−3.40)	(−2.73)
	Average β				
G10	−2.97	−3.06	−3.26	−2.74	−1.46
[95% CI]	[−4.85, −1.09]	[−4.39, −1.72]	[−4.29, −2.22]	[−3.47, −2.01]	[−2.17, −0.76]
Ex US	−2.65	−2.70	−2.99	−2.59	−1.29
[95% CI]	[−4.80, −0.51]	[−4.12, −1.27]	[−4.07, −1.91]	[−3.49, −1.69]	[−2.23, −0.35]
	Joint χ^2				
G10	17.22	29.29	43.19	81.87	52.87
[p-value]	[0.05]	[0.00]	[0.00]	[0.00]	[0.00]
Ex US	9.43	20.96	36.69	49.09	36.73
[p-value]	[0.18]	[0.01]	[0.00]	[0.00]	[0.00]

This table reports the coefficients and Hodrick (1992) t-statistics from forecasting regressions of the log change of the local currency index on the detrended ratio of the local residential investment to the nonresidential investment. The currency index is an equal-weighted exchange rates or currency excess returns against a basket of currencies, in unit of domestic currency. The control variables include domestic GDP, inflation, interest rate, and current level of currency index or excess returns. The table also reports the average coefficients across all countries, and the associated GMM 95% confidence interval is reported in brackets. The joint test chi-square test statistics are estimated via GMM, and the associated p-values are reported in brackets. Constants and coefficients of control variables are omitted from the table. The sample panel is unbalanced and the longest panel spans the period 1971:Q1 to 2016:Q4.

Table 7: **Relative Price Adjustments**

	Panel A: **Relative Price Changes**				
	$\frac{4}{h}\sum_{s=1}^{h+1} y_{t+s} = \alpha_0 + \beta \mathrm{I}_{HKt} + \varepsilon_{t+h}$				
h	1	2	4	8	12
	Univariate				
β	**−1.88**	**−1.97**	**−2.12**	**−2.06**	**−1.73**
	(−3.48)	(−3.50)	(−3.80)	(−3.87)	(−3.58)
R^2 (%)	6.25	9.83	19.03	29.76	31.95
	Controlling for IP and Gross Investment				
β	**−1.82**	**−2.08**	**−2.46**	**−2.45**	**−1.98**
	(−2.50)	(−2.87)	(−3.61)	(−4.11)	(−3.76)
IP	**−2.10**	**−1.78**	−0.71	0.24	0.26
	(−2.30)	(−2.07)	(−0.95)	(0.43)	(0.62)
I	1.07	1.33	1.06	0.85	0.74
	(1.18)	(1.65)	(1.63)	(1.73)	(1.85)
R^2 (%)	8.55	12.08	19.70	31.59	34.44
	Panel B: **Aggregate Output Growth**				
	$\log(Y_{t+h}/Y_t) = \alpha_0 + \beta \log(Y_{NTt+h}/Y_{NTt}) + \varepsilon_{t+h}$				
Condition	Low I_{HKt}			High I_{HKt}	
h	1-year	2-year		1-year	2-year
β	**0.68**	**0.64**		**0.90**	**0.92**
	(5.16)	(5.92)		(9.00)	(8.83)
R^2 (%)	54.72	62.71		77.87	78.59

Panel A reports results of forecasting regressions with the residential investment share. IP refers to the one-year US industrial production growth. I refers to the US gross investment growth. Panel B reports results of regressing the h-year growth rate of aggregate US gross output Y on that of nontradable gross output Y_{NT}, conditional on residential investment share. The relative price of nontradables to tradables is calculated according to Betts and Kehoe (2006), see texts for details. Constants are omitted from the table. Hodrick (1992) t-statistics with lags that equal to the number of overlapping windows are reported in the parenthesis. Coefficients for Panel A are scaled to be interpreted as percentage changes in annualized relative price changes associated with one standard deviation increase in the predictor. The sample is quarterly for Panel A and annual for Panel B, spanning 1971:Q1 to 2016:Q4.

