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Predicting Downside Risks to House Prices and Macro-Financial Stability

by Andrea Deghi, Mitsuru Katagiri, Sohaib Shahid, and Nico Valckx

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I N T E R N A T I O N A L M O N E T A R Y F U N D

IMF Working Paper
Monetary and Capital Markets Department

Predicting Downside Risks to House Prices and Macro-Financial Stability

**Prepared by Andrea Deghi, Mitsuru Katagiri,
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Abstract

This paper predicts downside risks to future real house price growth (house-prices-at-risk or HaR) in 32 advanced and emerging market economies. Through a macro-model and predictive quantile regressions, we show that current house price overvaluation, excessive credit growth, and tighter financial conditions jointly forecast higher house-prices-at-risk up to three years ahead. House-prices-at-risk help predict future growth at-risk and financial crises. We also investigate and propose policy solutions for preventing the identified risks. We find that overall, a tightening of macroprudential policy is the most effective at curbing downside risks to house prices, whereas a loosening of conventional monetary policy reduces downside risks only in advanced economies and only in the short-term.

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I. INTRODUCTION

Developments in the housing market are important for various economic agents—especially households, firms and banks. Housing serves both as a long-term investment and as a consumption good that generates considerable utility for households. Housing consumption and investment accounted for about one-sixth of the US and the euro area economies in 2017, representing one of the largest components of GDP in both cases. Drops in house prices decrease households' net worth and can thus reduce consumption since housing makes up a large share of households' wealth in many countries.² At the same time, mortgages and other housing-related lending make up a large fraction of banks' assets. Sudden and sharp house price declines can decrease the value of collateral pledged by borrowers and negatively impact banks' portfolio quality, profitability and stability (Kara and Vojtech 2017). Claessens, Kose, and Terrones (2012) show that recessions are deeper and last longer when house prices fall more and more quickly, and more than two-thirds of the nearly 50 systemic banking crises in recent decades were preceded by boom-bust patterns in house prices.³

In recent years, the simultaneous increase in house prices in many countries has raised concerns about the potential consequences of large and contagious declines in the near future. In many countries and cities, house prices have increased substantially—a pattern that reflects the increased synchronization of house prices.⁴ To the extent that the likelihood of large house price declines has increased amid the decades-long decline in interest rates and rising household leverage, it is important to ask how large the future downside risks to house prices exactly are, what they imply for financial stability and what we can do to prevent these risks from realizing.

In view of these questions, this paper proposes a novel non-parametric approach to predict future downside risks to house prices (i.e., house prices-at-risk) and their impact on the risk of future macroeconomic downturns. We first develop a macroeconomic model to motivate our empirical specification and then apply quantile regressions to show how current house price overvaluation, excessive credit growth, and tighter financial conditions can jointly forecast higher house-prices-at-risk up to three years ahead. Our measure of risk in the housing market in turn predicts future financial crises and economic downturns. Finally, our model puts forward several policy measures that could mitigate future sudden downturns, which we analyze in our prediction framework. We find that macroprudential policies are the most effective while conventional monetary policy only relieves pressure in advanced economies and in the very short term.

² In this context, Bernanke, Gertler, and Gilchrist (1996), show that endogenous developments in credit markets, such as variations in net worth or collateral, amplify and propagate shocks to the real economy.

³ Moreover, certain housing market characteristics, such as higher loan-to-value ratios and greater reliance on wholesale markets, are associated with even higher risks of crises (Cerutti, Dagher, and Dell'Ariccia 2015). The interactions between house prices and credit volumes may also result in self-reinforcing feedback loops where an increase in house prices facilitates an expansion in credit (through collateral effects) that puts further upward pressure on house prices. When that process is reversed, large declines in house prices may be followed by a collapse in credit and GDP growth. Such a pattern was observed in the run-up to the global financial crisis and its aftermath (Alter, Feng, and Valckx 2018).

⁴ See Chapter 3 of IMF (2018).

The houses-prices-at-risk measure we develop uses the 5th percentile of the forecasted house price growth distribution, reflecting the idea that it is large and sudden downturns in house prices that bear the largest risk for financial stability.⁵ Our model and quantile regressions find that it is mainly driven by past price dynamics and fundamental factors. While a tightening of financial conditions is associated with more negative future house prices at risk in general, higher real GDP growth foreshadows higher house price declines in the short- and medium-term horizons (one year to three years ahead) only in advanced economies. Credit booms further exacerbate the incidence of large negative house price corrections at short- and medium-term horizons. Importantly, we evaluate the out-of-sample performance of the model by replicating the analysis that an economist would have done in a country-level analysis by using the proposed methodology in real time. The stability of the recursive out-of-sample estimates thus shows that downside risk to house prices can be detected in real time.

Large declines in house prices, as captured by our house-prices-at-risk measure, in turn forecast future risks to economic growth and serves as a leading indicator for financial stability risks captured by the growth-at-risk (GaR) model of Adrian et al. (2018). For example, a reading of minus 12 percent on our gauge, indicates a 31 percent probability of a financial crisis two years later in advanced economies and a 10 percent probability in emerging markets. Overall, the highest impact of house prices at risk on financial stability is four to eight quarters into the future, with a 1 percentage point improvement in the house-prices-at-risk measure preceding on average a 0.3 percentage point improvement in growth at risk. This association is robust to adding various credit quantity measures and indirect measures of house price imbalances, such as the growth in house prices or overvaluation metrics.

To understand how house price downturns, arise and how policy can mitigate the associated financial stability risks, a comprehensive macroeconomic framework is developed. In the model, housing crises are a vicious cycle of real GDP and house price declines. When household debt levels are high, further borrowing by households in response to income declines makes the collateral constraint bind. Fire sales of homes follow, leading to a decline in house prices and further tightening of the collateral constraint. As a result, aggregate demand and household incomes drop and another round of deteriorating conditions ensues. Macroprudential measures, such as a Pigouvian tax on household debt, can alleviate the negative effects of housing crises on the real economy by preventing the tightening of collateral constraints from a decline in house prices. Monetary policy however does not have any direct effects on house price growth in times of distress other than through general financial conditions.

The predictions of the model are confirmed by our empirical analysis. Using our proposed house-prices-at-risk measure, we find that a tightening of macroprudential policies is associated with a

⁵ This is also in line with the growth-at risk measure put forward by Adrian, Boyarchenko and Giannone (2019). The growth-at-risk approach, a summary measure for financial stability, links current financial conditions to the distribution of future growth outcomes. Specifically, growth at risk refers to the set of outcomes that fall into the 5th percentile of (conditional) forecast densities of GDP growth. See also Adrian et al. (2018) and IMF (2017).

reduction of downside risks to house prices. This is especially the case for policies aimed at strengthening the resilience of borrowers, such as limits to the loan-to-value or debt-service-to-income ratios. The ability of monetary policy to mitigate downside risks to housing prices, beyond its relationship with financial conditions, seems more limited. Financial conditions, which are partly driven by monetary policy actions, have a clear relationship with downside risks to house prices. Beyond this indirect effect, the influence of conventional monetary policy seems to be limited to the short-term and to advanced economies.

Our findings are important for policy-makers and academics alike. For policy-makers, the house-prices-at-risk measure is an important and novel indicator of risks in the housing sector. We derive a quantitative framework to predict the house-prices-at-risk indicator also out-of-sample, which allows for real-time monitoring and forecasting with available data. So far, the academic literature on house prices has mainly focused on average house prices and on deviations from equilibrium house prices. Recent studies on house price valuation find that they are tied to household income, macro-financial conditions, and structural factors such as population growth and urbanization (see, e.g., Capozza et al. 2002, Girouard et al. 2006, Gattini and Hiebert 2010, Saiz 2010, and Algieri 2013). Others point to the role of leverage, credit constraints, and bank regulation (Duca, Muellbauer, and Murphy 2011, Favara and Imbs 2015 and Mian and Sufi 2016) and the presence of speculative bubbles in housing markets (Himmelberg, Mayer, and Sinai 2005, Black, Fraser, and Hoesli 2006, Shiller 2007, Granziera and Kozicki 2015, Cerutti et al. 2017, Kholodilin, Michelsen and Ulbricht 2017).

We focus on the left tail of the house price growth distribution, which we find to be an important predictor for future financial stability risks. A few other papers have looked at drops in house prices. For example, Agnello and Schuknecht (2011) find that domestic credit, interest rates, and international liquidity can influence the probability of house price busts, while Muellbauer and Murphy (2012) focus on the role of bank deregulation. Others, including Kaplan, Mitman, and Violante (2017), Burnside, Eichenbaum, and Rebelo (2016) and Fuster, Laibson, and Mendel (2010) documented that households' expectations of a continued increase in house prices played a significant role in the US housing boom and bust around the global financial crisis of 2008.⁶ Our contribution is in a precise and out-of-sample quantitative prediction using a quantile regressions approach. We have identified the 5th percentile as our measure of house-price-at-risk, but the flexibility of our non-parametric approach allows the results to be extended to other percentiles of the distribution.

We also contribute to the literature on the effect of policy measures in curbing housing bubbles and financial stability risks. While other studies have analyzed the effects of tax, monetary and macroprudential policies on house prices and housing market conditions (see, e.g., Poterba 1984, Gervais 2002, Aoki, Proudman and Vlieghe 2004, Dokko and others 2011, Iacoviello and Neri 2010, Floetotto, Kirker and Stroebe 2012, Vandenbussche, Vogel and Detragiache 2015, Cerutti, Claessens and Laeven 2015, Kelly, McCann and O'Toole 2018), we show how these policies can

⁶ Shiller (2013) made the point that during housing booms, households that extrapolate from recent trends are likely to increase their borrowing, which leads to "irrational exuberance" as it amplifies house price and leverage cycles and potentially impairs financial stability.

specifically target the downside risk in the house price growth distribution, which foreshadows future financial crisis. Our empirical findings on the effectiveness of macroprudential policies versus monetary policy are rationalized using a macroeconomic framework relating housing prices to the real economy.

The remainder of the paper is organized as follows. First, we set out a theoretical model on the determinants of house price risks and the effects of macroprudential and monetary policies. Then, we detail the panel quantile methodology and data. The next section presents the main findings on house prices-at-risk, including both in-sample and out-of-sample evaluations, the contribution of HaR to macro-financial stability, and the effects of monetary and macroprudential policies on HaR. The last section concludes.

II. THEORETICAL FRAMEWORK

This paper applies a nonlinear dynamic stochastic general equilibrium (DSGE) model with occasionally binding housing collateral constraints. The approach generally follows Guerrieri and Iacoviello (2017) but for simplicity, ignores interactions with the corporate sector and focuses on the household sector by distinguishing between two types of households with different discount factors: borrowers and lenders. Households maximize their utility by choosing consumption, leisure, and housing, subject to budget and collateral constraints. Housing is the only collateral for borrowing, and house prices are determined by a standard forward-looking asset pricing formula. The collateral constraint is not always but occasionally binding, depending on house prices, income, and debt level. Other parts of the model are in line with a standard DSGE model with Euler equations for each type of households, a new Keynesian Phillips curve, and a monetary policy rule.

More specifically, the economy consists of borrowers and lenders. In this economy, the borrower maximizes

$$E_t \sum_{t=0}^{\infty} \beta^t \left[\frac{c_t^{1-\sigma}}{1-\sigma} + \chi \log h_t - \frac{\Psi L_t^{1+\omega}}{1+\omega} \right] \quad (1)$$

where c_t denotes consumption of goods and services, h_t housing consumption, L_t labor (the complement of leisure), β^t is a discount factor, σ and ω are elasticities of substitution, Ψ and χ are preference parameters. E_t is the conditional expectations operator and t is a time subscript. Borrowers are subject to the budget constraint

$$c_t + \frac{b_t}{R_t} + q_t h_t = w_t L_t + \frac{b_{t-1}}{\pi_t} + q_t h_{t-1} \quad (2)$$

where b_{t-1} denotes real savings (or borrowing) in the previous period, w_t real wages, q_t is the house price, as in Guerrieri and Iacoviello (2017), R_t is the gross nominal interest rate and π_t is the inflation rate.

The borrower's collateral constraint is

$$-\frac{b_t}{R_t} \leq (1 - \gamma)\kappa q_t h_t - \frac{\gamma b_{t-1}}{\pi_t} \quad (3)$$

where κ determines the tightness of the collateral constraint and γ determines the degree of inertia in the borrowing limit as in Guerrieri and Iacoviello (2017) (both are positive factors). By assuming that the housing supply is fixed and $h_t = 1$ for all t , the equilibrium is characterized by the Euler equation for the borrower

$$\lambda_t = \beta E_t \left[\frac{R_t}{\pi_{t+1}} (\lambda_{t+1} - \mu_{t+1} \gamma) \right] + \mu_t \quad (4)$$

and the asset pricing formula for the house price

$$(\lambda_t - (1 - \gamma)\kappa \mu_t) q_t = \chi + \beta E_t [\lambda_{t+1} q_{t+1}] \quad (5)$$

where $\lambda_t = c_t^{-\sigma}$ and μ_t is a Lagrange multiplier for the collateral constraint, satisfying the complementary slackness. The latter condition implies that at least one of the following constraints must hold with equality in each period:

$$-\frac{b_t}{R_t} \leq (1 - \gamma)\kappa q_t - \frac{\gamma b_{t-1}}{\pi_t}; \quad \mu_t \geq 0 \quad \text{and} \quad \mu_t \left[(1 - \gamma)\kappa q_t - \frac{\gamma b_{t-1}}{\pi_t} + \frac{b_t}{R_t} \right] = 0 \quad (6)$$

The lender's problem is analogous to the borrower's problem, but the lender does not consume housing and does not face the borrowing constraint. The nominal interest rate R_t is set by the central bank following a Taylor rule, based on deviations of (year-on-year) inflation from its target and the output gap,

$$R_t = \bar{R} \left(\frac{\pi_t}{\pi^*} \right)^{\phi_\pi} \left(\frac{y_t}{y^*} \right)^{\phi_y} \quad (7)$$

where $\bar{R}$ is the steady-state interest rate, π^* the inflation target, y/y^* the output gap and ϕ_π and ϕ_y are the central bank preference parameters. The corporate sector follows a standard new Keynesian model, and the price and output dynamics are characterized by the new Keynesian Phillips curve. The model is numerically solved by the iteration method with discretized grid points for productivity and the borrower's debt.

