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# The real-time predictive content of asset price bubbles for macro forecasts

## Blinded Version

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#### Abstract

In light of the recent large swings in stock and housing prices accompanied by ample global liquidity, the role of monetary policy in the build-up of asset price bubbles has been questioned. This paper will contribute to the debate whether central banks can and should stronger "lean against the wind" of emerging bubbles. Against this background, the paper will reevaluate if new advances in real-time bubble detection, as brought forward by Phillips et al. (2011), can timely detect bubble emergences and collapses. Here, the paper suggests a combination approach of different bubble indicators to account for the uncertainty around start and end dates of asset price bubbles. Additionally, the paper will then investigate if these indicators carry predictive content for inflation, output growth and recession events when the real-time availability of all variables is considered. It finds that a combination approach of asset price bubbles is well suited to detect the most common stock and house price bubbles in the U.S. and shows that this indicator can improve output forecasts, however, only when the real-time availability of real variables is respected.

**Keywords**: Asset price bubbles, financial stability, leaning-against-the-wind, monetary policy, real-time forecasting, recession forecasting, unit root monitoring test. **JEL Classification**: C22; C53; E44; E47; G12

## 1 Introduction

Following the 'dot-com' crisis of the late 1990's and particularly the recent global financial crisis, the importance of asset price cycles for macroeconomic stability has pushed strongly onto the agenda of academic research and policy makers alike. Furthermore, the fact that recent asset price booms had been accompanied by ample levels of liquidity, has raised questions about the role of monetary policy in the propagation of asset price bubbles. Exemplary, former ECB president Jean-Claude Trichet has considered this "[...] to be one of the most challenging issues facing a modern central bank at the beginning of the 21st century" (Trichet, 2005). The responses of central banks to the recent global financial crisis cutting interest rates to the zero lower bound and providing additional lines of liquidity have raised these concerns even further.

Against this background, a more active role of monetary policy in combating asset price bubbles early in their development (coined as "leaning against the wind") has been called for by many observers. That is, in contrary to the current policy of only lowering interest rates immediately after a crash, central banks should respond symmetrically and cautiously increase rates as soon as an asset price bubble is identified. However, for such a policy to be implementable, it is foremost required that policy makers are able to identify emerging asset price bubbles in real-time. Second, asset price bubbles should also provide reliable signals for central banks' ultimate primary and secondary targets of price stability and output and/or employment near potential levels. If asset price bubbles do not signal stress in the real economy, there is no incentive to raise the policy rate and cut-off down real economic growth.<sup>1</sup>

This paper will therefore connect existing yet separate lines research on these two open issues. In specific, the goals of this paper are, first, to assess if recently suggested monitoring indicators can detect price bubbles in the S&P 500 and the U.S. housing market in real-time, and second, if these have additional value for predicting U.S. output growth and inflation in a real-time setting. Adding to the methodology of detecting bubbles, a new combination approach is suggested to account for the large uncertainty around the bubble emergence and collapse dates.

So far policy makers have mostly argued that the two requirements are likely not met as the detection of asset price bubbles has been considered to be impossible, not only expost but even more so in real-time (cf. Trichet, 2005 and Kohn, 2006). However, this view has recently been questioned following the seminal paper by Phillips et al. (2011) (PWY11, henceforth). Building on recursive right-side unit root tests on price and dividend series,

<sup>&</sup>lt;sup>1</sup>Additionally, asset price bubbles must also be sensitive to changes in the interest rate and the long-term expected benefits of pricking a bubble should exceed the immediate costs of lower output growth. This is however not within the scope of this paper.

the authors show that real-time monitoring approaches are capable of detecting periods that display patterns typical for asset price bubbles. This work has been developed further by Homm & Breitung (2012) (HB12, henceforth) and by Phillips et al. (2013) (PSY13, henceforth) who generalize the initial work of PWY11 and develop a monitoring procedure that is robust to multiple periodically collapsing bubbles. Yet, as PWY13 show, all tests differ in their detection ability depending on the number and timing of the bubble in the sample under considerations. This paper will further highlight that the detection abilities of the individual tests are sensitive to their exact specifications. Hence, all tests a-priori may provide some complementary value. Thus, this paper follows a recent suggestion by Harvey et al. (2015) and evaluates combinations building on the union set of these indicators along varying thresholds to account for uncertainty around the timing of bubbles. As Harvey et al. (2015) show for two ex-post tests suggested by PWY11 and HB12, this procedure can improve the detection power compared to employing individual indicators.

The first findings of this paper highlight that the choice of the indicator and its exact specification is not crucial. First, it matters if individual price and dividend series or the price-to-dividend ratio are tested for explosive roots. Second, the detection depends on the timing of the bubble. Against these limitations, plausible results are obtained for both stock and house prices only by the PWY13 and a rolling-window variant of the PWY11 indicator. Common bubble episodes detected by the majority of indicators describe the build-up of a stock price bubble prior to the 1987 crash, the dot-com bubble starting around 1996 and the recent house price bubble beginning in the early 2000's. Given the uncertainty around bubble indicators and their precise beginning and end points, indicator combinations are a promising way to aggregate information.

The only study so far investigating the predictive content of asset price bubble indicators for real economic variables is Assenmacher-Wesche & Gerlach (2010) (AWG10, henceforth). Yet, asset (and in particular stock) prices have long been considered to be valuable predictors for real economic variables as they are inherently forward-looking. Empirical evidence by Stock & Watson (2001), however, strongly questions their usefulness.<sup>2</sup> Yet, in addition to their forward-looking character, asset price developments can have immediate causal effects on real economic outcomes that are particularly relevant when considering the importance of bubble periods. Two transmission channels prominently discussed in the literature are the balance sheet (or collateral), and the lending channel (as introduced by Holmstrom & Tirole, 1997). Both channels suggest that rising asset prices can alleviate credit constraints for firms and households, and by this stimulate investment or consumption and ultimately output.<sup>3</sup>

<sup>&</sup>lt;sup>2</sup>The authors find that stock prices provide only little predictive ability for output growth and none for inflation compared to simple autoregressive forecasts. House prices have been studied to a far lesser extend, mostly because of data limitations. Nonetheless, the available studies suggest little predictive use, too.