Table 8: **Business Cycle and Risk Premium**

	Panel A: **Correlations**				
	IP Growth	Macro Uncertainty	EPU	VIX	Net Import
	0.30	−0.19	−0.54	−0.20	0.23
	$[0.19, 0.41]$	$[-0.31, -0.07]$	$[-0.66, -0.42]$	$[-0.34, -0.06]$	$[0.07, 0.39]$
	Interest Rate	Mortgage Rate	Term Spread	Default Spread	EBP
	0.14	0.10	−0.21	−0.33	−0.30
	$[-0.02, 0.31]$	$[-0.06, 0.26]$	$[-0.35, -0.08]$	$[-0.43, -0.22]$	$[-0.43, -0.17]$
	Panel B: **Additional Predictability**				
	$\frac{4}{h}\sum_{s=t+1}^{t+h} y_s = \alpha_0 + \beta I_{\mathrm{HKt}} + \varepsilon_{t+h}$				
h	1	2	4	8	12
	Equity Returns				
β	−2.64	−2.71	−3.01	**−3.56**	**−3.85**
	(−1.03)	(−1.19)	(−1.45)	(−2.00)	(−2.54)
R^2 (%)	0.58	1.14	2.95	8.96	17.17
	Bond Returns				
β	**−1.11**	**−1.14**	**−1.17**	**−1.08**	**−1.02**
	(−2.55)	(−2.85)	(−3.01)	(−3.21)	(−3.34)
R^2 (%)	3.73	6.94	12.67	21.82	28.93
	Dollar Volatility				
β	**−1.09**	**−1.07**	**−1.00**	**−0.86**	**−0.76**
	(−7.45)	(−5.44)	(−4.09)	(−3.19)	(−2.58)
R^2 (%)	23.39	23.69	23.99	24.99	22.89

This table reports business cycle properties of the residential investment share. Panel A reports the correlations between the residential investment share and contemporaneous and one-year forward-looking business cycle indicators. IP Growth refers to the growth rate of industrial production. Net import is the difference between total import and export scaled by GDP. Term spread, default spread and EBP are the difference between ten-year and one-year T-bill rate, the difference in BAA and AAA corporate bonds rate, and the excess bond premium, respectively. Interest rate is the three-month T-bill rate and the mortgage rate is the 30-Year Fixed Rate Mortgage Average. The bootstrapped 95% confidence interval are reported in the parenthesis. Table B reports the predictive regression coefficients, Hodrick t-statistics, and R-squared from forecasting regressions of log annualized CRSP value-weighted, Barclays BAA index returns, and dollar volatility on residential investment share. Volatility measures are calculated using a ten-year rolling window. Bold numbers indicate significance at five percent or higher level. Constants are omitted from the table. The longest sample spans the period 1971:Q1 to 2016:Q4.

Table 9: **Alternative Mechanisms**

	Panel A: **Capital Flows**			
Control	Debt Flow		Foreign Direct Investment	
h	One-quarter	Two-year	One-quarter	Two-year
	Full Sample			
I_{HK} Fitted	0.70	0.61	**−3.00**	−1.41
	(0.65)	(0.64)	(−2.80)	(−1.40)
I_{HK} Residual	**−3.64**	**−2.69**	**−2.76**	**−2.34**
	(−3.37)	(−2.57)	(−2.57)	(−2.28)
R^2 (%)	6.06	16.31	7.35	15.43
	Post-1990			
I_{HK} Fitted	−0.74	−0.28	**−3.69**	−1.26
	(−0.51)	(−0.23)	(−2.60)	(−1.04)
I_{HK} Residual	**−3.71**	**−2.91**	**−2.96**	−2.65
	(−2.56)	(−2.04)	(−2.08)	(−1.83)
R^2 (%)	5.97	17.26	9.36	16.71
	Panel B: **Limits to Arbitrage**			
Control	CIP Deviation		BD Leverage	
h	One-quarter	Two-year	One-quarter	Two-year
I_{HKt}	**−3.20**	−2.67	**−3.73**	**−2.55**
	(−2.33)	(−1.88)	(−3.46)	(−2.41)
$\mathrm{Control}_{t+h} \times I_{\mathrm{HKt}}$	−1.16	−0.20	−1.89	−0.85
	(−0.78)	(−0.14)	(−1.75)	(−0.87)
R^2 (%)	6.34	16.36	7.16	16.38