The model successfully replicates housing crises. The blue line in Figure 1 (panel 1) shows the ergodic distribution of output gaps (that is, the gap from the steady-state level) in the baseline simulation, indicating that the model can replicate huge declines in output during a housing crisis. In the model, housing crises are described as a vicious cycle of output and house price declines, due to the binding collateral constraint: when the level of household debt is high, further borrowing

by households in response to an income decline makes the collateral constraint bind. Then, households start "fire sales" of their houses (an alternative interpretation may be as foreclosures) because they cannot borrow, leading to a decline in house prices and further tightening of the collateral constraint. Since the binding collateral constraint prevents households from borrowing, it forces them to reduce their consumption, decreasing aggregate demand, output, wages, and household income, and thus leading to another round of deteriorating conditions within the vicious cycle.

Figure 1. Impact of Monetary and Macroprudential Policies in the Theoretical Model

1. Ergodic Distribution of the Output Gap

2. Credit-to-GDP and Real House Price Growth

3. Responses of Output, House Prices, Interest Rates, and Credit-to-GDP under Different Policy Regimes in a Crisis

a. Output Growth (percent)

b. House Price Growth (percent)

c. Interest Rate Change (percentage point change)

d. Change in Credit-to-GDP Ratio (relative to baseline, percent)

Note: Panel 2 shows different associations between debt-to-GDP and house price growth for the lower 5th percentile (red line), 50th percentile (median, orange line) and 95th percentile (green line). In panel 3, output growth less than -3 percent in the baseline model (Base) is defined as crisis period. MP1 = monetary policy rule augmented by the response to household debt-to-GDP; MP2 = monetary policy rule augmented by the response to credit spreads. MPM = macroprudential tax on credit-to-GDP ratio.

The model also predicts a positive association between the initial level of household debt and the incidence of housing crises. Figure 1 (panel 2) presents scatter plots of house price growth in period t (the vertical axis) against the debt-to-GDP ratios in period $t-1$ (the horizontal axis). The three lines are the estimated fifth, fiftieth, and ninety-fifth percentile. The figure indicates that while higher debt-to-GDP ratios have no effects (or slightly positive effects) on median growth of house prices, they significantly increase the probability of housing crises, which is consistent with this paper's empirical analysis using a quantile regression. The model, therefore, offers a theoretical foundation as to why debt-to-GDP ratios can be used as an early warning indicator.

Three policies measures to mitigate the adverse effects of housing crises are examined. First are macroprudential measures (MPMs). MPMs are modeled as a Pigouvian tax on debt following the literature (see, for example, Bianchi and Mendoza 2018). While the MPM rule to internalize the pecuniary externality is a complicated and nonlinear function of state variables, it can be well approximated by a linear function of household debt (that is, high taxes on debt when the debt level is high).⁷ The second policy measure is monetary policy augmented by a response to household debt. Under this monetary policy rule, nominal interest rates are positively linked to household debt levels, implying that the central bank increases interest rates in a run-up period while it lowers interest rates in response to deleveraging. The third policy measure is monetary policy augmented by a response to credit spreads, as argued by Cúrdia and Woodford (2011). The credit spread in the model is defined by the interest rate gap between secured and unsecured lending (i.e without housing collateral). Since the spread is negligible in normal times, the central bank behaves differently from the baseline case only in a crisis by lowering interest rates in response to higher credit spreads.

More specifically, to discuss the effect of MPMs, the Euler equation for the social planner (i.e., the authority) is derived from its optimization problem as

$$\lambda_t = \beta E_t \left[\frac{R_t}{\pi_{t+1}} (\lambda_{t+1} - \mu_{t+1} \{ (1 - \gamma) \kappa q'_{t+1}(b_t) - \gamma \}) \right] + \mu_t \quad (8)$$

and the house price q'_{t+1} is compared with the competitive equilibrium. The only difference from the borrower's first order condition is the term associated with the first derivative of the next period's house price with respect to the current level of household debt, $q'_{t+1}(b_t)$. This first derivative term is associated with the fact that the social planner can internalize the effects of their borrowing decisions on the house price while the market structure the social planner faces is the same as the one that the borrower faces. Note that the borrower cannot internalize them because the borrower is a price taker and the house price is exogenous variable for each borrower. To replicate the social planner's Euler equation in a decentralized economy, the macroprudential tax, ω_t , is imposed on household debt. With the macroprudential tax, the borrower's budget constraint is

⁷ Note that other MPMs including caps on loan-to-value ratios and surcharges on lending rates for household debt are mathematically equivalent to MPMs using taxes on debt in the model.

$$c_t + \frac{b_t}{(1 + \omega_t)R_t} + q_t h_t = w_t L_t + \frac{b_{t-1}}{\pi_t} + q_t h_{t-1} \quad (9)$$

In this case, the borrower should pay a macroprudential tax in addition to interest rate payments. The macroprudential tax rate is state contingent and chosen by the authority so that the Euler equation for the borrower matches the one for the social planner.

Macroprudential measures lower the probability of housing crises and mitigate their negative effects. The green line in Figure 1 (panel 1) shows the ergodic distribution of the output gap with MPMs. The figure shows that compared with the baseline case without MPMs (the blue line), MPMs significantly decrease the variance of the output gap, particularly by shrinking the left tail of the distribution. This result suggests that MPMs are effective in preventing and mitigating the impacts of housing crises. To see the policy effects during crisis periods more precisely, the first three charts in panel 3 of Figure 1 show output growth, house price growth, and nominal interest rates during crisis periods. In the figure, the crisis periods are defined as those with declines in output of more than 3 percent. The first and second figures in panel 3 show that MPMs mitigate the decline in both output growth and house price growth during a crisis, suggesting that MPMs mitigate the negative effects of housing crisis on the real economy by limiting the tightening of collateral constraints from declining house prices. The fourth figure in panel 3 shows that the average level of household debt is significantly lower than in the baseline case not only during run-up periods but also in normal times.

Monetary policy responding to household debt mitigates the negative effects of housing crises, but its policy effect is insignificant relative to MPMs. In this exercise, the monetary policy rule is augmented by a response to household debt, and the parameters are calibrated so that the steady-state debt level is at the same level as in the economy with MPMs (the fourth figure in panel 3). The results show that while monetary policy responding to household debt slightly mitigates the adverse effects on output growth in a crisis (panel 1), it does not have any effects on house price growth in crisis periods, in contrast to MPMs (panel 2). The decline in nominal interest rates in times of crises is larger than in the baseline case (panel 3) because the central bank now lowers rates in response to deleveraging. Hence, the augmented monetary policy rule does not improve house prices and only slightly mitigates the adverse effects on output growth by: (i) subduing debt accumulation before a crisis, and (ii) lowering nominal interest rates in response to deleveraging. The results suggest that monetary policy may be too blunt as a tool for crisis management, in line with Bernanke (2011).^{8,9}

⁸ Surcharges on lending rates for household debt are equivalent to MPMs using taxes on debt in the model. Hence, the augmented monetary policy performs worse than MPMs only because the monetary policy influences not only lending rates but also other relevant interest rates including deposit rates.

⁹ There are, however, several caveats. First, the analysis adopts a very specific form of monetary policy rule, namely a conventional Taylor rule augmented by a linear response to household debt. This does not mean that all monetary policy rules in a more general form may not work for crisis management. Second, in the midst of a crisis, monetary policy can respond more promptly than MPMs, and may be more practically useful for policymakers.

Monetary policy responding to credit spreads also mitigates the negative effects of housing crises, but its policy effect is also limited and assumes considerable room for policy reactions. As in the previous case, Figure 1 (panel 3) shows that monetary policy responding to credit spreads slightly mitigates the adverse effects on output growth in a crisis (panel 3, chart a) but does not bear any effects on house price growth in a crisis (panel 3, chart b). Hence, monetary policy under this rule does not prevent crises per se but mitigates their adverse effects on output growth by lowering nominal interest rates and thus boosting aggregate demand.

Figure 2. Historical Developments in Real House Prices

Advanced Economies

1. Annual Change in Real House Prices

(Percent, 1990:Q1–2018:Q2)

Emerging Market Economies

2. Annual Change in Real House Prices

(Percent, 1995:Q1–2018:Q1)

3. Frequency Distribution of Real House Price Growth

(Relative frequency of annualized real house price changes)

4. Frequency Distribution of Real House Price Growth

(Relative frequency of annualized real house price changes)

Sources: Bank for International Settlements; national statistical offices; Organisation for Economic Co-operation and Development; and IMF.

Note: Panels 1 and 2 show the distribution of four-quarter real house price changes (median, interquartile and 10th–90th percentile range) for advanced and emerging market economies. For Chile, the data are available up to 2017Q4; for Malaysia, up to 2016Q4.

Furthermore, the decline in nominal interest rates in a crisis are very pronounced (panel 3 chart c), reflecting the central bank's response to increases in credit spreads. Such a large decline of nominal interest rates, however, may not be possible in some countries in a low interest rate environment, rendering the feasibility of this monetary policy rule somewhat doubtful.

III. DATA AND METHODOLOGY

A. Data

House price data are collected for 22 major advanced economies and 10 emerging market economies. An effort was made to maintain regional balance by collecting quarterly data from North America (Canada, Mexico and U.S.), South America (Brazil, Chile and Colombia), Europe (16 countries including Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, four Nordic countries, Spain, Switzerland, U.K. plus Russia and Turkey), Asia-Pacific (Australia, China, Hong Kong SAR, Japan, Malaysia, New Zealand and Singapore), and Africa (South Africa is the only African country in the sample). Data typically go back to 1990:Q1 in advanced economies. In emerging market economies, data series generally start later, but efforts were made to combine different sources to expand the house price series towards the early 1990s. Various data sources were consulted, including the Bank for International Settlements, national statistical offices, the Organization for Economic Co-operation and Development and the IMF. House price data were deflated using the overall CPI index when nominal house prices were retrieved (see Annex I for details on data coverage, transformations and summary statistics).

House prices tend to co-move during crises, with some countries appearing more cyclical than others (Figure 2, panels 1 and 2). For example, during the early 1990s, some advanced economy countries suffered steep declines in real house prices of up to 20 percent, while others maintained a stable growth rate. During the European sovereign debt crisis in 2011-2012, similar differences were apparent; although during the global financial crisis of 2008-2009, most advanced economies saw a fall in house prices. In emerging market economies, three episodes of large declines stand out: the Asian crisis in the late 1990s, the global financial crisis of 2008-2009, and the turmoil in Russia and Brazil in 2015-2016. Historically, the average (annualized) one-year and three-year growth rates of real house prices stood at about 2 percent a year in advanced economies and 2.6 percent a year in emerging market economies (Figure 2, panels 3 and 4). Negative real growth in house prices occurs in about half of the observations in advanced economies and in a third of the observations in emerging market economies over a one-year horizon.

Variables related to fundamental house prices valuations and vulnerabilities are also informative about downside risks to housing. As described in the previous section, the conceptual framework relates house price risks to household leverage, financial conditions, overvaluation, and real GDP Growth. A simple look at the univariate relationship between these fundamental house price valuation variables and quantiles of the house prices distribution confirms the prediction.

The association between these variables and house price growth further varies with different parts of the house price distribution (Figure 3). Tighter financial conditions are associated with lower

house prices in the future, where the effect is most pronounced when house price growth is most negative, that is, in the left tail (5th percentile) of the distribution (Figure 3, panel 1). Lower real GDP growth, as a proxy for changes in household real income, is generally associated with lower house price growth (Figure 3, panel 2). The credit-to-GDP ratio, capturing movements in leverage of economic agents, also displays a negative relationship with house price growth when the ratio is above its long-term mean (Figure 3, panel 3). Finally, the price-to-GDP per capita ratio is a valuation metric for housing capturing the degree of deviation from fundamental valuation levels.¹⁰ Overall, the differences in slopes indicate a markedly stronger relationship for the left tail of the future house prices growth distribution relatively to the median and the 95th percentile of the distribution (Figure 3, panel 4).

Figure 3. Determinants of Real House Prices

Source: Authors' estimates.

Note: Panels 1–4, respectively, depict the association between one-year-ahead real house price growth and current financial conditions, real GDP growth, the detrended credit-to-GDP ratio, and the detrended price-to-GDP ratio. For detrending, a linear method was used, but robustness checks with different detrending methods produced very similar results. Lines show the estimated relationship between these variables and real house prices at the 5th (red line), 50th (yellow line), and 95th (green line) quantiles. t = current quarter; $t + 4$ = one year (four quarters) ahead. An increase in the FCI represents a tightening of the pricing of risk in the economy. FCI purged = financial conditions index, excluding house prices.

B. Modeling House Prices-at-Risk

House prices at risk (HaR) is defined as a measure of downside risk for the growth of real house prices over a given horizon at a 5 percent probability, corresponding to the fifth percentile of the distribution.¹¹ By focusing on different horizons, the estimated coefficients for a given factor in the HaR model establish a “term structure” of house price risks, reflecting short term versus long

¹⁰ Results are qualitatively similar when other misalignment measures are used, such as price-rent ratio, price-income ratio, or model-based measures that capture misalignments as deviations from fundamentals.

¹¹ Although our approach can be applied to any percentile of the distribution, we limit our attention to the fifth percentile. This captures the most negative real house price growth realizations in line with the paper's focus on downside risks and financial stability.

term responses of HaR to that factor. While the estimation uses panel data to increase statistical power, separate panels are run for advanced and emerging market economies to maintain some homogeneity in the structure of the financial system and real economy. Panel quantile regressions allow us to formally characterize the conditional relationship between future house prices growth and a set of key determinants across countries. The estimation is done using a two-step procedure for panel quantile regressions, following Canay (2011).