<sup>&</sup>lt;sup>3</sup>The balance sheet channel theorizes that rising asset prices increase the value of collateral that firms and

During a bubble, prices are, however, predominantly driven by speculative motives. This may increase investment in the respective asset class more than fundamentally justified, and imply an inefficient allocation of resources compared to other sectors. When prices eventually crash the feedback loop described above reverses, and additionally, the physical capital stock and/or employment in the bubble sector is likely to be inefficiently high, binding valuable resources. Bubble periods can thus intensify regular business cycle movements up to a degree that the economy overheats and severe and long-lasting recessions follow. Therefore, one can expect that information about emerging asset price bubbles can contain predictive content for forecasting output and inflation.

Against these theoretical considerations, and questioning the scope for an activist monetary policy, AWG10 do not find that bubble indicators provide valuable information for forecasting output, inflation and recession events in addition to information that is already contained in other standard predictor variables. Yet, the study suffers from two main shortcomings. First, it does not make use of the new indicators introduced above, but only considers indicators based on price deviations from a one-sided HP-filtered trend. Second, the paper does not consider the real-time dimension of all variables included in the forecasting exercise. As stock prices are available in real-time, they might contain information not included in real variables that are available with a lag only and are subject to revisions.

Therefore, the second contribution of this paper will be to reevaluate the predictive content of asset price bubbles for inflation and industrial production when including the state-of-the-art indicators and their combinations introduced above. Furthermore, this paper will be particularly considerate of the real-time availability of all predictors. Following AWG10, the forecast accuracy of a benchmark model including useful predictors as identified by Stock & Watson (2001) will be evaluated first. Going beyond AWG10, this benchmark will additionally be allowed to include autoregressive terms of all variables.

This paper finds that several asset price bubble indicators carry significant additional predictive content for output growth and inflation. Foremost, these are the indicator proposed by PWY13 and a combination indicator suggested in this paper. By this, the paper questions the findings of AWG10. The findings paper also indicate that considering the real-time dimension of all variables is crucial. Since stock prices and dividends are available in real-time, their predictive content is understated when ignoring publication lags and revisions. In contrast, the predictive content of house price bubble indicators is exacerbated, as these variables are available with a lag of two months only. Stock prices are particularly useful for horizons of up to 24 months, while house prices add to forecasts for even longer horizons. Furthermore, the findings on recession forecasts suggest that stock price bubble indicators

households can put up to borrow new funds. The lending channel refers to the role of financial intermediaries in credit supply. Rising asset prices boost banks' equity, thus making it easier for them to provide credit. Naturally, the reverse holds for falling prices.

are also helpful in predicting severe economic downturns in the short-run.

The paper is structured as follows. Section 2 introduces the indicators used for detecting asset price bubbles. Different specifications considered in the literature and their advantages are discussed and the results of individual indicators for stock and house prices in the U.S. are presented. Subsequently, the combinations of indicators are introduced and applied to the data. Section 3 then introduces the forecast models used for predicting inflation, industrial production and recession events and presents the real-time data set. Results of the forecast exercise are then presented and discussed in Section 4. Section 5 concludes.

## 2 Asset price bubbles: Real-time detection

### 2.1 Definition and testability of asset price bubbles

An asset price bubble is commonly defined as a situation in which an asset's price deviates from (and typically exceeds) its fundamental value (FV) due to unjustified beliefs about the asset's market price in the future. The key question in detecting a bubble is thus to determine the asset's unobservable underlying FV. The most prominent formulation and starting point for testing for the existence of (rational) bubbles is derived from the present value theory of finance and begins with the asset pricing equation

$$P_t = \frac{1}{1+r} E_t \left[ P_{t+1} + D_{t+1} \right] \tag{1}$$

where  $P_t$ ,  $D_t$  are the asset's market price in and dividend accrued over period t, respectively, and r is the (here time-constant) discount rate.<sup>4</sup> Note that this equation assumes risk-neutral agents.<sup>5</sup> Applying forward substitution one can show that (1) allows for the inclusion of a bubble component  $B_t$  that measures the deviation of the market price from the FV

$$P_{t} = \sum_{i=1}^{\infty} \left(\frac{1}{1+r}\right)^{i} E_{t} \left[D_{t+i}\right] + \lim_{i \to \infty} \left(\frac{1}{1+r}\right)^{i} E_{t} \left[P_{t+i}\right] \\ = P_{t}^{f} + B_{t},$$
(2)

where  $B_t > 0$ , if the usual transversality condition  $\lim_{i \to \infty} \left(\frac{1}{1+r}\right)^i E_t [P_{t+i}] \to 0$  does not hold.<sup>6</sup> Importantly, this implies that the bubble component  $B_t$  must grow exponentially with r

<sup>&</sup>lt;sup>4</sup>As Himmelberg et al. (2005) show, the fundamental determinants of house prices depend on several additional factors, including (among others) property taxes, tax deductibility of mortgage interest and maintenance or depreciation costs, that are assumed to be constant here.

<sup>&</sup>lt;sup>5</sup>See Gürkaynak (2008) for a thorough derivation and discussion of the model's underlying assumption.

<sup>&</sup>lt;sup>6</sup>For this general setting, it has been documented extensively that bubbles can emerge, even if only some of the strict assumptions of infinitely-lived, rational and risk-neutral agents as well as complete markets are loosened. See Camerer (1989) and Stiglitz (1990) for surveys on the early theoretical work on the existence of rational

for (1) to hold and for the bubble not to shrink to zero in present value or to outgrow the economy, i.e.  $B_t = \frac{1}{1+r}E_t[B_{t+1}]$ . Under the standard assumption that dividends follow a random walk (with drift), this has direct testable implications. When dividends follow a unit root process but a bubble is present, i.e.  $B_t > 0$ , the price series must contain an explosive root that can only come from the bubble process. In this sense, a bubble is detected if the price process decouples from the dividend process. If dividends grow exponentially, too, no inference on the existence of a bubble component is possible in this setting.