This table reports results of the forecasting regressions of h-quarter ahead dollar excess returns. The predictors in Panel A are residual and fitted value constructed by regressing the residential investment share on capital flows. Constants and first-step regression estimates are omitted from the table. The predictors in Panel B are the residential investment share and the share interacted with CIP deviation and broker-deal leverage. Hodrick (1992) t-statistics with lags that equal to the number of overlapping windows are reported in the parenthesis. Coefficients are scaled to be interpreted as percentage changes in annualized relative price changes associated with one standard deviation increase in the predictor. The debt flow is from the Flow of Funds (F.133, Line 22). FDI is from the Flow of Funds (F.133, Line 34). Data on the five-year government bond CIP deviation is from Du and Schreger (2016), and broker-dealer leverage is calculated based on Adrian, Etula, and Muir (2014). Bold numbers indicate significance at five percent or higher level. The longest common sample spans period 1971:Q1 to 2016:Q4.

Appendix

A The Randomization Methodology

In the standard time-series predictive regressions in which returns of various holding period are regressed on a variable measured at the end of the last period, the regression coefficient is subject to an upward small-sample bias if the innovations with the predictor are negatively correlated with contemporaneous returns (Stambaugh, 1999). To address this issue, we follow Nelson and Kim (1993) randomization method that requires the estimation of the autoregressive process for the residential investment share:

$$I_{HKt+h} = \theta + \rho I_{HKt} + \eta_{t+h}. \tag{A1}$$

The pairs (η_{t+h}, R_{t+h}) are then randomized by resampling without replacement. From this randomized series, pseudo-independent variables of I_{HKt+h} are created by substituting the randomized η_{t+h} in the estimate of Equation (A1) along with estimated θ and ρ. The initial value of I_{HKt} is picked from a random time period. We then estimate a univariate forecasting regression using these pseudo data and store the estimate of β. We repeat this randomization process for 1,000 iterations. The bias is defined as the sample mean of these 1,000 estimates of β. The associated one-sided p-value is computed as the estimated probability of obtaining a coefficient that is at least as large as the estimate of β based on the actual data. A p-value greater than 0.95 implies the coefficient is significantly negative at the five percent significance level.

B Supplementary Results

This section presents supplementary results.

B.1 Sector Tradability

Table A1 presents the tradability ratio, investment-to-sales ratio, and asset-to-sales ratio for the most and least tradable industries. The tradability ratio is from Tian (2018), calculated as the ratio of exports for the industry to total industry output. In order to obtain the data on investment, asset and sale at the industry level from Compustat, we further match the Input-Output industries (IO code) to NAICS industry code according to the concordance between the codes used in the I-O tables and the Census industry classification provided by BEA. The investment-to-sale ratio is defined as the ratio of "Property, Plant and Equipment" (PPEGT) to "Sales Turnover"(Sale). The asset-to-sale ratio is defined as the ratio of "Assets" (AT) to sales. For each industry, we report the time-series average of each ratio. The longest overlapping sample spans the period 1971Q2 to 2016Q4.

B.2 Controlling for Forward Rates

Arguably, the forward discount is a measure of interest rates that is more pertinent to the currency market. However, the forward data is only available from 1983 onwards. Lustig, Roussanov, and Verdelhan (2014) document that a two-factor model of the average forward discount and one-year US industrial production (IP) growth explains a large fraction of dollar carry variation at short and medium-horizons. We focus on the post-1983 sample and control for IP growth and the average forward discount simultaneously.