First step. The first step estimates unobserved fixed effects using within-estimators. We denote $\Delta_h Y_{i,t+h}$ the average log change in real house prices¹², h periods ahead, for country i and $X_{i,t}$ a vector of key determinants, including past log changes in real house prices:

$$\Delta_h Y_{i,t+h,\tau} = \alpha_{i,h,\tau} + \beta_{h,\tau} X_{i,t} + e_{i,t,h,\tau} \quad (10)$$

where $\Delta_h Y_{i,t+h,\tau}$ is the conditional distribution for adjusted log annualized changes in real house prices¹³, h periods ahead, for country i , at a specific quantile τ , estimated to depend on a vector of key determinants (X), including past changes in real house prices, $\beta_{h,\tau}$ is the (vector of) estimated coefficient(s) and e denotes the quantile regression error term. The estimated fixed effects from Equation (10), can then be simply eliminated as follows

$$\Delta_h \tilde{Y}_{i,t+h,\tau} \equiv \Delta_h Y_{i,t+h,\tau} - \hat{\alpha}_{i,h,\tau} \quad (11)$$

Second step. We estimate a quantile regression for each quantile τ and time horizon h . Formally, in a quantile regression of $\Delta_h \tilde{Y}_{i,t+h,\tau}$ on $X_{i,t}$, the regression slope $\beta_{h,\tau}$ is chosen to minimize the quantile weighted absolute value of errors:

$$\hat{\beta}(\tau) \equiv \operatorname{argmin} \mathbb{E}_{nT} [\rho_\tau(\Delta_h \tilde{Y}_{i,t+h} - X'_{it} \beta_{h,\tau})] \quad (12)$$

where $\rho(\cdot)$ denotes the indicator function, n the number of cross-sections and T the number of observations. The notation $\mathbb{E}_{nT}$ is used as short for $\mathbb{E}_{nT} \equiv (nT)^{-1} \sum_{t=1}^T \sum_{i=1}^n (\blacksquare)$. The predicted value from the previous regression is the quantile of $\Delta_h \tilde{Y}_{i,t+h,\tau}$ conditional on X_t :

$$\widehat{Q_{i,t+h|X_{i,t}}}(\tau) = X_{i,t} \hat{\beta} \quad (13)$$

Canay (2011) shows that $\widehat{Q_{i,t+h|X_{i,t}}}$ is a consistent linear estimator of the quantile function $Y_{i,t+h}$, under independence restrictions. Standard errors for this estimator can be also easily be computed from the asymptotically normal representation. House-prices-at-risk can be defined as the value at risk of future house prices growth, by

$$\Pr(\Delta_h \tilde{Y}_{i,t+h,\tau} \leq \text{HaR}_{i,h}(\tau|X_t)) = \tau \quad (14)$$

¹² Specifically, $\Delta_h Y_{i,t+h}$ is the expected average growth of real house prices, $\Delta_h P_{i,t+h} \equiv (\log P_{i,t+h} - \log P_{i,t})/h$.

¹³ For simplicity we will refer only to house prices changes henceforth.

Where $\text{HaR}_{i,h}(\tau|X_t)$ is the house price at risk for country i in h quarters in the future at a probability τ . By varying h , we estimate the term structure and intertemporal properties of HaR. For a given house price determinant, X , and a given quantile of the future house price distribution, τ , the sequence of β_τ coefficients estimated at different horizons, h , shows how an increase in X changes the τ^{th} quantile of future house price growth at those forecasting horizons, thus providing a “term structure” of HaR.

Figure 4. House Prices and Fundamental Factors: Quantile Regression Results

Advanced Economies

1. Impact of Fundamental Factors on House Price Growth
(One to sixteen quarters ahead, 5th quantile coefficients)

Emerging Market Economies

2. Impact of Fundamental Factors on House Price Growth
(One to sixteen quarters ahead, 5th quantile coefficients)

Source: Authors' estimates.

Note: Panels 1 and 2 show estimated panel quantile coefficients for four standardized variables in panel quantile regressions with real house price growth, estimated at the 5th percentile, over different horizons (1 to 16 quarters ahead). Black markers indicate insignificant coefficients, while colored circles denote significant coefficients at the 10 percent level or lower. All variables (except the credit boom dummy) are standardized so that magnitudes of coefficients indicate relative importance of variables. Colored bars indicate that the coefficients are statistically significant at the 10 percent level or lower. FCI = financial conditions index. Estimated coefficients are reported in Table 1.

IV. EMPIRICAL RESULTS

A. Baseline Estimations

House prices at risk appear to broadly respond to past price dynamics and fundamental factors. The estimation includes past growth in house prices, which captures momentum effects, and the four factors described in Section II.A. Lagged house prices are especially relevant because they may reflect the persistence in house price cycles as well as the role of persistent omitted variables, such as supply restrictions. Other, more structural variables that are considered in the literature, such as population growth and urbanization, cannot be included because of limited data availability. However, their effect can be partially absorbed using fixed effects, especially if they are slow moving in nature. The results are as follows (see Figure 4 and Table 1):

- *Financial conditions*: A one-standard-deviation tightening of financial conditions, reflecting a higher underlying price of risk for the economy, is associated with 0.3 to 0.7 percentage point

higher downside risk to house prices in the short term (with a stronger impact in emerging market economies).¹⁴ Over longer horizons, the impact diminishes to 0.1 percentage point in advanced economies and becomes insignificant for emerging market economies. Hence, the relationship between financial conditions and house prices at risk is strongest in the short term and diminishes over time. However, if measures of house price overvaluation are excluded, the medium-term association between financial conditions and house prices at risk becomes positive, which suggests that the channel through which easy financial conditions today impact downside risks to house prices in the future is through an overvaluation in current prices.¹⁵

- *Real GDP growth:* A one-standard-deviation higher real GDP growth does not significantly reduce downside risks to house prices one to three quarters ahead in advanced economies but appears to have the opposite and significant relationship over longer horizons. In emerging market economies, the association between GDP growth and downside risks to house prices is positive but not statistically significant.
- *Overvaluation (house price misalignment):*¹⁶ An increase in the ratio of house prices-to-GDP-per capita—a proxy for affordability—appears consistently and significantly related to higher downside risks to house prices over time. A one-standard deviation higher price misalignment ratio is linked to a 0.5 to 1.0 percentage point increase in downside risks to house prices in advanced economies and a 0.7 to 1.0 percentage point increase in emerging market economies.
- *Credit booms:*¹⁷ Finally, credit booms tend to be related to a worsening of the house-prices-at-risk measure by up to 0.5 percentage points at short horizons in advanced economies (three quarters ahead) and up to 1 percentage point at medium-term horizons (up to eight quarters ahead) in emerging market economies.

¹⁴ In comparison, the global financial crisis entailed a 2.3 standard deviation shock to financial conditions in advanced economies (1.4 standard deviations in emerging market economies). The GDP growth shock was 2.2 standard deviations in advanced economies and 1.7 standard deviations in emerging market economies, and the overvaluation shock was about 0.2 standard deviation across both groups.

¹⁵ When using noncumulative quarterly changes in house prices as the dependent variable, the trade-off is also more visible.

¹⁶ The overvaluation variable is an easily constructed valuation metric for housing (other indicators are less readily available for some countries) and captures the degree of deviation from fundamental valuation levels.

¹⁷ Credit booms are defined as periods during which the credit-to-GDP ratio is above the long-term trend. The fact that credit booms have an immediate effect on house price risk is likely due to the definition of the boom variable, which signals overstretched household balance sheets instantaneously, rather than gradually building up.

The impact of fundamental factors is generally more pronounced in the left tail than at the median of the house price distribution.¹⁸ For example, the strongest effect of tightening financial conditions is on the tail risk of house prices in both advanced and emerging market economies. In advanced economies, a higher real GDP growth is more strongly correlated with downside risks to house prices than median house prices. In emerging market economies, on the other hand, a higher GDP growth is correlated with lower downside risks to house prices, albeit not significantly. Finally, shocks to the ratio of house prices-to-per capita GDP and credit booms are more strongly related to downside house prices than to median house prices both advanced and emerging market economies. The model also captures the relative contribution of the different factors to house prices at risk. This can best be illustrated through concrete examples, such as the one-year-ahead house-prices-at-risk fluctuations for the United States and China, which are the largest advanced and emerging market economies respectively (Figure 5).

In the United States, house-prices-at-risk gradually deteriorated beginning in the early 2000s, leading up to the global financial crisis. This pattern was initially related to house price overvaluation. Over time, past house price movements and credit also started to have a negative effect, partially offset by relatively loose financial conditions. Once the global financial crisis set in, the tightening of financial conditions weighed negatively on house prices at risk. Since late 2016, US house-prices-at-risk appear to have deteriorated gradually due to overvaluation concerns and high credit growth, but they have been partly offset by still-easy financial conditions and past house price momentum.

¹⁸ See Table 2.

In China, house-prices-at-risk seem more volatile, partly following the volatility in overall house price growth. Easy financial conditions kept house price risks contained until 2010. After 2010, high credit-to-GDP gaps and tightening of financial conditions contributed to increased downside risks. Since 2016, house price overvaluation has also contributed to the deterioration of house-prices-at-risk.

B. Out-of-Sample Evidence and Additional Robustness Tests

The HaR model can be extended to analyze real-time data for real-world forecasting and surveillance. A model that only forecasts well within the data sample used to estimate it may not be able to predict future realizations in an out-of-sample manner. However, the latter is crucial for generating forecasts and warnings ahead of time, allowing policymakers and market participants to prepare a timely response. To this end, we perform a number of out-of-sample tests. First, we compare the quantiles of the distribution predicted using the full data sample versus those predicted strictly out of sample. We further evaluate the out-of-sample accuracy using an quantile based R^2 before analyzing the robustness of the density forecasts using probability integral transform (PIT).

Analyzing the United States and China, we show that the out-of-sample estimates closely track the in-sample predictions for one-year-ahead house price growth (Figure 6).¹⁹ This suggests that the model is able to accurately forecast house price vulnerabilities in real time, despite well-documented structural changes in financing structures over time. Quantitatively, the out-of-sample forecast accuracy can be evaluated using a quantile R^2 based on the quantile loss function ρ_τ :

$$\text{quantile } R^2 = 1 - \frac{\frac{1}{T} \sum_t [\rho_\tau(Y_{t+h} - \widehat{\alpha}_t - \widehat{\beta}_t X_t)]}{\frac{1}{T} \sum_t [\rho_\tau(Y_{t+h} - \widehat{q}_t)]} \quad (15)$$

The quantile R^2 captures the loss using the conditional distribution relative to the loss using the historical unconditional quantile estimate. The higher the value, the larger the improvement of the prediction by the model over a simple summary of historical data. In principle, the quantile R^2 could be also negative if the unconditional quantile offers a better forecast than the conditioning set of variables in the proposed baseline model. We also evaluate the statistical significance of the quantile R^2 by comparing the sequences of quantile forecasts losses based on the forecasting model (the numerator) to the quantile loss based on the historical unconditional quantile (the denominator) as in Diebold and Mariano (1995).²⁰

Figure 6 (panel 3 and panel 4) shows that the baseline model to estimate downside risk in the housing sector is significantly informative out-of-sample. The improvement over the performance of the historical quantile model is 36.4 percent for the United States and 14.4 percent for China in

¹⁹ Results are consistent also for the other countries considered in this study.

²⁰ The choice represents a compromise between the conceptual benefit of focusing on the lower tail of the distribution and the cost in efficiency while using few observations for country-specific estimates.

one-year ahead predictions. Results are statistically significant at the 5 percent level. Finally, we compute the empirical cumulative distribution of the Probability Integral Transform (PIT) of the data with respect to the density forecast model to assess the optimality of density forecasts.

Figure 6. Out-of-Sample Forecasting Accuracy

1. United States: In- and Out-of-Sample Predictions for One-Year-Ahead Real House Price Growth
(One-year-ahead annualized HaR)

2. China: In- and Out-of-Sample Predictions for One-Year-Ahead Real House Price Growth
(One-year-ahead annualized HaR)

3. Quantile R^2 for One-Year-Ahead Real House Price Growth Predictions
(percentage)

4. Statistical Significance of Quantile R^2 Estimates for One-Year-Ahead Real House Price Growth Predictions
(t-statistics)

Source: Authors' estimates.

Note: Panel 1 and 2 compares in-sample and out-of-sample forecasts, using the real house price baseline model from Figure 2.5 (blue lines) and using recursive estimation for the out-of-sample model (green lines). Panel 3 and 4 reports the quantile R^2 evaluated out-of-sample and the corresponding t-statistics of the forecast accuracy test, respectively. Overall, the out-of-sample analysis shown in Figure 6 uses a country-specific model instead of the panel model to illustrate the fit of the model in a concrete application. This reduces the estimation's degree of freedom and the robustness of the results when applied to low quantiles of the distribution. For that reason, the figure shows results for the 20th and 25th percentiles for the United States and China, respectively.

Specifically, the PIT measures the percentage of observations that are below any given quantile for each h-step ahead forecast. If the conditional density model is correctly specified, then the

probability integral transformed series should be i.i.d. $U[0,1]$.²¹ To test this, we divide the sample in I in-sample portions and O out-of-sample portions, such that $I + O - 1 + h = T+h$.

Let the estimated conditional predictive densities ϕ_{t+h} be denoted as $\{\hat{\phi}_{t+h}(Y_{t+h}|\Theta)\}_{t=I}^T$, where Θ is the information set at time t . Parameters of the function ϕ_{t+h} are re-estimated at each $t = I, \dots, T$ using expanding windows of I observations.²² The PIT for a given probability density function $\hat{\phi}_{t+h}$ corresponds to the cumulative density distribution (CDF) of the function evaluated at Y_{t+h} :

$$z_{t+h} = \int_{-\infty}^{Y_{t+h}} \hat{\phi}_{t+h}(\epsilon|\Theta) d\epsilon \equiv \hat{\Phi}_{t+h}(Y_{t+h}|\Theta) \quad (16)$$

Intuitively, the closer the empirical cumulative distribution function, z_{t+h} , is to the 45-degree line (i.e. the cumulative distribution of a uniform distribution), the more accurate is the model prediction. Following Adrian, Boyarchenko and Giannone (2019), we report confidence bands around the 45-degree line to account for sample uncertainty.²³

Figure 7. Tests on the calibration of the empirical distribution

1. United States: PIT for One-Year-Ahead Real House Price Growth Predictions

2. China: PIT for One-Year-Ahead Real House Price Growth Predictions

Source: Authors' estimates.