Nonetheless, there are important limitations to bubble testing. Most importantly, as Flood & Hodrick (1990) highlight, every test for the existence of rational bubbles per se relies on a correct specification of the FV. Thus, empirical tests in fact address the joint null hypothesis of the absence of bubbles and a correctly specified economic model. Hence, the rejection of the hypothesis cannot answer the question if a bubble is present indeed, or if simply a poor economic model has been employed. Still, empirical tests for bubbles can serve as specification tests for an economic model. Furthermore, for policy makers it is potentially of interest to detect common characteristics of "speculative bubbles" or "periods of exuberance" that can possibly indicate instabilities in the financial system based on past evidence (cf. Trichet, 2005). For this, however, the real-time detectability of asset price bubbles is crucial. Here, monitoring approaches can provide valuable insights.<sup>7</sup>

### 2.2 Real-time detection of explosive behavior

The literature on testing for bubbles has long focused on ex-post tests for the existence of bubbles over an entire historical dataset. A survey on this literature including variancebound, two-step specification and unit-root tests can be found both in Flood & Hodrick (1990) and Gürkaynak (2008).<sup>8</sup> While the first two approaches have suffered mostly from practical issues in their implementation and have lately not been pursued further, integration tests that build on the insights developed in the previous section, have recently seen a revival triggered by the seminal paper of PWY11. In this paper, the authors show that the original unit root tests of Diba & Grossman (1988) can be adapted to detect periodically collapsing bubbles (the central criticism of Evans (1991)) by running ADF tests based on forward recursive regressions. More recently, PSY13 have generalized this approach by allowing for

bubbles which focused predominantly on overlapping-generations models, the introduction of asymmetric information and/or incomplete markets restricting the opportunities for arbitrageurs. More recently, the role of agents' incentives, non-standard preferences (e.g. herding) and (partly) irrational behavior as well as market rigidities for initializing bubbles have been explored. A survey on this strand of literature can be found in Scherbina (2013).

<sup>&</sup>lt;sup>7</sup>For example, the Federal Reserve Bank of Dallas employs a real-time monitoring test to detect house price bubbles in its International House Price Database (http://www.dallasfed.org/institute/houseprice/ index.cfm, Grossman et al. (2013)).

<sup>&</sup>lt;sup>8</sup>Other tests for bubbles not included in this survey are Black et al. (2003) and Machado & Sousa (2006).

rolling windows of flexible size for estimation. Both these tests can also be used to date the emergence and collapse of asset price bubbles in real-time. Along the same lines, HB12 propose a number of flexible tests based on structural breaks in the autoregressive parameters or on forecast breakdowns, two of which that can also be employed for real-time monitoring and date-stamping.

The starting point for all tests is a variant of the autoregressive specification

$$z_{t} = \mu_{z} + \delta z_{t-1} + \sum_{j=1}^{J} \phi_{j} \Delta z_{t-j} + v_{t}, \quad t = 1, \dots, \tau, \quad v_{t} \stackrel{iid}{\sim} N(0, \sigma_{v}^{2})$$
(3)

where  $z_t = \{p_t, d_t\}$  or  $z_t = \{p_t - d_t\}$ , with  $p_t = \ln(P_t)$  and  $d_t = \ln(D_t)$ . All test employed in this paper are right-tailed ADF-type tests of the null hypothesis  $H_0: \delta = 1$  against the alternative  $H_1: \delta > 1$ . In specific, forward recursive regressions of (3) are carried out, providing a sequence of ADF-statistics  $ADF_{\tau}$  for all margins  $\tau_0, \tau_0 + 1, \ldots, T$ . The first regression hence includes  $\tau_0 = \lfloor r_0 T \rfloor$  observations, where  $r_0$  denotes the minimum share of the total sample size T for which (3) is estimated.

As outlined above, a bubble is detected when the price series shows explosive behavior while the fundamental series does not. The bubble emergence and collapse dates ( $\tau_e$  and  $\tau_f$ ) can then be estimated as the first date  $\tau$  for which the ADF statistic for the price series exceeds (falls below) the critical value  $cv_{\alpha_T}^{adf}(\tau)$ 

$$\hat{\tau}_e = \inf_{\tau \ge \tau_0} \left\{ \tau : ADF_\tau > cv_{\alpha_T}^{adf}(\tau) \right\}, \quad \hat{\tau}_f = \inf_{\tau \ge \hat{\tau}_e} \left\{ \tau : ADF_\tau < cv_{\alpha_T}^{adf}(\tau) \right\}.$$
(4)

If the dividend series is explosive at all dates  $\tau$  with  $\hat{\tau}_e \leq \tau \leq \hat{\tau}_f$ , no bubble is indicated. If the dividend series turns explosive at  $\tau$  with  $\hat{\tau}_e < \tau \leq \hat{\tau}_f$ , the bubble collapse date  $\hat{\tau}_f$  is reset to  $\hat{\tau}_f = \tau - 1$ . This algorithm yields a binary indicator series  $B_{\tau}, \tau = \tau_0, \tau_0 + 1, \ldots T$ with

$$B_{\tau} = \begin{cases} 1 & \text{if } \hat{\tau}_e \leq \tau \leq \hat{\tau}_f \\ 0 & \text{else.} \end{cases}$$

Importantly one can test both series individually (i.e.  $z_t = \{p_t, d_t\}$ ), or the ratio of the two (i.e.  $z_t = \{p_t - d_t\}$ ). The literature so far has considered both but has not discussed that this choice may carry important implications for the findings.<sup>9</sup> While dividends are typically assumed and found to follow a random walk (with drift), the log price-dividend ratio is assumed to be stationary (see e.g. Campbell & Shiller (1988) and Cochrane (1992)).

<sup>&</sup>lt;sup>9</sup>While PWY11 and Harvey et al. (2015) test the series individually, HB12, PWY13 and Grossman et al. (2013) run tests on the log price-to-dividend ratio.

Rewriting (2) into the alternative representation proposed by Campbell & Shiller (1987) given by

$$P_t - \frac{1}{r}D_t = \left(\frac{1+r}{r}\right)\sum_{i=1}^{\infty} \left(\frac{1}{1+r}\right)^i E_t \left[\Delta D_{t+i}\right] + B_t,\tag{5}$$

shows that the difference  $P_t - \frac{1}{r}D_t$  is stationary if  $D_t \sim I(1)$  and  $B_t = 0$ . Hence, it is reasonable to expect that the test on the individual series features a larger power against the null hypothesis than the more conservative test on the ratio. On the one hand, this implies that testing the series individually can provide a more timely detection of a bubble phase. On the other hand, this can also imply a more frequent detection of periods with exponential growth in dividends due to short-lived spikes. In this case, no bubble (or a collapse) would be signaled. Thus, testing the log price-to-dividend ratio can provide information on the relative growth rate of the two series. If both grow exponentially, but prices grow at a faster rate than dividends (indicating increasing imbalances), a unit root test on the ratio would indicate a bubble period that is missed by a test on the individual series. Therefore, this paper will evaluate both options.

