Online Annex 2.1. Data and Empirical Methodology

A. Data Sources and Transformations

Annex Table 2.1.1. Data Sources and Transformations

Variable	Description	Source
Capital Flow Measures	Real estate inflow restrictions and overall inflow restrictions	Fernández and others (2016); IMF staff calculations
Capital Flows	Foreign direct investment, portfolio, and other capital flows at quarterly frequency	IMF, Balance of Payments Statistics database; IMF staff calculations
Credit Growth	Percent change in the depository corporations' claims on the private sector	Bank for International Settlements; Haver Analytics; IMF, International Financial Statistics database
Credit-to-GDP Booms	Dummy for credit-to-GDP boom, as defined in Jordà and Taylor (2016)	Jordà and Taylor (2016)
Credit-to-GDP Ratio	Total credit provided to the private nonfinancial sector by domestic money banks as a share of GDP	Bank for International Settlements; Haver Analytics
Financial Conditions Index	For methodology and variables included in the FCI, refer to Annex 3.2 of the October 2017 *Global Financial Stability Report* (GFSR). Positive values of the FCI indicate tighter-than-average financial conditions.	IMF staff estimates
Global Financial Conditions Index	Based on a PCA of all FCIs estimated; Positive values of the FCI indicate tighter-than-average financial conditions. For methodology and variables included in the FCI, refer to Annex 3.2 of the October 2017 GFSR.	IMF, chapter 3 of the October 2017 GFSR.
Global Oil Prices	Petroleum prices, US dollar per barrel	Bloomberg Finance L.P.; IMF, Global Data Source database
Household Debt-to-GDP Ratio	Total credit to households and NPISH as a share of annual GDP; first difference	Bank for International Settlements; Haver Analytics
Macroprudential Policies	Macroprudential policy tools at quarterly frequency	IMF Integrated Macroprudential Policy Database database
Misalignment Measure	Standardized price to per capita GDP, price to income, price to rent, and misalignment based on fundamentals; detrended using a Hodrick-Prescott filter, linear detrending, exponential, and recursive smoothing	Organisation for Economic Co-operation and Development; Global Property Guide; IMF staff calculations
Monetary Policy Shocks	Identified by regressing a country's short-term rate on a set of controls and using the residuals as the identified shocks. The set of controls includes contemporaneous and lagged values of inflation, log GDP, log foreign GDP, as well as lagged values of the short-term rate and a quadratic time trend	IMF staff calculations
Nominal GDP	Nominal gross domestic product in purchasing-power-parity dollars	IMF, World Economic Outlook database
Real GDP	GDP at constant prices, seasonally adjusted	Haver Analytics; Organisation for Economic Co-operation and Development; IMF, Global Data Source database; IMF, World Economic Outlook database
Real House Price Indices	Residential property prices (seasonally adjusted) at country and city levels	Bank for International Settlements; CEIC Data Co. Ltd; Haver Analytics; IMF, Research Department house price dataset; Organisation for Economic Co-operation and Development; Thomson Reuters Datastream; IMF staff calculations
Real House Price-to-Income Ratio	Real house prices as a share of disposable income	Haver Analytics; IMF staff estimates
Real House Price-to-GDP per Capita Ratio	Real house prices as a share of GDP per capita	Haver Analytics; Organisation for Economic Co-operation and Development; IMF, Global Data Source database; IMF, World Economic Outlook database
Residential Investment	City-specific residential investment; scaled by regional GDP, seasonally adjusted	Haver Analytics
Short-Term Nominal Interest Rate	Three-month treasury bill or interbank rate	Bloomberg Finance L.P.; Haver Analytics; Thomson Reuters Datastream; IMF staff calculations
Systemic Banking Crisis	Dummy for systemic banking crisis, as defined in Laeven and Valencia (2018)	Laeven and Valencia (2018)

Source: IMF staff.
Note: FCI = financial conditions index; NPISH = non-profit institutions serving households; PCA = principal component analysis.

B. Methodology

1. For the aggregate analysis at the country level, this chapter estimates house prices at risk using panel quantile regression techniques. Estimation is carried out through a two-step procedure for panel quantile regressions, following Canay (2011).[1] In the first step, unobserved fixed effects are estimated, using within-estimators. In the second step, the dependent variable is adjusted with the fixed effects obtained from step one, and standard conditional quantile regressions are then estimated.[2] The conditional distribution for adjusted average log changes in real house prices ($\Delta_h \tilde{P}_{i,t+h,q}$), h periods ahead, for country (or city) i, at a specific quantile q, is estimated to depend on a vector of key determinants (X), in addition to past log changes in real house prices:

$$\Delta_h \tilde{P}_{i,t+h,q} = \alpha_{h,q} + b_{x,h,q} X_{i,t} + b_{p,h,q} \Delta P_{i,t} + e_{i,t,h,q} \qquad \text{(A.2.1.1)}$$

where b is the (vector of) estimated coefficient(s) and e denotes the quantile regression error term. The estimation of conditional forecasts by quantile regressions at the country level requires long time series. However, for short(er) time series available for most economies, using a panel approach enhances statistical power. However, to maintain some homogeneity for the cross-sectional dimension of the panels, the chapter estimated separate (unbalanced) panels for advanced and emerging market economies.[3]

2. The chapter evaluates the term structure and intertemporal properties of house prices at risk. For a given house price determinant, x, and a given quantile of the future house price distribution, q, the sequence of $b_{x,h,q}$ coefficients estimated at different horizons, h, shows how an increase in x changes the q^{th} quantile of future house price growth (say, at the 5th percentile) at those forecasting horizons, thus providing a "term structure" of HaR.