Note: Panel 1 and 2 show the empirical cumulative distribution of the Probability Integral Transform (PIT). The metric measures the percentage of observations that are below any given quantile. Critical values are obtained as in Adrian, Boyarchenko and Giannone (2019) and Rossi and Sekhposyan (2017).

Figure 7 shows that the PITs for the full conditional predictive distribution lie well within the confidence bands of the lower quantiles for both countries analyzed just like the benchmark distribution conditioning only on past house prices. These results lend support for the robustness of the predictive distributions against possible misspecification.

²¹ See Diebold et al. (1998).

²² As described in Rossi and Sekhposyan (2014), the rolling window estimation procedure is more robust to breaks in the conditional moments of the predictive densities and allows for a better calibration of the density distribution.

²³ PITs of the one-year-ahead predictive distributions, bands are computed by bootstrapping under the assumption of uniformity of the PIT.

Additional Robustness Tests

The sharp declines in house prices growth for many economies during the financial crisis in 2008, raises the possibility that this event might affect house prices-at-risk estimations. We test this possibility by dropping from the sample the years of the peaks of the financial crisis (2008 to 2009). Table 3 shows the coefficients from the baseline model using this alternative data sample. Further, we report in Table 4 the results of the adopting an alternative panel quantile estimation based on Powell (2016). Overall, the results are consistent with the baseline estimations.

C. Contribution of House Price-at-Risk to Macro-Financial Stability

Sharp declines in house prices help forecast risks to real GDP growth. Growth at risk measures the degree to which future GDP growth faces downside risks, and its relationship with measures of financial vulnerabilities, including in the housing sector, is a metric for financial stability (see IMF 2018 and Adrian et al. 2019). Given that large declines in house prices are associated with contractions in GDP growth and financial stability risks (see Section II), a deterioration in house prices at risk should help forecast downside risks to GDP growth, over and above other measures of house price imbalances that are only indirectly related to future risks. To this aim, we run the following model:

$$\Delta_h y_{i,t+h,\tau} = \alpha_{i,h,\tau} + \theta_{h,\tau} y_{i,t} + \beta_{h,\tau} HaR_{i,t,\tau}^{t+h} + \lambda_{h,\tau} FCI_{i,t} + e_{i,t,h,\tau} \quad (17)$$

Where $\Delta_h y_{i,t+h,\tau}$ refers to average GDP growth and $HaR_{i,t,\tau}^{t+h}$, to the estimated house-prices-at-risk indicator h quarters ahead at time t . The empirical findings confirm this hypothesis (Figure 8, panels 1 and 2, and Table 2).²⁴ An increase in downside risks to house prices (a lower, more negative house-prices-at-risk measure) is associated with an increase in future downside risk to GDP growth. Furthermore, the association with downside risks is stronger than with median growth, consistent with studies on booms and busts in house prices and recessions (see, e.g., Claessens, Kose and Terrones 2012).

The largest impact of house prices at risk is four to eight quarters ahead, with a 1 percent improvement in the house-prices-at-risk measure preceding on average a 0.3 percentage point improvement in growth at risk (Table 3). This association is robust to adding various credit quantity measures to the growth-at-risk model, indicating that it is not simply capturing the correlation of growth at risk with credit, and to adding indirect measures of house price imbalances, such as the growth in house prices or overvaluation metrics. Thus, the house-prices-at-risk measure serves as a leading indicator for financial stability risks as captured by the growth-at-risk model.

²⁴ The house-prices-at-risk measure also reduces the impact effect of the financial conditions index on growth at risk. When the effect of the financial conditions index on growth at risk is looked at alone, the downside risk of the financial conditions index in the short term is higher. However, when the house-prices-at-risk measure is added to the growth-at-risk model, the downside risk from financial conditions indices is mitigated in the short term, indicating that the house-prices-at-risk measure is absorbing some of the effect of the financial conditions index.

The house-prices-at-risk measure also helps predict episodes of financial crisis. Another way of evaluating the usefulness of the house-prices-at-risk measure for financial stability surveillance is to study whether a more adverse level of house-prices-at-risk indicator helps predict the occurrence of financial crises.²⁵ We test this by estimating the probability of financial crises with a fixed effects logit model. Formally, the crisis's probability can be expressed as a non-linear function of a given set of explanatory variables:

$$(\Pr Y_{i,t+h} = 1) = \Lambda(X_t'\beta) = \frac{e^{X_t\beta}}{1 + e^{X_t\beta}} \quad (18)$$

where $Y_{i,t+h}$ is a forward-looking crisis variable equal to 1 if economy i is experiencing a financial crisis h quarters ahead; $\Lambda(X_t'\beta)$ denotes the CDF of the logistic distribution. Condition (18) defines the conditional probability that the economy i experiences a systemic banking crisis at time t as a function of selected indicators denoted X_t .

The analysis shows that adding the house-prices-at-risk measure to standard statistical models for crisis prediction that relate the probability of a crisis to GDP growth, financial conditions, and the credit-to-GDP gap helps improve the accuracy of the models. This occurs across all horizons (one, two, and three years) and for both advanced and emerging market economies. According to the estimates, an annual house-prices-at-risk measure of -12 percent—that is, an estimated 5 percent probability of a 12 percent decline in real house prices two years ahead—implies a 31 percent probability of a financial crisis two years ahead in advanced economies and a 10 percent probability in emerging market economies (Figure 8, panels 3 and 4, and Table 4).²⁶

D. Policies to Mitigate Downside Risks to House Prices

Finally, we explore the relationship between policies and house-prices-at-risk. We examine whether tighter macroprudential or monetary policy shifts the whole term structure of HaR. To this aim, we expand our baseline model (10) as follows

$$\Delta_h y_{i,t+h,\tau} = \alpha_{i,h,\tau} + \beta_{h,\tau} X_{i,t} + \lambda_{h,\tau} M_{i,t} + \gamma_{h,\tau} M_{i,t} * FCI_{i,t} + e_{i,t,h,\tau} \quad (19)$$

where $M_{i,t}$ is the proxy for policy measures and $X_{i,t}$ denotes all other variables. In the specification we control also for the interaction of $M_{i,t}$ with FCI. Two coefficients are especially relevant in this forecasting equation: $\beta_{h,\tau}$ and $\lambda_{h,\tau}$. The first one represents the marginal effects of policy tightening itself while the second one represents the policy effects conditional on other variables $X_{i,t}$, that is, how much the policy measure mitigates the marginal effects of $X_{i,t}$ on HaR over a

²⁵ Financial crises correspond to systemic banking crises, as identified by Laeven and Valencia (2018). Crises are rare and need to be identified carefully through qualitative and quantitative criteria. The growth-at-risk framework, as used in Adrian and others (2018), provides an alternative approach.

²⁶ An additional analysis to test the relationship between HaR and systemic banking crises is to compare crisis predictability power, using the Area Under Curve (AUC) metric. We show results for these analysis in Appendix II.

specific horizon, as well as over time. This study can also usefully illustrate the different effects of, say, macroprudential and monetary policies at various points in the future (while being mindful of the risks of overfitting).

Figure 8. House Prices at Risk and Financial Stability

Advanced Economies

1. Regression Coefficient of HaR in GaR Model

(One to sixteen quarters ahead)

3. Marginal Probability of HaR in Financial Crisis Model

(Estimated effect and confidence bounds for given house price at risk, two-year-ahead annualized growth rate)

Emerging Market Economies

2. Regression Coefficient of HaR in GaR Model

(One to sixteen quarters ahead)

4. Marginal Probability of HaR in Financial Crisis Model

(Estimated effect and confidence bounds for given house price at risk, two-year-ahead annualized growth rate)

Source: Authors' estimates.

Note: Panels 1 and 2 depict a positive and significant association between GaR and HaR, at the 5th quantile and at the median over different projection horizons. Black markers indicate insignificant coefficients; colored circles denote significant coefficients at the 10 percent level or lower. Estimated coefficients are reported in Table 5 and Table 6. Panels 3 and 4 show marginal probabilities of real house price declines (HaR) at given values on the occurrence of a financial (banking) crisis from a model with country fixed-effects, output growth, the financial conditions index, credit-to-GDP gap, and HaR. Vertical lines delineate the 95 percent confidence bounds around the point estimates. GaR = growth at risk. HaR = house prices at risk. Estimated coefficients are reported in Table 7.

Our first policy measure is a proxy for macroprudential policy. As a measure of macroprudential policy, we use the IMF's Integrated Macroprudential Policy (iMaPP) database, which has data on tightening and loosening for a range of macroprudential policy measures (see Alam and others forthcoming). While not directly reflecting the level or intensity of the measures, rolling-sums²⁷ of scores proxy that to some extent (where tightening increases, and loosening lowers, the measures' unit scores). The measure used here combines information on caps to loan-to-value and debt-

²⁷ Specifically, rolling sums are calculated with a time window of three years size.

service-to-income ratios, which are the most relevant measures for the housing sector and are often employed together (Kuttner and Shim 2016).

As a second policy measure, we use a proxy for unexpected changes in monetary policy. Isolating the role of monetary policy from that of financial conditions is difficult because the latter is a key channel through which monetary policy operates. We focus therefore on “shocks” to traditional monetary policy, understood as unexpected deviations of the short-term rate from an expanded Taylor rule. These are obtained by regressing the short-term rate on a set of controls and using the residuals as the identified shocks.

$$\text{Short Term Rate}_{i,t} = \lambda_0 + \lambda_1 Z_{i,t} + u_{i,t} \quad (20)$$

The set of controls $Z_{i,t}$ includes contemporaneous and lagged values of inflation, log GDP, lagged values of short-term rate and a time trend. The formulation is similar to a Cholesky identification in a VAR that orders the short-term rate as last and is consistent with the theoretical framework in Section II.

Results

Empirical results show that macroprudential policies help reduce downside risks to future house prices. Macroprudential policy measures have a direct effect where tightening these measures reduces house-prices-at-risk—consistent with macroprudential policy measures leading to the accumulation of buffers, so that house-prices-at-risk is lower for any combination of factors. Especially a tightening of borrower-based macroprudential policy measures, caps on loan-to-value and debt-service-to-income ratios, reduces overall the probability of a large price correction by shifting the entire term structure of house prices at risk upward (Figure 9, panels 1 and 2; and Table 5). In advanced economies, the effect seems to have a maximum impact between four and eight quarters ahead, while in emerging market economies, the impact is highest in the short term, but remains mostly steady until about 12 quarters ahead.²⁸ Specifically, a one-unit tightening of macroprudential measures could lower the three-years-ahead annualized average house prices at risk by 0.68 in emerging market economies under normal financial conditions.

Monetary policy tightening contributes to a deterioration of house prices at risk over a short horizon in advanced economies. The analysis shows that these shocks have a short-lived, negative relationship with house prices at risk only in advanced economies (Figure 9, panels 3 and 4, and Table 6). The latter result might be explained by the fact that housing markets in advanced economies are more developed and integrated with capital markets than those in emerging market economies, such that changes in the short-term policy rate would directly pass through to house prices. The fact that monetary policy shocks could influence house prices at risk might affect the

²⁸ According to Choi, Kodres, and Lu (2018), tightening nine macroprudential policies on annual house prices from a broad set of countries appeared to take two years to have the intended effect, and in the first year after implementation real housing prices rose instead of falling. For European countries, IMF (2018) finds mixed evidence on the ability of macroprudential policies to contain house price growth amid accommodative monetary policy.

way monetary policymakers think about this transmission channel. Moreover, the inclusion of these monetary policy shocks weakens the short-term relationship between financial conditions and house prices at risk, indicating that part of this relationship was associated with changes in the short-term policy rate.

Figure 9. Effects of Macroprudential Policy and Monetary Policy on House Prices at Risk

1. Advanced Economies: Macroprudential Policy

2. Emerging Market Economies: Macroprudential Policy

3. Advanced Economies: Monetary Policy

4. Emerging Market Economies: Monetary Policy

Source: Authors' estimates.

Note: Panels show the coefficients of different policies on the house-price-at-risk estimation. In Panels 1 and 2, macroprudential policy measures have a statistically significant level-shifting effect on house prices at risk (reducing downside risk). The macroprudential policy variable used here is based on a three-year rolling window of debt-service-to-income and loan-to-value measures, and is purged of credit-to-GDP to remove potential endogeneity. In Panels 3 and 4, for advanced economies, monetary policy, as captured by predicted residuals of a feedback rule, has a significant effect (initially increasing downside risks, but less so over time). Dashed lines in panels 1–4 denote 95 percent confidence bounds for statistical significance. Estimated coefficients are reported in Table 8 and Table 9.

V. CONCLUSION

This paper lays out a new methodology to predict downside risk to house prices and finds it to be a useful early-warning indicator that can be used for financial stability surveillance. Using panel quantile regression techniques based on the growth-at-risk model of Adrian et al. (2019), the paper finds that house-prices-at-risk—the 5th percentile of house price growth over a given time horizon—reflect fundamental factors and overvaluation, as well as recent price dynamics. House prices at risk in turn have a significant impact on growth at risk—a summary measure for financial stability risk. Moreover, downside risks to house prices contribute to the financial stability monitoring toolkit over and above existing market-based house price (valuation) measures and

could complement information from house price expectations surveys.²⁹ Policymakers can use or adapt this methodology for surveillance of financial stability risks from the housing sector and to assess measures that mitigate adverse spillovers from house price downside risks.

We also shed light on the policy solutions for preventing and mitigating future shocks to house prices and financial stability. Some macroprudential policies appear to reduce house prices at risk. Although macroprudential policy focuses on building buffers and reducing vulnerabilities and should not target house prices, heightened downside risks to house prices signal a build-up of systemic risks and could complement other indicators for the activation of macroprudential policies. The impact of macroprudential policy measures is also consistent with a theoretical model described in Section II. The relationship between macroprudential policy measures and house-prices-at-risk is especially significant for borrower-based measures, i.e., caps on loan-to-value and debt-service-to-income ratios, which is another reason countries should add this type of measures to their macroprudential policy toolkit and monitor their development over time (besides their general usefulness for systemic risk management). This is in line with a risk management approach to macroprudential policy, which should target some level of downside risk.