### 2.3 Real-time detectors

This section will provide the exact specifications of the test statistics applied in this paper. An overview of all tests can be found in Table 1.

#### 2.3.1 Forward recursive sup ADF Test (PWY11)

First, the original indicator of Phillips et al. (2011) will be applied by estimating (3) either recursively or by rolling windows. The lag order J is determined by the Akaike Information Criterion (AIC) with  $J^{max} = 12$ . As PWY11, this paper will set  $r_0 = \{0.1, 0.2\}$  for recursive and rolling-windows estimation, respectively. In order to account for over-rejection in the multiple testing setting, the significance level  $\alpha_T$  needs to approach zero asymptotically for an overall significance level of 5% to hold. Correspondingly  $cv_{\alpha_T}^{adf}(\tau)$  must diverge to infinity. PWY11 thus suggest to use  $cv_{\alpha_T}^{adf}(\tau) = \ln(\ln(\tau))/100$ , yielding significance levels around 4%.

#### 2.3.2 Generalized sup ADF Test (PSY13)

Phillips et al. (2013) extend the work of PWY11 by not only allowing the end point (here  $\tau_2$ ) to move forward for each recursive regression from  $\tau_0 = \lfloor r_0 T \rfloor$  to T, but by also allowing the start point  $\tau_1$  for a given  $\tau_2$  to vary between all values from 0 to  $\max(\tau_2 - \tau_0, 0)$ . Thus, the test augments the forward recursive regressions by estimating and testing all possible backward extending windows from the current margin  $\tau_2$ . For a given end point  $\tau_2 \in [\tau_0, T]$ 

and the varying start point  $\tau_1 \in [0, \tau_2 - \tau_0]$ , the sequence of ADF test statistics is denoted by  $\{ADF_{\tau_1}^{\tau_2}\}$ . Taking the supremum of this sequence then provides the backward sup ADF statistic for the test margin  $\tau_2$  denoted by  $BSADF_{\tau_2} = \sup_{\tau_1 \in [0, \tau_2 - \tau_0]} \{ADF_{\tau_1}^{\tau_2}\}$ .

Similar to PWY11, emergence and collapse dates are then defined as the first date for which the BSADF statistic exceeds (falls below) the respective right-tailed critical value<sup>10</sup>

$$\hat{\tau}_e = \inf_{\tau 2 \in [\tau_0, T]} \left\{ \tau_2 : BSADF_{\tau_2} > cv_{\alpha_T}^{bsadf}(\tau_2) \right\},$$

$$\hat{r}_f = \inf_{\tau 2 \in [\hat{\tau}_e, T]} \left\{ \tau_2 : BSADF_{\tau_2} < cv_{\alpha_T}^{bsadf}(\tau_2) \right\}.$$
(6)

Based on extensive simulations PSY13 suggest an initial sample size of  $r_0 = 0.01 + \frac{1.8}{\sqrt{T}}$ . Following a suggestion of PSY13, the lag order in (3) is fixed and set to J = 1.

#### 2.3.3 FLUC Test (HB12)

While the FLUC test developed by Homm & Breitung (2012) follows the notion of PWY, it differs in the regression specifications and also in the simulated critical values.<sup>11</sup> Similarly to PWY11, the ADF-statistic  $ADF_{\tau}$  is computed for all  $\tau = T_0 + 1, T_0 + 2, \ldots, T$  and the null hypothesis of a random walk is rejected if  $ADF_{\tau} > \kappa_{\tau}$ , with  $\kappa_{\tau} = \sqrt{cv_{r_0,\alpha}^{fluc} + \ln(\tau/T_0)}$ . However, the time series of real prices and dividends are detrended first by running an OLS estimation of the log series on a constant and a linear time trend prior to estimating the Dickey-Fuller regression equation, given by

$$\tilde{z}_t = \delta \tilde{z}_{t-1} + v_t, \quad t = 1, \dots, \tau, \quad v_t \stackrel{iid}{\sim} N(0, \sigma_v^2), \tag{7}$$

where  $\tilde{z}_t$  denotes the detrended series. To overcome the problem of possibly negative critical values, standardized ADF statistics  $\left(\frac{ADF_{\tau}-m_{ADF}}{\sigma_{ADF}}\right)$ , with  $m_{ADF} = -2.1814$  and  $\sigma_{ADF} = 0.7499$ ) are computed. To compare the results of the FLUC test with PWY11, this paper sets  $r_0 = \{0.1, 0.2\}$  and  $T_0 = r_0 T$ .

#### 2.3.4 HP-Filter

Prior to the seminal contribution of PWY11, the literature has defined asset price bubbles predominantly by evaluating the deviation of the real price series from its one-sided

<sup>&</sup>lt;sup>10</sup>Critical values where simulated using the MATLAB code provided by Shu-Ping Shi on her website (https: //sites.google.com/site/shupingshi/home/research), adapted for the respective sample size T and the parameter  $r_0$ .

<sup>&</sup>lt;sup>11</sup>HB12 also suggest a CUSUM test based on the detection of forecast breakdowns. As they find this test to exhibit a lower power and longer delay until detection for all specifications compared to the FLUC test, this paper will refrain from using it.

HP-filtered trend. This builds on the assumption that the asset's fundamentals follow a slow-moving trend. As such, this indicator can potentially capture periods in which large deviations of prices from their past history occur, regardless of the speed of this accumulation process. Hence, this paper will also reevaluate the findings of AWG10, and define a bubble if the real asset price deviates from its trend beyond a threshold  $\kappa$ , with  $\kappa = 10\%$  for equity and  $\kappa = 7.5\%$  for house prices. In estimating the trend component of the price series, the smoothing parameter is set to  $\lambda = 100,000 * 3^4$  and both a recursive and rolling (window size  $\omega = 96$ ) estimation is used.<sup>12</sup> Past estimates of the trend component are not updated as new observations arrive.

## 2.4 Stock and house price bubbles in the U.S.

This paper will in the following explore the predictive content of bubble periods in stock and house prices in the U.S. The U.S. is chosen as it is the only country for which long series on stock and house prices as well as their fundamentals are readily available on a monthly frequency. Also, financial cycles are considered to be highly pronounced and particularly important for the U.S. (cf. Borio, 2012). The data can be obtained from the online data supplement<sup>13</sup> of Shiller (2005) starting in 1871M01 for stock prices and 1953M01 for house prices. However, the analysis here is restricted to the period from 1975M01 to 2014M07 as the forecasting exercise of Section 3 is carried out for the post-high inflation period starting around 1983M01.<sup>14</sup> This paper will look at broad, aggregate indices only since it is foremost bubbles in widely held asset classes that can be expected to carry implications for real economic development in their emergence or unwinding. Thus, the stock price index of interest is the S&P 500. House prices are measured by a national index of repeat sales accounting for quality changes published by the U.S. Office of Housing Enterprise Oversight for the period from 1975-1987 and by Fiserv CSV, Inc. since 1987. All individual series are deflated by the U.S. Consumer Price Index for All Urban Consumers provided by FRED, Federal Reserve Bank of St. Louis.