Table A2 reports results from multivariate forecasting regression of log dollar changes on residential investment ratio, average forward discount, and one-year US IP growth. Our residential investment share still significantly predicts the dollar in short, medium, and long horizons after controlling for the two-factor model. Magnitudes of our predictive coefficients are very close to the univariate baseline estimation. For example, the coefficient is -2.72% per annum over the two-year horizon in the univariate regression and -2.52% when controlling for the two-factor model. In terms of controls, both IP growth and average forward discounts retain statistical explanatory power in short to medium horizons. In short, the residential investment share captures different information from sector-neutral business cycle variations, captured by IP growth and forward discounts.

B.3 Additional Controls

In this section, we further control for additional currency predictors or potential forces that drive housing cycles. Table A3 reports results from multivariate prediction regressions of future dollar changes or excess returns on the residential investment share and control variables. For control variables, we first include two business cycle predictors: the excess bond premium (EBP) based on credit spreads from Gilchrist and Zakrajšek (2012), and the slope of the Treasury yield curve, measured by the term spread. Second, we include the credit-to-GDP ratio and the broker-dealer leverage to capture credit or financial cycles. Credit cycles have been proposed to be a potential source of housing cycles. Adrian, Etula, and Groen (2011) finds that the latter predicts expected currency returns. We also control for the real exchange rate level. Dahlquist and Penasse (2017) find that the level of the real exchange rate is a strong predictor of currency returns at longer horizons. We finally conduct a "kitchen-sink" horserace that includes all control variables above and all control variables included in Table 2.

In all cases, Table A3 shows that the residential investment share still exhibits substantial forecasting power for changes in future exchange rates and excess returns in both one-quarter and two-year horizons. The coefficients of the share remain statistically significant and the magnitudes are largely unchanged from the univariate estimates reported in Table 1. These findings show that the share contains independent information from existing predictors.

B.4 Univariate International Evidence

Table A4 reports the GMM estimation results for G10 currency indices with no controls. Most point estimates are negative for various countries and horizons. The average coefficient is significantly negative at 5% or higher significance across all horizons. For exchange rate changes, the coefficients are jointly different from zero at 5% or higher significance from 4-quarter onwards. For currency excess returns, coefficients are jointly different from zero at 5% or higher significance from 2-quarter onwards.

C An Incomplete Markets Framework

We now benchmark our results against complete markets to understand the nature of the incompleteness that our results imply. Under complete markets, the expected dollar premium reflects the riskiness of US and foreign SDFs:

$$E_t rx_{t+1} = \frac{1}{2}\sigma_t^2(m_{t+1}^*) - \frac{1}{2}\sigma_t^2(m_{t+1}). \tag{A2}$$

In words, the dollar premium is higher when the US marginal utilities are less risky, or the dollar premium is procyclical. A casual examination of the relation between dollar and US business cycles or other asset classes would suggest little cyclicality. Lustig, Roussanov, and Verdelhan (2014) provides evidence of countercyclical foreign currency premium or procyclical dollar premium. Our evidence identifies a form of the countercyclical dollar premium instead, which goes against the implication of complete markets. In sum, our evidence points to market incompleteness and time varying limited risk sharing.

We now take a reduced form approach and now characterize the necessary conditions under incomplete markets. Following Backus, Foresi, and Telmer (2001), exchange rate changes and premium can be rewritten as

$$\begin{aligned}\Delta q_{t+1} &= m_{t+1} - m^*_{t+1} + \eta_{t+1}, \\ rx_{t+1} &= \frac{1}{2}\sigma^2_t(m^*_{t+1}) - \frac{1}{2}\sigma^2_t(m_{t+1}) + \eta_{t+1},\end{aligned} \tag{A3}$$

where η is a wedge between the Backus-Smith condition under generic preferences and captures a time-varying distance from market completeness. Because the dollar premium is countercyclical in housing cycles, the wedge needs to be countercyclical in housing cycles as well. Formally, empirical results suggest that the dollar premium falls when the US SDF is less risky, or $cov_t(rx_{t+1}, \frac{1}{2}\sigma^2_t(m_{t+1})) > 0$. The condition implies

$$cov_t(\sigma^2_t(m_{t+1}), E_t\eta_{t+1}) > 0, \tag{A4}$$

or in words, a countercylical expected wedge in housing cycles.