The ability of monetary policy to mitigate downside risks to housing prices, beyond its impact on financial conditions, seems more limited. Financial conditions, which are partly driven by monetary policy actions, have a clear relationship with downside risks to house prices. Beyond this indirect effect, conventional monetary policy shocks seem to have only a short-term influence in advanced economies, where an unexpected loosening reduces the house-prices-at-risk measure for a few quarters. Thus, in general, monetary policy has an effect on downside risks to house prices mainly through its impact on financial conditions—an issue that has been much discussed recently (see IMF 2017). That said, the short-term association documented in advanced economies may be a useful consideration in cases where the macroprudential toolkit is incomplete or the macroprudential decision-making process is inadequate.

Other policies, such as capital flow management measures and real estate tax policies, may also have an impact on house price risks and are worth exploring in future work. For example, there is anecdotal evidence that capital inflows are associated with higher house prices in the short term and hence may result in more downside risks to house prices in the medium term, which might justify capital flow management measures under some conditions.³⁰ IMF (2019) provided some initial evidence on these effects. Similarly, real estate taxation may affect house prices and incentives for households to increase their leverage (e.g., by increasing mortgage interest deductibility or reducing income tax rates), and hence indirectly affect future house price risks (Valckx 2019).

²⁹ See the Royal Institution of Chartered Surveyors' (RICS) global residential surveys, for example.

³⁰ IMF (2012) notes that (1) capital flows should be handled primarily through macroeconomic policies, in turn supported by sound financial supervision and regulation; (2) in certain circumstances, capital flow measures can be useful to support macroeconomic adjustment and safeguard financial stability; and (3) capital flow measures should not substitute for warranted macroeconomic adjustment (see also Group of Twenty 2018).

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TABLE 1. Baseline Estimations of House prices-at-Risk**Advanced Economies Panel**

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
House Prices Growth (t)	1.289*** (0.130)	1.151*** (0.139)	0.908*** (0.089)	0.820*** (0.107)	0.775*** (0.106)	0.562*** (0.088)	0.414*** (0.112)	0.344*** (0.107)	0.361*** (0.086)	0.381*** (0.085)	0.391*** (0.060)	0.392*** (0.072)	0.372*** (0.063)	0.357*** (0.067)	0.324*** (0.065)	0.300*** (0.056)
GDP Growth (t)	0.197* (0.102)	0.069 (0.091)	0.052 (0.095)	-0.095 (0.101)	-0.204* (0.118)	-0.227** (0.095)	-0.215*** (0.079)	-0.156* (0.082)	-0.196*** (0.071)	-0.141* (0.077)	-0.138*** (0.045)	-0.140** (0.056)	-0.128*** (0.057)	-0.145*** (0.051)	-0.138*** (0.059)	-0.114 (0.076)
House Prices Misalignment (t)	-0.473*** (0.158)	-0.779*** (0.129)	-0.788*** (0.147)	-0.874*** (0.087)	-0.931*** (0.106)	-0.976*** (0.077)	-1.033*** (0.072)	-1.014*** (0.061)	-0.971*** (0.051)	-0.956*** (0.042)	-0.919*** (0.035)	-0.928*** (0.048)	-0.944*** (0.056)	-0.985*** (0.047)	-0.981*** (0.054)	-0.987*** (0.039)
FCI (t)	-0.339** (0.166)	-0.283** (0.135)	-0.114 (0.125)	-0.205** (0.091)	-0.220** (0.092)	-0.218*** (0.074)	-0.233*** (0.066)	-0.238*** (0.070)	-0.196*** (0.055)	-0.150*** (0.052)	-0.164*** (0.052)	-0.161*** (0.050)	-0.119** (0.046)	-0.102** (0.041)	-0.135*** (0.042)	-0.121** (0.050)
Credit Boom (t)	-0.275 (0.334)	-0.483** (0.241)	-0.543** (0.212)	-0.481** (0.208)	-0.321* (0.189)	-0.385** (0.176)	-0.409** (0.165)	-0.359** (0.167)	-0.344*** (0.133)	-0.304** (0.150)	-0.241** (0.118)	-0.293** (0.129)	-0.260** (0.120)	-0.207* (0.106)	-0.216* (0.111)	-0.227** (0.110)
Constant	-2.656*** (0.212)	-2.198*** (0.152)	-2.007*** (0.153)	-2.008*** (0.113)	-1.955*** (0.090)	-1.810*** (0.074)	-1.730*** (0.089)	-1.626*** (0.089)	-1.499*** (0.071)	-1.343*** (0.053)	-1.278*** (0.057)	-1.197*** (0.066)	-1.126*** (0.067)	-1.106*** (0.067)	-1.073*** (0.072)	-1.025*** (0.074)
Observations	2,389	2,367	2,345	2,323	2,301	2,279	2,257	2,235	2,213	2,191	2,169	2,147	2,125	2,103	2,081	2,059

Emerging Market Economies Panel

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
House Prices Growth (t)	0.494* (0.271)	1.025*** (0.205)	0.665*** (0.200)	0.529*** (0.182)	0.478** (0.199)	0.528** (0.230)	0.521** (0.219)	0.469** (0.236)	0.474*** (0.183)	0.371** (0.166)	0.428** (0.182)	0.261* (0.138)	0.200* (0.103)	0.211** (0.095)	0.203*** (0.071)	0.183*** (0.070)
GDP Growth (t)	0.182 (0.276)	0.120 (0.253)	0.204 (0.215)	0.133 (0.271)	0.260 (0.178)	0.083 (0.217)	0.163 (0.162)	0.149 (0.164)	0.096 (0.142)	0.141 (0.139)	0.098 (0.108)	0.009 (0.114)	-0.002 (0.072)	-0.004 (0.073)	0.028 (0.083)	0.022 (0.080)
House Prices Misalignment (t)	-0.748*** (0.280)	-0.812*** (0.153)	-0.837*** (0.143)	-0.846*** (0.147)	-0.962*** (0.152)	-0.965*** (0.118)	-0.976*** (0.127)	-1.015*** (0.102)	-1.085*** (0.116)	-1.076*** (0.075)	-1.015*** (0.089)	-1.051*** (0.077)	-1.047*** (0.078)	-1.037*** (0.091)	-0.978*** (0.096)	-1.023*** (0.101)
FCI (t)	-0.619** (0.276)	-0.525*** (0.191)	-0.660*** (0.203)	-0.674*** (0.203)	-0.539*** (0.181)	-0.453*** (0.167)	-0.225 (0.148)	-0.157 (0.160)	-0.094 (0.111)	-0.029 (0.094)	-0.020 (0.082)	-0.042 (0.077)	-0.086 (0.059)	-0.088 (0.080)	-0.048 (0.085)	-0.105 (0.083)
Credit Boom (t)	-0.526 (0.675)	-0.685** (0.348)	-0.934*** (0.312)	-1.039*** (0.342)	-0.959*** (0.328)	-1.106*** (0.364)	-1.065*** (0.308)	-0.784** (0.352)	-0.561* (0.301)	-0.282 (0.193)	-0.125 (0.168)	-0.134 (0.170)	-0.084 (0.150)	-0.013 (0.223)	0.017 (0.212)	0.164 (0.247)
Constant	-3.839*** (0.399)	-2.854*** (0.309)	-2.601*** (0.263)	-2.390*** (0.234)	-2.334*** (0.210)	-2.148*** (0.205)	-1.961*** (0.185)	-2.072*** (0.182)	-1.945*** (0.165)	-1.860*** (0.139)	-1.748*** (0.139)	-1.656*** (0.127)	-1.604*** (0.126)	-1.585*** (0.165)	-1.484*** (0.164)	-1.418*** (0.194)
Observations	948	938	928	918	908	898	888	878	868	858	848	838	828	818	808	798

Source: Authors' estimates.

Note: The tables report the estimated coefficients for the 5th percentile of the key determinants of downside risk for each quarter of the forecasting horizon. Standard errors are bootstrapped and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 2. Baseline Estimations of Median House Prices Growth**Advanced Economies Panel**

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
House Prices Growth (t)	1.446*** (0.073)	1.235*** (0.052)	1.088*** (0.047)	0.933*** (0.044)	0.839*** (0.043)	0.749*** (0.050)	0.699*** (0.040)	0.633*** (0.041)	0.595*** (0.042)	0.543*** (0.037)	0.506*** (0.030)	0.461*** (0.025)	0.445*** (0.025)	0.414*** (0.026)	0.391*** (0.021)	0.366*** (0.022)
GDP Growth (t)	0.084** (0.042)	0.010 (0.035)	-0.009 (0.030)	-0.037 (0.030)	-0.052 (0.032)	-0.042 (0.033)	-0.058** (0.028)	-0.051** (0.024)	-0.052** (0.021)	-0.044*** (0.017)	-0.037** (0.017)	-0.047** (0.018)	-0.037* (0.022)	-0.028 (0.022)	-0.031 (0.020)	-0.032 (0.020)
House Prices Misalignment (t)	-0.257*** (0.039)	-0.291*** (0.031)	-0.353*** (0.028)	-0.434*** (0.031)	-0.495*** (0.038)	-0.537*** (0.033)	-0.566*** (0.029)	-0.603*** (0.026)	-0.626*** (0.025)	-0.683*** (0.024)	-0.699*** (0.023)	-0.729*** (0.021)	-0.755*** (0.019)	-0.772*** (0.022)	-0.789*** (0.021)	-0.808*** (0.023)
FCI (t)	-0.158*** (0.038)	-0.173*** (0.034)	-0.164*** (0.028)	-0.163*** (0.030)	-0.134*** (0.037)	-0.130*** (0.032)	-0.121*** (0.025)	-0.109*** (0.024)	-0.099*** (0.027)	-0.093*** (0.025)	-0.076*** (0.022)	-0.074*** (0.018)	-0.062*** (0.017)	-0.051** (0.022)	-0.037 (0.023)	-0.026 (0.019)
Credit Boom (t)	-0.060 (0.053)	-0.077 (0.051)	-0.070 (0.046)	-0.086* (0.047)	-0.114** (0.055)	-0.122** (0.056)	-0.088* (0.046)	-0.071 (0.047)	-0.072* (0.038)	-0.047 (0.045)	-0.030 (0.043)	-0.043 (0.040)	-0.020 (0.042)	0.000 (0.045)	0.018 (0.046)	0.039 (0.036)
Constant	-0.037 (0.044)	-0.056* (0.032)	-0.061** (0.029)	-0.071* (0.036)	-0.047 (0.042)	-0.054 (0.042)	-0.077** (0.033)	-0.071** (0.030)	-0.090*** (0.028)	-0.098*** (0.034)	-0.093*** (0.030)	-0.078*** (0.028)	-0.059** (0.028)	-0.073*** (0.028)	-0.070*** (0.026)	-0.084*** (0.025)
Observations	2,389	2,367	2,345	2,323	2,301	2,279	2,257	2,235	2,213	2,191	2,169	2,147	2,125	2,103	2,081	2,059

Emerging Market Economies Panel

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
House Prices Growth (t)	1.141*** (0.106)	0.946*** (0.154)	0.778*** (0.103)	0.781*** (0.078)	0.671*** (0.075)	0.600*** (0.083)	0.491*** (0.095)	0.494*** (0.072)	0.482*** (0.087)	0.428*** (0.078)	0.370*** (0.081)	0.357*** (0.065)	0.332*** (0.062)	0.329*** (0.047)	0.299*** (0.047)	0.283*** (0.054)
GDP Growth (t)	0.201* (0.111)	0.031 (0.112)	0.106 (0.069)	0.076 (0.072)	0.043 (0.076)	0.037 (0.075)	0.093 (0.066)	0.060 (0.050)	0.017 (0.051)	0.012 (0.051)	0.010 (0.053)	0.023 (0.048)	0.026 (0.042)	0.006 (0.042)	-0.008 (0.036)	-0.029 (0.040)
House Prices Misalignment (t)	-0.311*** (0.099)	-0.388*** (0.080)	-0.399*** (0.084)	-0.395*** (0.088)	-0.482*** (0.090)	-0.541*** (0.070)	-0.554*** (0.080)	-0.631*** (0.067)	-0.673*** (0.074)	-0.744*** (0.080)	-0.782*** (0.078)	-0.824*** (0.080)	-0.822*** (0.064)	-0.829*** (0.050)	-0.825*** (0.041)	-0.829*** (0.044)
FCI (t)	-0.427*** (0.105)	-0.318*** (0.083)	-0.184*** (0.071)	-0.165** (0.068)	-0.157** (0.076)	-0.126 (0.077)	-0.138* (0.072)	-0.094** (0.045)	-0.092** (0.046)	-0.097** (0.045)	-0.104** (0.052)	-0.098*** (0.032)	-0.073** (0.033)	-0.066** (0.033)	-0.059* (0.034)	-0.038 (0.032)
Credit Boom (t)	0.021 (0.174)	0.034 (0.159)	-0.146 (0.121)	-0.076 (0.099)	-0.094 (0.094)	-0.094 (0.106)	-0.089 (0.098)	-0.078 (0.084)	-0.048 (0.107)	-0.014 (0.091)	0.050 (0.090)	0.074 (0.077)	0.071 (0.071)	0.056 (0.056)	0.068 (0.064)	0.062 (0.075)
Constant	-0.097 (0.119)	-0.181* (0.101)	-0.113 (0.081)	-0.114 (0.085)	-0.064 (0.061)	-0.116* (0.066)	-0.106 (0.078)	-0.099* (0.057)	-0.088 (0.087)	-0.109 (0.075)	-0.110* (0.064)	-0.102** (0.051)	-0.100** (0.042)	-0.084** (0.039)	-0.076* (0.042)	-0.077 (0.051)
Observations	948	938	928	918	908	898	888	878	868	858	848	838	828	818	808	798

Source: Authors' estimates.