The choice of the underlying fundamental series for house prices is more controversial than for stock prices. In principal, this "dividend" can be thought of as the rent that an owner saves by living in the house (Himmelberg et al., 2005). However, relying on rent series is problematic as these are generally measured with great error only, or do not account for the

<sup>&</sup>lt;sup>12</sup>The setting of thresholds is highly arbitrary as is setting the smoothing parameter. Also, the method can tend to generate more booms in the later part of the sample as the trend estimates becomes less sensitive to new information under recursive estimation. Furthermore, for prolonged or strong bubble periods, the trend component will also capture part of the excessive development, underestimating the bubble.

<sup>&</sup>lt;sup>13</sup>Available at http://www.econ.yale.edu/~shiller/data.htm.

<sup>&</sup>lt;sup>14</sup>This is particularly relevant from policy maker's perspective as Stock & Watson (2007) show that inflation forecasts from an autoregressive model became harder to beat following the Volcker era at the FED.

intrinsic value of owning a house. Additionally, the causality structure between rental and purchase prices for housing is ambiguous. In case of high market power on the home owners' side, it is possible that rising purchase prices induce rising rents, thus leading to explosive growth in both series during a housing bubble. Eventually, this development is likely not to be sustainable, yet a bubble would not be signaled. Hence, this paper will follow Grossman et al. (2013) and rely on real disposable income per capita as a measure for the fundamental determinant of house prices.<sup>15</sup> The idea behind this is to measure the affordability of housing. Assuming that households devote a constant share of their total income to renting, house prices can only grow sustainably at the rate of per capita real disposable income. This consideration is in direct spirit of the assessment of financial stability that is the goal of this paper.

Figure 1 shows the detected bubble periods in the S&P 500. The picture immediately reveals that detection differs largely across all indicators. Yet, some common findings prevail. A first bubble period prior to the stock market crash on "Black Monday" on 19 October 1987 is found by three specifications of the PWY11, one specification of the PSY13 and both HP filters. Second, the "dot-com bubble" from around 1995/96 to 2000 is detected by all but the FLUC indicators. However, the detection accuracy varies largely with emergence being signaled from as early as 1995M05 to as late as 1996M11 and collapse dates ranging from 1999M08 to 2000M10, about seven months prior and past the peak. Finally, the FLUC, the rolling PWY11 and the PSY13 indicate the financial crisis period from around 2008M10 to 2009M04, all when applied to ratios only though. This period is special as the exponential trend in the price-to-dividend ratio comes from a drastic crash in prices, while dividends decreased only slightly. In that sense, this episodes describes a "negative bubble", a situation that could be controlled for by accounting for the sign of price changes. At the current margin, only the HP-filters indicate a stock market bubble.

In sum, the indicators by PWY11 and PSY13 appear to signal the most likely bubble periods, while the FLUC indicators by HB12 fail to detect relevant bubbles. The HP indicators tend to detect too many bubbles to be plausible. It is then reasonable to expect the PWY11 and PSY13 indicators to be most useful for forecasting, if bubble periods indeed matter for real economic outcomes.

Figure 2 displays the detected bubble episodes for house prices. Here, the overall picture is less clear. There is wide consensus about the most recent house price bubble up to around 2006/07. However, the emergence dates vary from 2000M09 as indicated by the recursive HP-filter to 2003M10 as signaled by the FLUC indicators on the ratios. Similarly, the rolling PWY11 indicator signals a collapse at the peak of the price-to-income ratio in 2006M04, while the FLUC indicators on the individual series find the bubble to last until 2007M09. Beyond

<sup>&</sup>lt;sup>15</sup>The data is obtained from FRED. Series identifier: A229RX0.

that, it is difficult to judge which indicators perform well, as the price-to-income ratio has overall been much more stable with even a small downward trend. It appears though that the PWY13 indicator on the ratio detects far too many bubble episodes while the recursive PWY11 indicator detects too few. Overall, the forecast ability of bubble indicators that only detect the recent housing bubble should be limited also due to practical reasons in estimation.

Overall, there are considerable differences between all indicators and their specifications, with few providing continuous bubble periods. Instead, collapse and re-emergence dates alternate frequently. This is a particular problem for the PWY13 indicator which is likely due to the flexible window specification, allowing for a detection of short-lived explosive trends in the dividend series. To circumvent this issue, the literature has generally suggested to bridge bubble periods that are only a few months apart. While this might be feasible employing hindsight in an ex-post analysis, it is not possible in a real-time forecasting context. Hence, the lack of continuity will lead forecast models to interpret each determination of a bubble period as a collapse, potentially decreasing their predictive ability. Testing for an explosive root in the ratio instead of in the individual series does not seem to matter much for stock prices. For house prices, however, tests on the ratio find additional bubble periods for the Phillips tests but less bubble episodes for the FLUC tests. Yet, it cannot be observed that tests on the ratio provide "more continuous" bubble episodes.

The large differences in the detected bubble episodes are generally in line with the simulations in Phillips et al. (2013). They find that for the single-bubble case, the PWY11 procedure is superior in detecting bubbles that start early in the sample and are short-lived. The advantage of employing flexible backward-rolling windows for estimation in PSY13 starts to pay off from the middle of the sample. Also the length of a bubble matters for it's detection. Here, PSY13 show that the PWY11 indicator performs best for longer bubbles of at least 15 periods. However, this superiority does not translate to the case when there are multiple collapsing bubbles in a sample. Here, the PWY11 procedure frequently fails to detect a second bubble, which can be seen in the top left panel in 2. The problem is less pronounced in case the second bubble is of longer duration, as in the case of the dot-com bubble shown in the top left panel in 1. Employing either rolling window estimation for the PWY11 or applying the PSY13 indicator clearly helps to circumvent this issue.