Furthermore, the variance of the dollar premium can be calculated as follows:

$$\sigma^2_t(rx_{t+1}) = \sigma^2_t(\eta_{t+1}) \tag{A5}$$

Because we show that the dollar premium volatility is countercylical, the wedge needs to heteroskedastic with a countercylical time-varying conditional variance as well. In conclusion, the new evidence of currency predictability suggests market incompleteness and time-varying international risk sharing.

Table A1: **Most and Least Tradable Industries**

Industry	Tradability Ratio	Investment/Sales	Asset/Sales
	Top Tradable Sectors		
Optical Instrument and lens manufaturing	0.88	2.96	7.96
Fishing	0.74	16.51	19.48
Oil and gas field machinery manufaturing	0.64	3.22	9.38
Aircraft equipment manufaturing	0.57	1.72	4.07
Electronic component manufaturing	0.50	4.57	10.99
	Bottom Tradable Sectors		
Auto repair and maintenance service	0.000019	0.63	1.46
Funds, Trusts, and other financial vehicles	0.000014	0.77	5.77
Weight and diet control service	0.000012	0.22	2.99
Child day care service	0.000002	0.97	2.58
Personal care service	0.000001	0.39	3.61

This table reports the tradability ratio, investment-to-sale ratio, and asset-to-sale ratio for top and bottom tradable sectors. The tradability ratio is from Tian (2018). The data on investment, total asset, and sale at the industry level is from Compustat. The sample spans the period 1971:Q1 to 2016:Q4.

Table A2: **Controlling for LRV Two-factor Model**

$\frac{4}{h}\sum_{s=t+1}^{t+h}\Delta\log(dollar_s)=\alpha_0+\beta \mathrm{I}_{HKt}+\gamma\mathbf{X}_t+\varepsilon_{t+h}$					
h	1	2	4	8	12
	Panel A: **Nominal Dollar Index**				
I_{HKt}	**−2.71**	**−3.09**	**−3.05**	**−2.52**	**−2.11**
	(−2.11)	(−2.60)	(−2.84)	(−2.53)	(−2.20)
IP	0.86	**1.17**	**1.29**	**0.98**	**0.69**
	(1.64)	(2.46)	(3.12)	(2.80)	(2.28)
AFD	−1.78	−1.91	−1.27	−0.55	−0.23
	(−1.40)	(−1.64)	(−1.22)	(−0.59)	(−0.26)
R^2 (%)	10.94	15.42	25.58	29.26	25.98
	Panel B: **Real Dollar Index**				
I_{HKt}	**−2.96**	**−3.47**	**−3.47**	**−2.83**	**−2.30**
	(−2.20)	(−2.76)	(−3.09)	(−2.71)	(−2.17)
IP	0.87	**1.23**	**1.37**	**1.06**	**0.77**
	(1.60)	(2.45)	(3.17)	(2.92)	(2.36)
AFD	−1.78	−1.91	−1.34	−0.65	−0.23
	(−1.35)	(−1.55)	(−1.24)	(−0.66)	(−0.24)
R^2 (%)	12.20	15.78	27.11	32.14	26.92
	Panel C: **Dollar Excess Return**				
I_{HKt}	**−2.75**	**−3.11**	**−3.02**	**−2.45**	−2.05
	(−2.14)	(−2.63)	(−2.76)	(−2.23)	(−1.80)
IP	0.81	**1.13**	**1.27**	**1.03**	**0.74**
	(1.57)	(2.39)	(3.01)	(2.67)	(2.09)
AFD	**−3.29**	**−3.57**	**−2.79**	−1.66	−1.05
	(−2.51)	(−3.02)	(−2.61)	(−1.60)	(−1.04)
R^2 (%)	14.79	21.55	31.79	31.96	24.99