Note: The tables report the estimated coefficients for the 50th percentile of the key determinants of downside risk for each quarter of the forecasting horizon. Standard errors are bootstrapped and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 3. Baseline Estimations of House prices-at-Risk Excluding the Global Financial Crisis**Advanced Economies Panel**

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
House Prices Growth (t)	1.233*** (0.143)	1.152*** (0.113)	0.930*** (0.091)	0.879*** (0.079)	0.802*** (0.086)	0.623*** (0.088)	0.450*** (0.137)	0.385*** (0.122)	0.412*** (0.097)	0.381*** (0.099)	0.395*** (0.063)	0.395*** (0.079)	0.330*** (0.065)	0.300*** (0.065)	0.268*** (0.057)	0.258*** (0.056)
GDP Growth (t)	0.174 (0.133)	-0.015 (0.117)	-0.019 (0.112)	-0.220** (0.106)	-0.228** (0.105)	-0.207** (0.082)	-0.154** (0.069)	-0.178** (0.076)	-0.139 (0.090)	-0.154** (0.077)	-0.178*** (0.059)	-0.164** (0.072)	-0.165*** (0.061)	-0.167*** (0.061)	-0.184*** (0.061)	-0.172*** (0.067)
House Prices Misalignment (t)	-0.493*** (0.140)	-0.695*** (0.129)	-0.658*** (0.113)	-0.844*** (0.103)	-0.900*** (0.094)	-0.923*** (0.092)	-0.989*** (0.092)	-0.960*** (0.063)	-0.929*** (0.055)	-0.917*** (0.044)	-0.904*** (0.036)	-0.892*** (0.054)	-0.871*** (0.049)	-0.871*** (0.043)	-0.884*** (0.042)	-0.886*** (0.029)
FCI (t)	-0.446*** (0.146)	-0.394*** (0.129)	-0.241** (0.121)	-0.283*** (0.102)	-0.266*** (0.088)	-0.241*** (0.075)	-0.268*** (0.075)	-0.281*** (0.062)	-0.221*** (0.056)	-0.192*** (0.051)	-0.202*** (0.044)	-0.184*** (0.048)	-0.172*** (0.047)	-0.135*** (0.047)	-0.148*** (0.040)	-0.117*** (0.042)
Credit Boom (t)	-0.093 (0.288)	-0.399** (0.172)	-0.422** (0.208)	-0.383 (0.238)	-0.374** (0.185)	-0.467** (0.202)	-0.518*** (0.179)	-0.393** (0.165)	-0.461*** (0.148)	-0.403*** (0.142)	-0.296*** (0.095)	-0.333** (0.141)	-0.367*** (0.116)	-0.367*** (0.128)	-0.384*** (0.107)	-0.346*** (0.094)
Constant	-2.566*** (0.193)	-2.137*** (0.139)	-1.952*** (0.118)	-1.971*** (0.107)	-1.956*** (0.092)	-1.792*** (0.085)	-1.701*** (0.096)	-1.647*** (0.077)	-1.495*** (0.072)	-1.357*** (0.064)	-1.303*** (0.056)	-1.187*** (0.074)	-1.107*** (0.070)	-1.007*** (0.062)	-0.959*** (0.056)	-0.899*** (0.050)
Observations	2,213	2,191	2,169	2,147	2,125	2,103	2,081	2,059	2,037	2,015	1,993	1,971	1,949	1,927	1,905	1,883

Emerging Market Economies Panel

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
House Prices Growth (t)	0.470 (0.315)	0.781*** (0.176)	0.633*** (0.194)	0.552*** (0.188)	0.597*** (0.138)	0.624*** (0.123)	0.559*** (0.128)	0.550*** (0.133)	0.527*** (0.125)	0.479*** (0.110)	0.511*** (0.088)	0.402*** (0.104)	0.284*** (0.109)	0.206** (0.103)	0.238*** (0.077)	0.162* (0.085)
GDP Growth (t)	-0.007 (0.272)	0.029 (0.163)	0.134 (0.183)	0.345 (0.215)	0.387** (0.175)	0.486*** (0.177)	0.293 (0.189)	0.341** (0.168)	0.235 (0.154)	0.192 (0.168)	0.195* (0.108)	0.063 (0.113)	0.029 (0.101)	-0.036 (0.083)	0.054 (0.086)	0.037 (0.085)
House Prices Misalignment (t)	-0.624** (0.295)	-0.593*** (0.167)	-0.761*** (0.156)	-0.687*** (0.112)	-0.783*** (0.120)	-0.838*** (0.112)	-0.925*** (0.108)	-0.956*** (0.113)	-0.944*** (0.115)	-0.949*** (0.101)	-1.108*** (0.081)	-1.105*** (0.089)	-1.121*** (0.093)	-1.050*** (0.100)	-1.049*** (0.092)	-1.000*** (0.105)
FCI (t)	-0.565** (0.281)	-0.328* (0.194)	-0.481** (0.208)	-0.399** (0.168)	-0.332* (0.176)	-0.193 (0.213)	-0.082 (0.150)	-0.004 (0.164)	0.001 (0.136)	0.073 (0.096)	-0.001 (0.069)	-0.013 (0.083)	-0.078 (0.071)	-0.105 (0.075)	-0.048 (0.084)	-0.082 (0.080)
Credit Boom (t)	-0.408 (0.610)	-1.052*** (0.306)	-0.914*** (0.264)	-1.118*** (0.267)	-0.815*** (0.212)	-0.670** (0.304)	-0.844** (0.339)	-0.712** (0.285)	-0.635** (0.279)	-0.346 (0.236)	-0.184 (0.162)	-0.019 (0.162)	-0.023 (0.160)	-0.001 (0.157)	-0.024 (0.185)	0.077 (0.170)
Constant	-3.760*** (0.368)	-2.637*** (0.234)	-2.594*** (0.220)	-2.084*** (0.164)	-2.189*** (0.149)	-2.106*** (0.152)	-2.029*** (0.158)	-1.999*** (0.148)	-1.837*** (0.138)	-1.750*** (0.139)	-1.749*** (0.135)	-1.723*** (0.124)	-1.593*** (0.111)	-1.527*** (0.117)	-1.390*** (0.149)	-1.419*** (0.156)
Observations	868	858	848	838	828	818	808	798	788	778	768	758	748	738	728	718

Source: Authors' estimates.

Note: The tables report the estimated coefficients for the 5th percentile of the key determinants of downside risk for each quarter of the forecasting horizon excluding the Global Financial Crisis peak years of 2008 to 2009 to test the robustness of the model. Standard errors are bootstrapped and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 4. Alternative Panel Quantile Estimation based on Powell**Advanced Economies Panel**

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
House Prices Growth (t)	1.367*** (0.008)	1.292*** (0.013)	0.999*** (0.001)	1.010*** (0.006)	0.851*** (0.005)	0.656*** (0.026)	0.552*** (0.006)	0.366*** (0.005)	0.453*** (0.008)	0.365*** (0.003)	0.327*** (0.012)	0.397*** (0.009)	0.284*** (0.022)	0.232*** (0.010)	0.202*** (0.005)	0.248*** (0.001)
GDP Growth (t)	0.261*** (0.017)	0.176*** (0.011)	0.050*** (0.000)	-0.048*** (0.006)	-0.120*** (0.003)	-0.037 (0.028)	-0.046*** (0.011)	-0.065*** (0.012)	-0.066*** (0.019)	-0.084*** (0.005)	-0.094*** (0.010)	-0.019 (0.018)	-0.065*** (0.022)	-0.058*** (0.004)	-0.065*** (0.003)	-0.020*** (0.003)
House Prices Misalignment (t)	-0.429*** (0.010)	-0.590*** (0.058)	-0.785*** (0.004)	-0.758*** (0.004)	-0.852*** (0.004)	-1.077*** (0.032)	-0.989*** (0.041)	-1.009*** (0.018)	-1.077*** (0.032)	-1.030*** (0.004)	-1.002*** (0.016)	-0.911*** (0.054)	-0.966*** (0.031)	-1.024*** (0.009)	-1.002*** (0.012)	-0.900*** (0.008)
FCI (t)	-0.427*** (0.029)	-0.300*** (0.028)	-0.144*** (0.002)	-0.209*** (0.004)	-0.245*** (0.004)	-0.102*** (0.015)	-0.164*** (0.016)	-0.095*** (0.008)	-0.144*** (0.014)	-0.145*** (0.008)	-0.119*** (0.008)	-0.095*** (0.008)	-0.068*** (0.015)	-0.063*** (0.011)	-0.060*** (0.011)	0.023*** (0.003)
Credit Boom (t)	-0.165*** (0.011)	-0.330*** (0.068)	-0.309*** (0.003)	-0.169*** (0.011)	-0.060*** (0.007)	-0.106*** (0.022)	-0.042 (0.036)	0.003 (0.010)	-0.064* (0.038)	-0.057*** (0.010)	-0.023* (0.012)	-0.058 (0.050)	-0.034*** (0.011)	-0.029 (0.019)	-0.019** (0.008)	-0.076*** (0.004)
Observations	2,389	2,367	2,345	2,323	2,301	2,279	2,257	2,235	2,213	2,191	2,169	2,147	2,125	2,103	2,081	2,059

Emerging Market Economies Panel

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
House Prices Growth (t)	0.796*** (0.036)	1.021*** (0.015)	0.711*** (0.039)	0.522*** (0.016)	0.408*** (0.008)	0.490*** (0.009)	0.258*** (0.040)	0.601*** (0.016)	0.162*** (0.051)	0.459*** (0.039)	0.517*** (0.016)	0.471*** (0.006)	0.144*** (0.018)	0.320*** (0.033)	0.261*** (0.060)	0.147*** (0.035)
GDP Growth (t)	0.214*** (0.020)	-0.165*** (0.022)	-0.131*** (0.020)	-0.046** (0.020)	0.033*** (0.007)	-0.050*** (0.009)	-0.026*** (0.007)	0.053*** (0.015)	-0.060*** (0.013)	-0.004 (0.032)	0.153*** (0.013)	0.017*** (0.005)	-0.045 (0.046)	0.037*** (0.005)	-0.027 (0.042)	-0.035* (0.018)
House Prices Misalignment (t)	-0.739*** (0.017)	-0.984*** (0.027)	-0.958*** (0.090)	-1.095*** (0.018)	-0.909*** (0.005)	-0.999*** (0.031)	-1.189*** (0.022)	-0.984*** (0.007)	-1.030*** (0.024)	-0.909*** (0.022)	-1.142*** (0.029)	-1.036*** (0.008)	-1.216*** (0.036)	-0.947*** (0.019)	-0.973*** (0.033)	-1.074*** (0.009)
FCI (t)	-0.535*** (0.025)	-0.777*** (0.029)	-0.480*** (0.048)	-0.354*** (0.014)	-0.378*** (0.009)	-0.576*** (0.012)	-0.219*** (0.015)	-0.171*** (0.015)	-0.113*** (0.010)	0.018 (0.024)	-0.094*** (0.013)	-0.116*** (0.004)	-0.116*** (0.007)	-0.132*** (0.011)	-0.073*** (0.011)	-0.011 (0.008)
Credit Boom (t)	-0.177*** (0.024)	-0.977*** (0.011)	-0.743*** (0.096)	-0.382*** (0.079)	-0.997*** (0.004)	-0.949*** (0.021)	-0.787*** (0.098)	-0.503*** (0.015)	-0.129*** (0.034)	-0.009 (0.045)	-0.119*** (0.021)	-0.143*** (0.011)	-0.059*** (0.011)	0.057*** (0.018)	0.087*** (0.019)	0.121*** (0.013)
Constant																
Observations	948	938	928	918	908	898	888	878	868	858	848	838	828	818	808	798

Source: Authors' estimates.

Note: The tables report the estimated coefficients for the 5th percentile of the key determinants of downside risk for each quarter of the forecasting horizon using an alternative panel quantile estimator based on Powell (2016) to test the robustness of the model. Standard errors are bootstrapped and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 5. Effects of House Prices-at-Risk on Future GDP Growth**Advanced Economies Panel**

	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
GDP Growth (t)	-0.055 (0.057)	-0.012 (0.046)	-0.003 (0.044)	-0.000 (0.039)	-0.002 (0.040)	-0.041 (0.033)	-0.040 (0.052)	-0.019 (0.042)	-0.052 (0.036)	-0.029 (0.032)	-0.021 (0.029)	-0.017 (0.026)	-0.008 (0.025)	0.018 (0.023)	0.006 (0.019)	0.027 (0.017)
FCI (t)	-0.398*** (0.083)	-0.272*** (0.076)	-0.141** (0.059)	-0.099* (0.058)	-0.053 (0.052)	0.022 (0.038)	0.084* (0.043)	0.119*** (0.042)	0.114*** (0.036)	0.134*** (0.027)	0.132*** (0.028)	0.135*** (0.025)	0.138*** (0.023)	0.133*** (0.021)	0.128*** (0.018)	0.135*** (0.018)
HaR 1 year ahead (t)	0.193*** (0.059)	0.218*** (0.047)	0.269*** (0.040)	0.257*** (0.041)	0.253*** (0.036)	0.268*** (0.030)	0.252*** (0.029)	0.215*** (0.030)	0.200*** (0.033)	0.175*** (0.026)	0.164*** (0.022)	0.157*** (0.019)	0.159*** (0.015)	0.158*** (0.015)	0.161*** (0.010)	0.154*** (0.012)
Constant	-1.261*** (0.105)	-0.904*** (0.083)	-0.728*** (0.069)	-0.667*** (0.077)	-0.634*** (0.072)	-0.560*** (0.067)	-0.549*** (0.083)	-0.627*** (0.088)	-0.584*** (0.085)	-0.596*** (0.063)	-0.568*** (0.057)	-0.536*** (0.046)	-0.500*** (0.034)	-0.467*** (0.034)	-0.426*** (0.024)	-0.406*** (0.024)
Observations	2,394	2,372	2,350	2,328	2,306	2,284	2,262	2,240	2,218	2,196	2,174	2,152	2,130	2,108	2,086	2,064

Emerging Market Economies Panel

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
GDP Growth (t)	0.337*** (0.122)	0.230*** (0.089)	0.094 (0.090)	-0.090 (0.072)	-0.047 (0.061)	-0.054 (0.041)	-0.049 (0.033)	-0.035 (0.029)	0.009 (0.034)	0.002 (0.029)	0.032 (0.023)	0.009 (0.032)	0.002 (0.017)	-0.026 (0.030)	-0.013 (0.037)	-0.043** (0.022)
FCI (t)	0.061 (0.290)	0.293 (0.223)	0.595*** (0.220)	0.713*** (0.137)	0.624*** (0.081)	0.658*** (0.080)	0.596*** (0.062)	0.548*** (0.047)	0.463*** (0.039)	0.422*** (0.042)	0.327*** (0.039)	0.327*** (0.042)	0.252*** (0.034)	0.272*** (0.034)	0.248*** (0.046)	0.249*** (0.052)
HaR 1 year ahead (t)	0.160 (0.151)	0.250* (0.147)	0.408*** (0.156)	0.429*** (0.099)	0.341*** (0.062)	0.315*** (0.054)	0.277*** (0.038)	0.222*** (0.028)	0.181*** (0.028)	0.186*** (0.025)	0.182*** (0.022)	0.195*** (0.025)	0.182*** (0.013)	0.186*** (0.022)	0.158*** (0.021)	0.160*** (0.023)
Constant	-2.038*** (0.466)	-1.424*** (0.361)	-0.993*** (0.379)	-0.838*** (0.231)	-0.843*** (0.168)	-0.776*** (0.143)	-0.686*** (0.106)	-0.716*** (0.082)	-0.747*** (0.089)	-0.670*** (0.087)	-0.671*** (0.074)	-0.586*** (0.086)	-0.526*** (0.048)	-0.426*** (0.087)	-0.480*** (0.087)	-0.421*** (0.070)
Observations	953	944	935	926	917	907	897	887	877	867	857	847	837	827	817	807

Source: Authors' estimates.