## 2.5 Combination of indicators

Against these limitations of the individual indicators, a promising approach to summarize the information content on bubble emergence and collapse is to use combinations. By this, one can potentially make use of the different strengths of all indicators regarding the timing and lengths of potential bubbles. In specific, this paper will employ the union set of all individual indicators along different thresholds. A similar approach has recently been proposed by

Harvey et al. (2015) for two ex-post tests by PWY11 and HB12. In detail, a bubble is detected if any of the two indicators rejects the null hypothesis of a unit root. To assure that the asymptotic size of this union of rejections decision rule is equal to the nominal size, the critical values of each test are rescaled. The necessary rescaling constants are obtained by simulations.

This paper, however, relies on a much larger set of indicators that all potentially entail different valuable information on the development of asset price bubbles in real-time. Hence, an adjustment of critical values by simulations of the limiting distributions of all test statistics is impossible. A possible sidestep around this problem is to explore the detected bubble periods resulting from union set combinations along different thresholds. Thus, the combined indicator  $B_{\tau,\kappa}^{Comb}$  will signal a bubble in period  $\tau$  if at least  $\kappa$  individual indicators detect an asset price bubble, i.e.

$$B_{\tau,\kappa}^{Comb} = \begin{cases} 1 & \text{if } \sum_{\bullet \in \mathfrak{B}} B_{\tau}^{\bullet} \ge \kappa \\ 0 & \text{else,} \end{cases}$$

with  $\mathfrak{B} = \{PWY11_s^i, PWY11_s^r, PWY11_l^i, PWY11_l^r, FLUC_s^i, FLUC_s^r, FLUC_l^i, FLUC_l^r, PSY13^i, PSY13^r, HP_{rec}, HP_{rol}\}, i:$  individual series, r: price-dividend ratio and  $\kappa = 1, \ldots, K$  with  $K \leq |\mathfrak{B}|$ . The smaller  $\kappa$ , the more bubble episodes will be detected, implying an "overdetection". The larger  $\kappa$ , the more indicators need to signal a bubble, eventually implying an "underdetection". A priori, the choice of the optimal threshold  $\kappa$  is not clear.

Figure 3 shows the combination indicators for the S&P 500 for  $\kappa = 1, \ldots, 8$ . For  $\kappa = 1$ , several periods that do not feature a prominent increase in the price-to-dividend ratio are classified as bubbles, suggesting overdetection. Increasing the threshold to  $\kappa = 2$  alleviates this issue, yet the dot-com bubble period extends far beyond the crash in 2000M3. Thus it is questionable if this indicator can provide an accurate measure for asset price bubbles, especially towards their ending. For  $\kappa = 3$  and  $\kappa = 4$ , the pre-crash periods are detected relatively early for the 1987 crash and the 2000 dot-com bubble, and the crisis period in 2008/2009 is identified. Also, the crashes are detected in real-time. Setting  $\kappa = 5$  still detects the 1987 and dot-com bubble reasonably early, yet does not indicate the "negative bubble in 2008". Thus, it will be be particularly interesting to compare the forecasting performance of the combinations with  $\kappa = 3$ , 4, 5. Increasing  $\kappa$  further deteriorates the emergence detection in this case, especially with  $\kappa > 5$ , as fewer crises are detected and the end of the bubble is frequently signaled before the ultimate peak. It might be suspected that, if at all, indicators with  $3 \leq \kappa \leq 5$  are most useful for forecasting.

A similar picture is obtained for house prices as shown in Figure 4. Setting  $\kappa \leq 2$  seems to provide too many bubble periods, especially in times when income growth exceeds growth

in prices. A similar conclusion can be drawn for  $\kappa = 3$  and  $\kappa = 4$  with regard to bubbles being detected around 1993 and 2012. Yet, the number of bubbles is already clearly reduced. With  $\kappa > 4$ , only the recent housing price bubble starting in late 2001/early 2002 is detected. A priori it is not clear which measure, if any, will be most useful for forecasting which is also due to the practical problems for estimation arising from lack of bubble episodes.

## **3** Forecasts using asset price bubble indicators

The previous section has shown that there are promising new measures to detect asset price bubbles in real-time and early before their collapse, especially when their information content is aggregated. Hence, it is not entirely clear that an active, leaning-against-the-wind monetary policy is doomed to fail due to the impossibility to identify bubbles. Following the argumentation of Kohn (2006) and AWG10 it is now of interest to evaluate if these indicators also carry predictive content for central banks' target variables. Analyzing the U.S., those target variables are, most importantly, inflation and a measure for real economic activity (Mishkin, 2007) such as employment and output. This paper will foremost follow AWG10 as closely as possible and investigate the predictive content of bubble indicators for inflation and an output measure, here industrial production.<sup>16</sup> Also, the importance of asset price cycles for severe recession periods has been stressed frequently. Hence, the predictive content of asset price bubbles for recession periods will be analyzed in probit model.

Employing the indicator based on a one-sided, recursive HP filter only, AWG10 do not find any predictive content of stock and house price bubble indicators for predicting inflation, the output gap or output growth.<sup>17</sup> Yet, this finding, potentially suffers from limitations on two dimensions that this paper addresses. First, this paper will extend the set of bubble indicators by the ones discussed above. Second, AWG10 do not take into account the real-time dimension of the predictor variables. Most real economic variables such as industrial production (IP) and employment data are subject to publication lags and revisions. Stock prices, however, are available in real-time and are not revised.<sup>18</sup> The next subsections will outline the real-time forecasting models employed here, and discusses data issues. The recession forecasts will be evaluated following Bussiere & Fratzscher (2006) by

<sup>&</sup>lt;sup>16</sup>The Federal Reserve Act of 1977 calls on the Federal Reserve to use its policy instruments "to promote effectively the goals of maximum employment, stable prices, and moderate long-term interest rates" (95th United States Congress, 1977). While inflation is the primary target variable for all developed economies' central banks, the mandate of targeting employment is less common and often also addresses related variables such as output (as in the standard Taylor rule).

<sup>&</sup>lt;sup>17</sup>In contrast to the finding of Stock & Watson (2001), AWG10 do find some predictive content of asset prices for output growth when using quarterly growth rates of prices as predictors.

<sup>&</sup>lt;sup>18</sup>The importance of this issue has been well documented since the argumentation outlined in Croushore & Stark (2003) and Orphanides (2003).

different criteria including the RMSPE, the percentage of correct signals to total observations, the number of recessions to total recessions and the number of correct alarms to total alarms.