This table reports the predictive regression estimates of the log change of the US dollar index and dollar excess returns on the residential investment share and control variables. For comparison, reported predictive coefficients are scaled to be interpreted as the percentage change in expected annual dollar changes or returns resulting from a one standard deviation increase in each predictor variable. Control variables include one-year IP growth (IP), average forward discount (AFD), and the current level of the dependent variable. Hodrick(1992) t-statistics are reported in parentheses. Constants and coefficients for current levels of the dependent variable are omitted from the table. Bold numbers indicate significance at five percent or better level. The sample spans the period 1983:Q1 to 2016:Q4.

Table A3: **Additional Controls**

$$\frac{4}{h}\sum_{s=t+1}^{t+h}\Delta\log(dollar_s)=\alpha_0+\beta \mathrm{I}_{HKt}+\gamma\mathbf{X}_t+\varepsilon_{t+h}$$

Controls	Excess Bond Premium	Term Spread	Credit/GDP	Broker-dealer Leverage	Real Dollar	All
Panel A: Nominal Dollar Index						
One-quarter						
I_{HKt}	**−3.73**	**−3.91**	**−4.11**	**−3.67**	**−3.97**	**−3.54**
	(−3.21)	(−3.63)	(−3.72)	(−3.46)	(−3.63)	(−2.89)
Control	−1.56	−1.63	−1.78	1.01	−1.51	
	(−1.38)	(−1.52)	(−1.61)	(0.95)	(−1.36)	
R^2 (%)	5.64	7.04	7.19	6.33	6.82	12.22
Two-year						
I_{HKt}	**−3.23**	**−3.23**	**−3.13**	**−2.76**	**−3.16**	**−3.81**
	(−3.24)	(−3.90)	(−3.26)	(−2.85)	(−3.37)	(−4.46)
Control	**−2.23**	**−2.45**	−1.48	0.40	**−2.06**	
	(−2.75)	(−3.16)	(−1.49)	(0.50)	(−2.03)	
R^2 (%)	25.85	32.07	22.61	18.19	26.48	45.01
Panel B: Dollar Excess Return						
One-quarter						
I_{HKt}	**−3.88**	**−4.00**	**−3.81**	**−3.66**	**−3.67**	**−3.60**
	(−3.27)	(−3.65)	(−3.35)	(−3.37)	(−3.26)	(−2.87)
Control	−2.12	−2.10	−0.83	1.01	−0.43	
	(−1.85)	(−1.92)	(−0.73)	(0.93)	(−0.37)	
R^2 (%)	6.17	7.47	5.87	6.41	5.67	12.64
Two-year						
I_{HKt}	**−3.22**	**−3.11**	**−2.77**	**−2.66**	**−2.82**	**−3.80**
	(−3.13)	(−3.31)	(−2.54)	(−2.53)	(−2.61)	(−4.18)
Control	**−2.81**	**−2.37**	−0.58	−0.46	−0.96	
	(−3.35)	(−2.71)	(−0.51)	(0.54)	(−0.82)	
R^2 (%)	27.59	26.91	15.48	15.29	16.52	42.69

This table reports the coefficients, Hodrick t-statistics and R^2 from forecasting regressions of h-quarter ahead log change of nominal dollar index or dollar excess returns on residential investment share and control variable X specified in each column header. The sources of control variables are described in the text. Constants and coefficients of control variables from the specification with all controls are omitted from the table. The longest sample spans period 1971:Q1 to 2016:Q4.