3. The effects of macroprudential and monetary policies and capital flows on house prices at risk are also discussed. Namely, the chapter asks whether tighter macroprudential or monetary policy shifts the whole term structure of house prices at risk by examining:

$$\Delta_h \tilde{P}_{i,t+h,q} = \alpha_{h,q} + b_{x,h,q} X_{i,t} + b_{m,h,q} m_{i,t} + b_{xm,h,q} X_{i,t} m_{i,t} + b_{p,h,q} \Delta P_{i,t} + e_{i,t,h,q}, \qquad \text{(A.2.1.2)}$$

where $m_{i,t}$ is the proxy for macroprudential or monetary policy measures and e denotes the quantile regression error term. Equation (A.2.1.2) can be expanded to study the effect of capital flows, the

[1]The results are robust to alternative estimation methods, such as Galvao (2011) and Powell (2016).

[2]The first step estimates $\Delta_h P_{i,t+h} = \alpha_{i,h} + b_{x,h} X_{i,t} + b_{p,h} \Delta P_{i,t} + e_{i,t,h}$ by a standard fixed effect estimation and then constructs $\Delta_h \tilde{P}_{i,t+h} \equiv \Delta_h P_{i,t+h} - \hat{\alpha}_{i,h}$ for all i and h. Here, $\Delta_h P_{i,t+h}$ is the expected average cumulative growth of real house prices, $\Delta_h P_{i,t+h} \equiv (\log P_{i,t+h} - \log P_{i,t})/h$. The second step runs a quantile regression for each quantile q: $\Delta_h \tilde{P}_{i,t+h,q} = \alpha_{h,q} + b_{x,h,q} X_{i,t} + b_{p,h,q} \Delta P_{i,t} + e_{i,t,h,q}$.

[3]The 22 advanced economies in the sample are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong Special Administrative Region, Ireland, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. The 10 emerging market economies in the sample are: Brazil, Chile, China, Colombia, India, Malaysia, Mexico, Russia, South Africa, and Turkey.

degree of capital account openness, or the effects of capital flows measures. Two coefficients are especially relevant in this forecasting equation: $b_{m,h,q}$ and $b_{xm,h,q}$. The first represents the marginal effects of policy tightening, while the second represents the policy effects conditional on other variables $X_{i,t}$.: that is, how much the policy measure mitigates the marginal effects of X_t on house prices at risk over a specific horizon, as well as over time.

4. For the city-level analysis in Box 2.2, a two-stage approach was followed, as in Adrian, Boyarchenko, and Giannone (forthcoming).

In the first stage, quantile regression models are estimated for each city. Specifically, a quantile regression is run with city-level residential real house prices (HP) as the dependent variable:

$$CityHP_{i,t+h,q} = \rho_{1,h,q}CityHP_{i,t} + \rho_{2,h,q}HP2INC_{i,t} + \rho_{3,h,q}ResInv_{i,t} + \beta_{1,h,q}\Delta HHD_t + \beta_{2,h,q}FCI_t + \beta_{3,h,q}FDI_t + \beta_{4,h,q}OtherCF_t + \epsilon_{i,h,q,t} \quad , \text{(A.2.1.3)}$$

where h is the horizon (four quarters ahead), q is the quantile (q=0.1, 0.25, 0.5, 0.75 and 0.9), and ε is the error terms. Household debt (HHD), foreign direct investments (FDI), and other capital inflows (Other CF) are scaled by overall GDP. FCI is the price-based financial conditions index, estimated from 1980:Q1 to 2017:Q4, from Chapter 3 of the 2017 October *Global Financial Stability Report*. The HP-to-income ratio (HP2INC) and residential investment (ResInv) are at the city or regional level.[4]

In a second stage, a skewed-*t* distribution is fitted for each city house price series at each point in time. The distribution uses the predicted values for each quantile obtained in the first stage. Finally, house prices at risk refers to the lower 5th quantile of the city-specific left tail, using the fitted distribution.

5. To test the robustness of the results, alternative models are estimated. For instance, smaller models are estimated, and additional controls, such as oil prices and portfolio investments, are added. Equation (A.2.1.3) is the one with highest pseudo-R^2 across all cities. The coefficients of the capital inflow variables from equation (A.2.1.3) remain broadly consistent across specifications, while portfolio inflows are never significant. Across all quantiles, the average pseudo-R^2 for US and Canadian cities is 0.46 and 0.35, respectively.

---

[4]Residential investment is replaced by residential housing starts for US cities because of data limitations.