### 3.1 Forecasting output and inflation

First, output (as proxied by IP) and inflation will be predicted by single-equation models including predictors that are certainly included in the information (and target) set of the central bank and have been documented to frequently show significant predictive content as in Stock & Watson (2001). Hence, the benchmark model against which the marginal predictive content of all bubble indicators is measured, contains includes IP (when inflation is the target), inflation (when output growth is the target), the unemployment rate, the effective funds rate as measure for the policy rate and the term spread between 10-year and 3-months government bond yields. This paper hence differs from AWG10 by adding unemployment and the term spread as key predictors.

Regarding the different real-time availability of the predictors, it is helpful to introduce some notation following Clark & McCracken (2009). Here,  $y_{\tau}(t)$  denotes the vintage t observation of y at time  $\tau$ , where it must hold that  $t \geq \tau$ . Hence, for variable y published with a lag of q months, the observations available at time t are  $\{y_{\tau}(t)\}_{\tau=1}^{t-q}$ . The full sample then includes observations for the target variable y and the vector of predictors  $\{[y_{\tau}(t), x'_{\tau}(t)]_{\tau=1}^t\}_{t=R}^T$ , where  $x_k$ -specific publication lags and number of revisions are considered (see Table 2). The forecast evaluation is carried out against the final revised values  $y_{\tau+h}(T)$  and the evaluation criterion for forecast accuracy is the root mean square prediction error (RMSPE). Direct h-step forecasts for y are obtained for each margin  $t = R, \ldots, T - h - q$ . The evaluation sample is thus of size P = T - h - q - R + 1. Given this notation, the forecast equation for model m can then be written as

$$y_{\tau+h}(t) = x'_{m,\tau}(t)\beta_m + \varepsilon_{m,\tau+h}(t), \quad \varepsilon_t a u \stackrel{iid}{\sim} N(0, \sigma_{\varepsilon}^2)$$
(8)

where the parameter vector  $\beta_m$  is obtained from recursive least-squares estimation. The benchmark model only includes the "classical" predictors discussed above. This benchmark model is then augmented by all indicators introduced in Section 2, first for stock and house prices separately, and second for a joint indicator taking the value 1 if there is a bubble in either stock or house prices to circumvent the issue of lack of bubble episodes.<sup>19</sup> When an indicator does not signal a single bubble episode in the estimation window  $\tau = 0, \ldots, t - h - q$ for forecasting margin t, the model cannot be estimated. Instead, the benchmark forecast is

<sup>&</sup>lt;sup>19</sup>Note that the publication lag of house price bubbles is respected. Also, the models were evaluated using an indicator that adds both stock and house price bubbles. As a joint occurrence of bubbles in both asset classes is rare, this left the results almost unaltered. Finally, the models where evaluated including both bubble indicators separately. Again, the results do not change notably.

applied at that margin. That is, the benchmark and the augmented model are identical until the first time that at least one bubble period is detected.

Direct forecasts are applied since an iterative forecasting procedure would require predictions up to h - 1 for all variables in x. While this might be feasible for the benchmark model, forecasting the path of the bubble is not.<sup>20</sup> AWG10 argue that the target horizon of central banks, especially when a leaning-against-the-wind policy should be conducted, includes horizons beyond 2 years. Therefore, monthly forecast are carried out for horizons h = 1, 3, 6, 9, 12, 18, 24, 36, 48, 60.

Adding to AWG10, this paper will also allow for additional lags in the forecasting equation, as it is not obvious that last available data will provide the best forecasts.<sup>21</sup> In specific, this paper will employ a specific-to-general lag length selection following the procedure described by Herwartz (2010). That is, for all lags up to  $p = 1, \ldots, p_{max}$ , with  $p_{max} = 3$ , in-sample significant regressors are iteratively added from a minimum set including only a constant until the marginal explanatory content of the variables added is not significantly different from zero. This allows for studying the robustness of the findings to the choice of the benchmark. If benchmark forecasts can be improved more by a flexible lag length selection than by the inclusion of bubble indicators, there is less evidence suggesting a potential for an activist monetary policy.

#### **3.2** Forecasting recession periods

Considering that monetary policy makers could be most concerned about macroeconomic crises, it is also interesting to see if asset price bubble indicators can improve upon recession forecasts. Furthermore, the literature on asset price cycles as brought forward by Borio (2012) has stressed the importance of asset price bubbles and crashes on the business cycle. It has been postulated that following asset price crashes, recessions are likely to occur and are typically larger than regular recessions of the business cycle. Therefore, AWG10 estimate a panel probit model with fixed effects to predict adverse macroeconomic conditions.<sup>22</sup> Again, the authors do not find any additional predictive content of the HP-filter bubble indicator. In addition to the limitations of the study discussed above, a particular problem of the panel probit model is that the effects of asset price bubbles on the crisis likelihood can differ across

<sup>&</sup>lt;sup>20</sup>In addition, a large literature documents that direct forecasts are more robust to model misspecification (cf. Marcellino et al., 2006).

<sup>&</sup>lt;sup>21</sup>Also, a fixed lag length estimation procedure for all variables in x was carried out with  $p = 0, 1, \ldots, p_{max}$ , with  $p_{max} = 3$ . The results in Section 4 are for p = 0 only, as this parsimonious model provided the best forecasts for all forecast horizons. For p > 0, the benchmark forecast and the bubble indicator augmented forecasts deteriorate, leaving the model with p = 0 to be the toughest benchmark.

<sup>&</sup>lt;sup>22</sup>These are defined as states where the average output gap for the current and next 3 quarters is less than -1% or where the annual inflation rate is negative or falls by more than two percentage points over the next three quarters.

countries, shedding doubt on the forecasting capability of the model.