Note: The tables report the estimated coefficients for the 5th percentile from the Growth-at-Risk specification for each quarter of the forecasting horizon. Standard errors are bootstrapped and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 6. Effects of House Prices-at-Risk on Future Median GDP Growth**Advanced Economies Panel**

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
GDP Growth (t)	0.134*** (0.028)	0.116*** (0.027)	0.086*** (0.018)	0.071*** (0.020)	0.065*** (0.017)	0.048*** (0.013)	0.038** (0.018)	0.034* (0.018)	0.026 (0.016)	0.014 (0.014)	0.016 (0.013)	0.007 (0.009)	0.012 (0.009)	0.009 (0.010)	0.008 (0.013)	0.019* (0.011)
FCI (t)	-0.162*** (0.028)	-0.105*** (0.024)	-0.080*** (0.019)	-0.047** (0.020)	-0.027* (0.015)	0.001 (0.016)	0.008 (0.020)	0.034* (0.018)	0.046** (0.023)	0.054*** (0.016)	0.072*** (0.015)	0.074*** (0.015)	0.079*** (0.011)	0.088*** (0.014)	0.107*** (0.013)	0.113*** (0.012)
HaR 1 year ahead (t)	0.113*** (0.016)	0.120*** (0.015)	0.136*** (0.013)	0.133*** (0.014)	0.137*** (0.012)	0.139*** (0.011)	0.132*** (0.012)	0.138*** (0.012)	0.139*** (0.014)	0.141*** (0.011)	0.142*** (0.009)	0.143*** (0.011)	0.136*** (0.009)	0.134*** (0.010)	0.131*** (0.010)	0.123*** (0.009)
Constant	-0.137*** (0.034)	-0.084*** (0.031)	-0.032 (0.025)	-0.025 (0.032)	-0.011 (0.024)	-0.006 (0.021)	0.016 (0.022)	0.004 (0.022)	0.015 (0.024)	0.019 (0.021)	0.018 (0.019)	0.023 (0.019)	0.020 (0.018)	0.028 (0.020)	0.021 (0.019)	0.016 (0.018)
Observations	2,394	2,372	2,350	2,328	2,306	2,284	2,262	2,240	2,218	2,196	2,174	2,152	2,130	2,108	2,086	2,064

Emerging Market Economies Panel

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
GDP Growth (t)	0.196*** (0.051)	0.104*** (0.029)	0.065*** (0.025)	0.055* (0.032)	0.054** (0.021)	0.030 (0.025)	0.035 (0.028)	0.012 (0.023)	0.017 (0.020)	0.003 (0.016)	0.002 (0.016)	-0.001 (0.019)	0.004 (0.021)	-0.000 (0.016)	0.006 (0.017)	-0.010 (0.014)
FCI (t)	-0.245*** (0.079)	-0.157*** (0.056)	-0.139*** (0.042)	-0.091* (0.054)	-0.042 (0.045)	0.028 (0.046)	0.068* (0.038)	0.126*** (0.034)	0.137*** (0.033)	0.155*** (0.030)	0.141*** (0.028)	0.108*** (0.032)	0.134*** (0.030)	0.137*** (0.027)	0.127*** (0.026)	0.134*** (0.023)
HaR 1 year ahead (t)	0.040 (0.043)	0.070* (0.036)	0.082*** (0.029)	0.077** (0.032)	0.083*** (0.026)	0.100*** (0.024)	0.104*** (0.027)	0.138*** (0.024)	0.127*** (0.023)	0.123*** (0.018)	0.117*** (0.018)	0.093*** (0.018)	0.080*** (0.017)	0.067*** (0.016)	0.059*** (0.014)	0.058*** (0.012)
Constant	-0.086 (0.136)	-0.054 (0.082)	-0.030 (0.080)	-0.115* (0.065)	-0.142* (0.073)	-0.101 (0.064)	-0.075 (0.074)	0.023 (0.074)	0.008 (0.059)	0.031 (0.051)	0.028 (0.052)	-0.016 (0.054)	-0.028 (0.048)	-0.040 (0.047)	-0.037 (0.046)	-0.024 (0.038)
Observations	953	944	935	926	917	907	897	887	877	867	857	847	837	827	817	807

Source: Authors' estimates.

Note: The tables report the estimated coefficients for the 50th percentile from the Growth-at-Risk specification for each quarter of the forecasting horizon. Standard errors are bootstrapped and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 7. House Prices-at-Risk and Financial Stability

Advanced Economies Panel

HaR (H=8)	Predictive Margin	Std. Err.	z	P>z	[95% Conf. Interval]
-14	0.433	0.145	2.980	0.003	0.148 0.717
-12	0.306	0.082	3.740	0.000	0.146 0.466
-10	0.203	0.029	6.960	0.000	0.146 0.260
-8	0.128	0.006	22.140	0.000	0.117 0.140
-6	0.078	0.017	4.480	0.000	0.044 0.113
-4	0.047	0.020	2.340	0.019	0.008 0.086
-2	0.028	0.018	1.570	0.116	-0.007 0.062
0	0.016	0.014	1.180	0.238	-0.011 0.043
2	0.009	0.010	0.950	0.344	-0.010 0.029

Emerging Market Economies Panel

HaR (H=8)	Predictive Margin	Std. Err.	z	P>z	[95% Conf. Interval]
-14	0.183	0.041	4.430	0.000	0.102 0.264
-12	0.101	0.012	8.580	0.000	0.078 0.124
-10	0.054	0.011	4.930	0.000	0.032 0.075
-8	0.028	0.011	2.540	0.011	0.006 0.049
-6	0.014	0.008	1.670	0.095	-0.002 0.031
-4	0.007	0.006	1.240	0.217	-0.004 0.018
-2	0.004	0.004	0.980	0.327	-0.004 0.011
0	0.002	0.002	0.810	0.416	-0.003 0.006
2	0.001	0.001	0.690	0.488	-0.002 0.003

Source: Authors' estimates.

Note: The tables show the marginal probabilities of real house price declines (HaR) estimated for eight quarters ahead at given values on the occurrence of a financial (banking) crisis from a model with fixed effects, output growth, the financial conditions index, credit-to-GDP gap, and HaR.

TABLE 8. Effects of Macroprudential Policy on House prices-at-Risk

Advanced Economies Panel

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
House Prices Growth (t)	0.508*** (0.041)	0.459*** (0.056)	0.346*** (0.041)	0.330*** (0.032)	0.303*** (0.043)	0.228*** (0.044)	0.172*** (0.045)	0.154*** (0.036)	0.147*** (0.033)	0.161*** (0.034)	0.159*** (0.023)	0.170*** (0.026)	0.155*** (0.025)	0.145*** (0.022)	0.142*** (0.024)	0.126*** (0.021)
GDP Growth (t)	0.179* (0.096)	0.056 (0.107)	0.018 (0.099)	-0.186* (0.105)	-0.204** (0.089)	-0.206** (0.090)	-0.161** (0.066)	-0.145** (0.064)	-0.127** (0.057)	-0.116* (0.061)	-0.130*** (0.048)	-0.127** (0.051)	-0.127** (0.053)	-0.094* (0.052)	-0.099 (0.062)	-0.098* (0.058)
House Prices Misalignment (t)	-3.058*** (0.935)	-5.793*** (0.959)	-5.933*** (0.937)	-7.035*** (0.698)	-7.157*** (0.511)	-7.205*** (0.637)	-7.494*** (0.671)	-7.241*** (0.474)	-7.143*** (0.364)	-6.987*** (0.284)	-6.903*** (0.352)	-6.925*** (0.376)	-7.146*** (0.378)	-7.180*** (0.308)	-7.349*** (0.342)	-7.315*** (0.253)
Credit Boom (t)	-0.279 (0.299)	-0.484* (0.251)	-0.675*** (0.250)	-0.503*** (0.161)	-0.322* (0.171)	-0.336* (0.175)	-0.418*** (0.141)	-0.350*** (0.126)	-0.353*** (0.124)	-0.388*** (0.138)	-0.332*** (0.121)	-0.271** (0.122)	-0.243* (0.135)	-0.228** (0.103)	-0.206** (0.092)	-0.160 (0.104)
FCI (t)	0.339** (0.152)	-0.349** (0.137)	-0.189 (0.170)	-0.234** (0.099)	-0.263** (0.126)	-0.228** (0.112)	-0.236** (0.093)	-0.298*** (0.096)	-0.243*** (0.081)	-0.203*** (0.072)	-0.171** (0.078)	-0.167*** (0.061)	-0.153*** (0.049)	-0.128*** (0.039)	-0.153*** (0.048)	-0.105** (0.048)
Macroprudential Policy Intensity (t)	0.105 (0.112)	0.070 (0.114)	0.223*** (0.065)	0.223*** (0.053)	0.266*** (0.047)	0.260*** (0.058)	0.276*** (0.046)	0.234*** (0.044)	0.188*** (0.048)	0.172*** (0.046)	0.153*** (0.050)	0.086 (0.063)	0.066 (0.062)	0.051 (0.046)	0.069 (0.045)	0.029 (0.044)
Macroprudential Policy Intensity * FCI (t)	0.626*** (0.199)	0.646*** (0.220)	0.250 (0.165)	0.116 (0.182)	0.087 (0.153)	0.047 (0.113)	0.081 (0.090)	0.016 (0.087)	-0.018 (0.092)	-0.030 (0.077)	-0.034 (0.109)	-0.116 (0.089)	-0.137 (0.094)	-0.140** (0.069)	-0.122* (0.067)	-0.170** (0.073)
Constant	-2.585*** (0.198)	-2.157*** (0.152)	-1.979*** (0.132)	-1.954*** (0.112)	-1.937*** (0.089)	-1.724*** (0.087)	-1.579*** (0.086)	-1.528*** (0.092)	-1.376*** (0.073)	-1.274*** (0.072)	-1.159*** (0.068)	-1.131*** (0.080)	-1.065*** (0.070)	-1.035*** (0.058)	-1.004*** (0.055)	-0.972*** (0.077)
Observations	2,389	2,367	2,345	2,323	2,301	2,279	2,257	2,235	2,213	2,191	2,169	2,147	2,125	2,103	2,081	2,059

Emerging Market Economies Panel

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
House Prices Growth (t)	0.187** (0.093)	0.343*** (0.069)	0.219*** (0.058)	0.159** (0.072)	0.152** (0.060)	0.172** (0.079)	0.173** (0.071)	0.142* (0.075)	0.149*** (0.055)	0.146** (0.061)	0.158*** (0.060)	0.121** (0.047)	0.078** (0.038)	0.062** (0.029)	0.065*** (0.025)	0.058*** (0.017)
GDP Growth (t)	-0.003 (0.224)	0.073 (0.164)	0.063 (0.159)	0.070 (0.171)	0.153 (0.099)	0.065 (0.126)	0.101 (0.095)	0.074 (0.107)	0.023 (0.087)	0.089 (0.067)	0.047 (0.044)	-0.004 (0.044)	-0.007 (0.040)	-0.004 (0.035)	0.026 (0.041)	-0.021 (0.045)
House Prices Misalignment (t)	-6.356*** (2.003)	-5.816*** (1.184)	-6.077*** (0.784)	-6.107*** (0.965)	-6.639*** (1.000)	-7.343*** (0.922)	-6.917*** (0.671)	-7.309*** (0.810)	-7.423*** (0.711)	-7.574*** (0.577)	-7.749*** (0.644)	-7.468*** (0.596)	-7.467*** (0.496)	-7.126*** (0.506)	-7.242*** (0.673)	-6.881*** (0.562)
Credit Boom (t)	-0.643 (0.632)	-0.654** (0.322)	-0.952*** (0.289)	-0.928*** (0.310)	-1.018*** (0.227)	-0.894** (0.387)	-0.986*** (0.286)	-0.839** (0.352)	-0.651** (0.307)	-0.315 (0.232)	-0.314* (0.165)	-0.060 (0.211)	-0.057 (0.173)	0.058 (0.202)	0.105 (0.182)	0.127 (0.177)
FCI (t)	-0.871*** (0.296)	-0.668*** (0.255)	-0.874*** (0.233)	-0.872*** (0.200)	-0.674*** (0.246)	-0.655*** (0.252)	-0.234 (0.247)	-0.132 (0.221)	-0.149 (0.200)	-0.022 (0.160)	-0.025 (0.141)	-0.039 (0.131)	-0.103 (0.115)	-0.133 (0.093)	-0.124 (0.097)	-0.126 (0.104)
Macroprudential Policy Intensity (t)	0.234 (0.326)	0.124 (0.178)	0.162 (0.164)	0.203 (0.183)	0.124 (0.177)	0.080 (0.156)	0.054 (0.130)	0.237 (0.165)	0.165 (0.130)	0.045 (0.115)	0.110 (0.087)	0.174** (0.068)	0.138** (0.055)	0.202*** (0.077)	0.191*** (0.052)	0.154*** (0.049)
Macroprudential Policy Intensity * FCI (t)	0.025 (0.390)	0.046 (0.195)	0.147 (0.170)	0.121 (0.189)	0.185 (0.158)	0.021 (0.174)	-0.037 (0.160)	0.048 (0.179)	0.059 (0.114)	0.022 (0.134)	-0.107 (0.106)	-0.086 (0.089)	-0.119* (0.071)	-0.051 (0.059)	-0.043 (0.044)	-0.052 (0.053)
Constant	-3.788*** (0.436)	-2.936*** (0.318)	-2.597*** (0.287)	-2.512*** (0.254)	-2.408*** (0.214)	-2.334*** (0.294)	-2.110*** (0.177)	-2.086*** (0.225)	-1.954*** (0.183)	-1.936*** (0.195)	-1.751*** (0.155)	-1.744*** (0.198)	-1.625*** (0.148)	-1.630*** (0.183)	-1.555*** (0.172)	-1.436*** (0.167)
Observations	948	938	928	918	908	898	888	878	868	858	848	838	828	818	808	798

Source: Authors' estimates.