Table A4: **Univariate International Evidence**

	Exchange Rates					**Excess Returns**				
h	1	2	4	8	12	1	2	4	8	12
AUS	−0.72	−0.90	−0.38	−0.17	0.04	−3.38	−3.44	−2.68	−2.01	−1.69
	(−0.26)	(−0.40)	(−0.20)	(−0.11)	(0.03)	(−1.24)	(−1.59)	(−1.49)	(−1.39)	(−1.28)
CAN	−1.83	−1.53	−1.08	−0.99	−0.79	−1.28	−0.92	−0.34	0.02	0.45
	(−1.18)	(−1.17)	(−0.95)	(−1.08)	(−1.04)	(−0.81)	(−0.67)	(−0.28)	(0.02)	(0.52)
EUR	−0.49	−0.06	0.15	0.09	0.03	−1.09	−0.43	−0.07	0.14	0.11
	(−0.47)	(−0.08)	(0.22)	(0.16)	(0.06)	(−0.99)	(−0.53)	(−0.09)	(0.24)	(0.26)
GBR	−1.01	−0.91	−0.79	−0.76	−0.91	0.39	0.55	0.84	1.10	1.07
	(−0.66)	(−0.69)	(−0.62)	(−0.62)	(−0.76)	(0.25)	(0.39)	(0.60)	(0.80)	(0.81)
JPN	−4.35	−6.24	−6.90	−5.95	−5.50	−2.93	−3.79	−4.14	−5.91	−3.00
	(−1.73)	(−2.23)	(−3.63)	(−3.54)	(−1.87)	(−1.62)	(−2.04)	(−3.13)	(−2.77)	(−1.17)
NOR	−0.62	−0.21	−0.30	−1.08	−1.09	−0.63	−0.27	−0.41	−0.89	−0.80
	(−0.52)	(−0.23)	(−0.43)	(−2.32)	(−2.86)	(−0.52)	(−0.29)	(−0.55)	(−1.50)	(−1.46)
NZL	1.02	1.08	1.11	0.73	0.75	−3.18	−2.87	−2.57	−2.19	−1.53
	(0.44)	(0.61)	(0.72)	(0.58)	(0.64)	(−1.37)	(−1.65)	(−1.80)	(−1.85)	(−1.43)
SWE	−1.51	−1.67	−1.91	−1.89	−1.63	−0.06	−0.19	−0.38	−0.27	0.05
	(−1.22)	(−1.46)	(−1.83)	(−2.29)	(−2.40)	(−0.04)	(−0.16)	(−0.34)	(−0.29)	(0.05)
USA	−2.56	−2.44	−2.25	−1.82	−1.59	−3.20	−3.01	−2.67	−1.99	−1.65
	(−2.03)	(−2.11)	(−2.01)	(−1.74)	(−2.59)	(−2.45)	(−2.40)	(−2.09)	(−2.60)	(−2.37)
Average β	−1.90	−1.87	−2.13	−1.94	−1.25	−2.42	−2.29	−2.37	−1.82	−0.90
[95% CI]	[−3.33, −0.47]	[−3.08, −0.66]	[−3.14, −1.13]	[−2.54, −1.34]	[−1.70, −0.80]	[−3.86, −0.97]	[−3.49, −1.09]	[−3.36, −1.38]	[−2.48, −1.15]	[−1.50, −0.30]
Joint χ^2	11.54	14.62	33.22	78.64	89.84	16.23	21.71	46.83	72.08	36.73
[p-value]	[0.14]	[0.10]	[0.00]	[0.00]	[0.00]	[0.06]	[0.01]	[0.00]	[0.00]	[0.00]

This table reports the coefficients and Hodrick (1992) t-statistics from univariate forecasting regressions of the log change of the local currency index on the detrended ratio of the local residential investment to the nonresidential investment. The currency index is an equal-weighted exchange rates or currency excess returns against a basket of currencies, in unit of domestic currency. The table also reports the average coefficients across all countries, and the associated GMM 95% confidence interval is reported in brackets. The joint test chi-square test statistics are estimated via GMM, and the associated p-values are reported in brackets. Constants are omitted from the table. The sample panel is unbalanced and the longest panel spans the period 1971:Q1 to 2016:Q4.