Note: The tables show the coefficients of macroprudential policies on the 5th percentile house-price-at-risk estimation once added to the HaR baseline model for each quarter of the forecasting horizon. The regression control for the interaction of the policy measure with the FCI. Standard errors are bootstrapped and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 9. Effects of Monetary Policy Shocks on House prices-at-Risk**Advanced Economies Panel**

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
House Prices Growth (t)	0.546*** (0.069)	0.478*** (0.037)	0.383*** (0.039)	0.340*** (0.045)	0.302*** (0.057)	0.214*** (0.042)	0.159*** (0.045)	0.135*** (0.042)	0.161*** (0.035)	0.142*** (0.032)	0.159*** (0.029)	0.160*** (0.036)	0.151*** (0.029)	0.131*** (0.031)	0.117*** (0.031)	0.117*** (0.022)
GDP Growth (t)	0.159* (0.087)	0.062 (0.061)	0.031 (0.084)	-0.110 (0.093)	-0.217** (0.107)	-0.234*** (0.086)	-0.177** (0.075)	-0.144*** (0.048)	-0.165** (0.065)	-0.117* (0.062)	-0.119** (0.054)	-0.120** (0.055)	-0.091** (0.044)	-0.107** (0.050)	-0.098* (0.055)	-0.084 (0.062)
House Prices Misalignment (t)	-2.814*** (0.947)	-5.153*** (0.816)	-5.763*** (1.035)	-6.542*** (0.804)	-7.321*** (0.751)	-7.200*** (0.645)	-7.152*** (0.513)	-7.405*** (0.488)	-7.066*** (0.398)	-7.093*** (0.402)	-6.942*** (0.396)	-7.140*** (0.423)	-7.081*** (0.398)	-7.183*** (0.359)	-7.291*** (0.380)	-7.419*** (0.298)
Credit Boom (t)	-0.163 (0.314)	-0.614*** (0.211)	-0.663*** (0.203)	-0.597*** (0.228)	-0.426** (0.210)	-0.395** (0.180)	-0.461*** (0.152)	-0.435*** (0.136)	-0.337*** (0.126)	-0.294** (0.117)	-0.355*** (0.108)	-0.373*** (0.121)	-0.339*** (0.104)	-0.272*** (0.084)	-0.196** (0.086)	-0.154 (0.097)
FCI (t)	-0.313 (0.222)	-0.002 (0.160)	-0.023 (0.171)	-0.067 (0.170)	-0.136 (0.151)	-0.267*** (0.095)	-0.251** (0.105)	-0.165** (0.079)	-0.159*** (0.055)	-0.152*** (0.056)	-0.123* (0.066)	-0.062 (0.060)	-0.059 (0.042)	-0.089** (0.040)	-0.088 (0.056)	-0.091* (0.054)
Monetary Policy Shock (t)	-0.775** (0.305)	-0.641*** (0.202)	-0.549** (0.261)	-0.318 (0.293)	-0.445* (0.256)	-0.478*** (0.154)	-0.389*** (0.098)	-0.223* (0.122)	-0.161 (0.114)	-0.119 (0.131)	-0.149 (0.120)	-0.156 (0.121)	-0.135 (0.112)	-0.140 (0.111)	-0.138 (0.110)	-0.101 (0.086)
Monetary Policy Shock*FCI (t)	0.063 (0.205)	0.116 (0.124)	0.104 (0.127)	-0.008 (0.143)	0.020 (0.165)	-0.008 (0.116)	0.046 (0.075)	0.045 (0.094)	0.076 (0.075)	0.047 (0.090)	0.119 (0.083)	0.098 (0.076)	0.096 (0.063)	0.096 (0.075)	0.104 (0.072)	0.092 (0.079)
Constant	-2.561*** (0.174)	-2.103*** (0.125)	-1.984*** (0.132)	-1.894*** (0.121)	-1.854*** (0.126)	-1.724*** (0.097)	-1.586*** (0.107)	-1.470*** (0.074)	-1.392*** (0.065)	-1.294*** (0.053)	-1.177*** (0.064)	-1.110*** (0.069)	-1.027*** (0.067)	-1.016*** (0.058)	-1.031*** (0.060)	-1.009*** (0.062)
Observations	2,230	2,208	2,186	2,164	2,142	2,120	2,098	2,076	2,054	2,033	2,012	1,991	1,970	1,948	1,926	1,904

Emerging Market Economies Panel

VARIABLES	(1) t+1	(2) t+2	(3) t+3	(4) t+4	(5) t+5	(6) t+6	(7) t+7	(8) t+8	(9) t+9	(10) t+10	(11) t+11	(12) t+12	(13) t+13	(14) t+14	(15) t+15	(16) t+16
House Prices Growth (t)	0.241** (0.103)	0.403*** (0.081)	0.307*** (0.090)	0.317*** (0.087)	0.318*** (0.091)	0.228** (0.089)	0.179** (0.081)	0.203** (0.081)	0.234** (0.093)	0.170** (0.072)	0.194*** (0.062)	0.133** (0.059)	0.111** (0.048)	0.110*** (0.038)	0.094*** (0.025)	0.084*** (0.022)
GDP Growth (t)	-0.022 (0.223)	-0.118 (0.225)	-0.032 (0.199)	-0.012 (0.197)	0.043 (0.111)	0.044 (0.142)	0.134 (0.104)	0.073 (0.103)	0.059 (0.087)	0.096 (0.075)	0.081 (0.058)	0.012 (0.062)	0.030 (0.050)	0.003 (0.045)	-0.005 (0.044)	-0.007 (0.042)
House Prices Misalignment (t)	-7.736*** (2.106)	-7.358*** (1.088)	-7.945*** (1.073)	-7.131*** (0.885)	-7.194*** (0.972)	-7.613*** (0.843)	-7.437*** (0.909)	-7.645*** (0.914)	-8.048*** (0.899)	-7.773*** (0.556)	-7.952*** (0.551)	-8.523*** (0.583)	-8.627*** (0.558)	-8.138*** (0.552)	-8.187*** (0.580)	-8.113*** (0.617)
Credit Boom (t)	0.012 (0.564)	-0.515 (0.360)	-0.680* (0.356)	-0.807** (0.336)	-0.814** (0.358)	-0.835** (0.329)	-1.098*** (0.334)	-0.611* (0.339)	-0.412 (0.279)	-0.253 (0.220)	-0.214 (0.176)	-0.075 (0.180)	-0.020 (0.180)	0.111 (0.166)	0.166 (0.150)	0.225 (0.164)
FCI (t)	-1.484*** (0.409)	-1.087*** (0.311)	-1.308*** (0.320)	-1.176*** (0.250)	-0.728*** (0.234)	-0.647*** (0.243)	-0.480* (0.247)	-0.239 (0.251)	-0.170 (0.242)	-0.078 (0.168)	-0.195 (0.158)	-0.296** (0.117)	-0.342*** (0.096)	-0.324*** (0.102)	-0.363*** (0.094)	-0.355*** (0.086)
Monetary Policy Shock (t)	0.075 (0.171)	-0.029 (0.088)	-0.007 (0.081)	-0.063 (0.063)	-0.033 (0.059)	-0.023 (0.050)	-0.035 (0.060)	-0.109* (0.057)	-0.095 (0.067)	-0.020 (0.071)	-0.005 (0.068)	0.032 (0.068)	0.036 (0.058)	0.003 (0.051)	0.018 (0.041)	0.018 (0.034)
Monetary Policy Shock*FCI (t)	-0.174 (0.215)	-0.017 (0.136)	-0.078 (0.123)	-0.095 (0.076)	-0.081 (0.062)	-0.078 (0.078)	-0.055 (0.067)	-0.017 (0.065)	-0.034 (0.063)	0.005 (0.056)	-0.012 (0.084)	0.034 (0.084)	0.045 (0.064)	0.030 (0.031)	0.053** (0.026)	0.041 (0.029)
Constant	-3.860*** (0.466)	-2.802*** (0.310)	-2.655*** (0.332)	-2.354*** (0.288)	-2.231*** (0.261)	-2.216*** (0.276)	-2.090*** (0.235)	-2.121*** (0.222)	-2.139*** (0.231)	-2.031*** (0.183)	-1.856*** (0.163)	-1.717*** (0.174)	-1.656*** (0.179)	-1.523*** (0.164)	-1.473*** (0.152)	-1.420*** (0.193)
Observations	861	852	843	834	825	815	805	795	785	775	765	755	745	735	725	715

Source: Authors' estimates.

Note: The tables show the coefficients of monetary policy shocks on the 5th percentile house-price-at-risk estimation once added to the HaR baseline model for each quarter of the forecasting horizon. The regression control for the interaction of the policy measure with the FCI. Standard errors are bootstrapped and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX I. Data Sources and Definitions

Table A.I.1. Data Sources

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 <i>Global Financial Stability Report</i> (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: Authors.

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

Table A.I.2. Country Coverage

Advanced Economies			Emerging Market Economies		
	Start Date	End Date		Start Date	End Date
Australia	1990q2	2017q4	Brazil	1994q4	2017q4
Austria	1990q3	2017q4	Chile	1992q4	2017q4
Belgium	1990q2	2017q4	China	1996q2	2017q4
Canada	1990q2	2017q4	Colombia	1994q1	2017q4
Denmark	1993q2	2017q4	India	2001q1	2017q4
Finland	1990q3	2017q4	Malaysia	1991q1	2016q4
France	1990q2	2017q4	Mexico	1990q2	2017q4
Germany	1990q2	2017q4	Russia	1996q1	2017q4
Hong Kong SAR	1990q2	2017q4	South Africa	1990q2	2017q4
Ireland	1990q2	2017q4	Turkey	1990q2	2017q4
Italy	1990q3	2017q4			
Japan	1990q2	2017q4			
Korea	1990q2	2017q4			
Netherlands	1990q2	2017q4			
New Zealand	1990q2	2017q4			
Norway	1990q3	2017q4			
Singapore	1998q2	2017q4			
Spain	1990q2	2017q4			
Sweden	1990q2	2017q4			
Switzerland	1990q2	2017q4			
United Kingdom	1990q2	2017q4			
United States	1990q2	2017q4			

Note: Data coverage is limited by the joint availability of all variables in the baseline model.

Table A.I.3. Summary Statistics

	Mean	St.dev.	p25	p50	p75	Min	Max
Advanced Economies							
Real House Prices (YoY)	2.23	7.42	-1.95	1.95	6.13	-40.55	46.53
Real House Prices (QoQ)	0.48	2.36	-0.66	0.51	1.64	-18.32	16.50
Real GDP Growth (YoY)	2.53	3.00	1.09	2.47	3.79	-9.55	29.07
Real GDP Growth (QoQ)	0.61	1.13	0.13	0.60	1.04	-7.28	20.41
Total Credit to GDP	160.2	47.5	125.6	154.2	187.5	62.0	398.5
Misalignment	0.00	0.14	-0.09	0.00	0.08	-0.55	0.50
FCI	0.15	0.89	-0.44	0.01	0.53	-3.33	4.15
FCI ex house prices	0.00	0.81	-0.53	-0.11	0.33	-2.24	4.02
Credit boom	0.49	0.50	0	0	1	0	1
Emerging Market Economies							
Real House Prices (YoY)	2.78	8.60	-1.38	2.32	6.39	-25.87	67.48
Real House Prices (QoQ)	0.63	3.02	-0.86	0.54	2.11	-26.04	20.60
Real GDP Growth (YoY)	4.57	4.20	2.28	4.73	7.37	-12.53	16.76
Real GDP Growth (QoQ)	1.09	1.59	0.40	1.15	1.94	-10.58	7.52
Total Credit to GDP	69.5	40.2	39.8	58.5	95.9	14.1	213.4
Misalignment	0.00	0.14	-0.08	-0.01	0.07	-0.40	0.47
FCI	-0.14	0.79	-0.65	-0.16	0.32	-5.14	3.13
FCI ex house prices	-0.01	0.76	-0.45	-0.01	0.43	-3.82	3.15
Credit boom	0.50	0.50	0	0	1	0	1

Note: Table shows summary statistics of main variables across panel of advanced economies (AE) and emerging market economies (EM). AE sample size = 2384 quarterly observations. EM sample size = 960 quarterly observations. St.dev. = standard deviation; p25, p50 and p75 are the 25th, 50th (median) and 75th percentile of the distribution; Min = minimum and Max = maximum.

APPENDIX II. House Prices-at-Risk and Systemic Banking Crises Forecasting

Another way to look at the relationship between HaR and systemic banking crises is to compare crisis predictability power, using the Area Under Curve (AUC) metric. We compare four models, with respectively (1) only country fixed-effects (FE) (mod0); (2) country FE and output growth (mod1); (3) mod1 plus the level of FCI similarly to the baseline Growth-at-Risk (GaR)³¹ specification (mod2); and (4) FE, output growth, FCI and HaR (4q ahead) (mod3). The performance of mod3 model with AUC at about 0.82 dominates the mod1 (0.61) and mod2 (0.75) which in turn do a better job than the uninformative null hypothesis where AUC equals 0.5 (reference) and the model with country FE only (mod0). Overall, adding HaR increases the early warning properties of GaR baseline specification.

Source: Authors' estimates.

³¹ See Adrian, Boyarchenko, and Giannone (2019).