Employing data at the monthly frequency, it is possible to estimate the model on a single country level. Similarly to the previous section, this paper hence estimates a probit model accounting for the real-time dimension. The model can be written as

$$r_{\tau+h}(t) = \Phi(x'_{m,\tau}(t)\beta_m) \tag{9}$$

where  $r_{\tau+h}(t)$  denotes the time t expectation of the binary recession variable  $r_{\tau}$ , taking the value 1 in case of a recession at the horizon h.  $\Phi(.)$  denotes the standard normal cumulative distribution function. As for the direct OLS forecast models,  $x'_{m,\tau}(t)$  contain the predictors of model m, vintage t. Given the large computational burden to estimate this model, the large order here is fixed to  $p = 0.2^{3}$ 

From model *m*, recession probabilities  $pr(r_{\tau+h} = 1) = \Phi(x'_{m,\tau}(t)\beta_m)$  are obtained. These are contrasted to the realized recession values  $r_{\tau+h}$ . The forecast error from which the RMSPE is computed is hence defined as the difference between the predicted recession probability and the realized value of the binary recession indicator. To further evaluate the model forecast, it is interesting to analyze if the model provides accurate signals for future recessions. For this, a threshold level must be chosen above which the predicted probability sends a reasonably strong signal for a recession. This choice obviously involves a trade-off between type I and II errors. The larger the threshold is, the fewer recessions are signaled and more recession periods might be missed (type I error). The lower the threshold is, the more recessions are signaled, hence the number of wrong signals is likely to be high (type II error) (see Table 4). As there is no guidance on what an optimal threshold level is, this paper suggests using a level of 30%. Further, this paper follows Bussiere & Fratzscher (2006) and defines that a recession is correctly signaled if the recession actually occurs within the 12 months following the signaled horizon. This is due to the fact that predicting the exact timing of recessions is highly complicated. From this, it is possible to evaluate the forecasts along several dimensions, namely by the ratio of observations correctly signaled to the total number of observations  $\left(\frac{A+D}{A+B+C+D}\right)$ , the ratio of detected recessions to total recession periods  $\left(\frac{A}{A+C}\right)$  and the ratio of correct alarms to total alarms  $\left(\frac{A}{A+B}\right)$ .

In order to avoid the need to estimate an output gap, the recession indicator is constructed following Harding & Pagan (2002). This indicator is based on the turning points of a business cycle reference series. Here, industrial production smoothed by a moving average (MA(3)) process will be employed as the reference series and the vintages of recession dates

<sup>&</sup>lt;sup>23</sup>In the future, a dynamic probit model including lags of the dependent binary recession variable  $r_{\tau}(t)$  will be evaluated. Adding lags of the predictors complicates the likelihood-optimization such that the estimator often does not converge.

will be constructed according to the real-time data of IP.<sup>24</sup> Peaks and troughs are identified as  $peak = \{Y_{t-k} < Y_t > Y_{t+k}, k = 1, ..., 5\}$  and  $trough = \{Y_{t-k} > Y_t < Y_{t+k}, k = 1, ..., 5\}$ .  $k_{max} = 5$  hence denotes the recession recognition lag, which is similar to the average publication lag of official NBER recession dates. The recession indicator  $r_t$  takes the value 1 for all t from peak to trough if the size of the potential recession  $j, S_j > 0.005$ .  $S_j$  is given by  $S_j = 0.5 \times \text{Deepness}_j \times \text{Duration}_j$  where  $Deepness_j = |y_{peak,j} - y_{trough,j}|/y_{peak,j}$ . Figure 5 displays the recessions as defined by this algorithm when applied to revised data in 2014M2. The recession dates largely agree with the NBER dates for the recessions in the early 1990's, the early 2000's and the recent crisis. In addition, three small recessions are detected; two between 1985 and 1990 and one prior to 2005.

## 3.3 Real-time data description

As outlined above, the target and predictor variables include monthly observations of industrial production, inflation, the unemployment rate, the effective funds rate and the spread between 10-year to 3-month government bond yields. Details on the variables, especially on the publication and revision lags can be found in Table 2. All real-time data is obtained from the Real-Time Data Set for Macroeconomists of the Federal Reserve Bank of Philadelphia.<sup>25</sup> Non-revised data is obtained from Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis.<sup>26</sup>

All data are transformed to be stationary, if necessary. This implies that industrial production and the consumer price index (CPI) are log-differenced. The stationarity assumption on the remaining variables cannot be rejected consistently by standard tests (ADF and KPSS), hence no transformations are applied.<sup>27</sup> Real-time data on the unemployment rate are available for monthly observations yet in quarterly vintages, only. As unemployment numbers were always published in the first week of a month for the sample and revisions are small, a set of monthly vintages is generated. For this, interim monthly vintages are constructed to contain all information from the previous quarterly vintage (that is, assuming no past revisions) and new observations up to publication date from the next quarterly vintage (that is, assuming no future revisions). See Table 3 for an illustration. Similarly, monthly

<sup>&</sup>lt;sup>24</sup>Relying on official recession dates as published by NBER complicates the real-time forecasting procedure as the publication lag varies over time. In the future, also the Chicago Fed National Activity Index (CFNAI) could be employed, yet the real-time database reaches back only until vintage 2001M1 so far (https://www. chicagofed.org/research/data/cfnai/historical-data).

 $<sup>^{25}</sup>$ https://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/

<sup>&</sup>lt;sup>26</sup>http://research.stlouisfed.org/fred2/

<sup>&</sup>lt;sup>27</sup>The unemployment series does not exhibit a trend over the full sample and all variants of the ADF and KPSS tests accounting for an intercept, suggest stationarity. The real interest rate is found to be trend stationary over the full sample. Due to changing trend estimates depending on the forecast margin, no transformation is applied. The term spread is found to be stationary.

vintages for CPI become available in 1998M11 only. Since 1994Q3, quarterly vintages with monthly observations are published on the Fed Philadelphia website. Those datasets are merged in the same fashion to obtain monthly vintages from the start of the forecasting exercise.

Accounting for the change in inflationary regimes around the end of the first term of Paul Volcker as Chairman of the U.S. Fed in 1983, the forecasting exercise will rely only on data starting in 1983M1 with pre-sample data used for variable transformations. Following the period of high inflation, the monetary policy setting is likely to have changed. First evidence that this structural change in monetary policy setting matters also for forecasting was provided by Giacomini & Rossi (2009), who find that an inflation forecast model building on the Phillips curve suffered from a breakdown from around 1980-1983 when the U.S. Fed drastically increased policy rates to combat high levels of inflation.

The initial training sample includes R = 180 observations, and runs until 1997M12 (the first forecast margin). Hence, the evaluation period includes the dot-com and the housing price bubble, and the crisis period around 2008-2009.

## 4 Results

In this section, the predictive performance of all bubble indicators discussed in section 2 will be presented. First, the forecast accuracy of the benchmark and the bubble indicator augmented models will be discussed for inflation and output forecasts. The predictive content will be evaluated separately for stock and house prices, and for the joint indicator that signals a bubble whenever there is a bubble in stock or house prices. Subsequently, the findings will be compared for forecasts that consider the real-time availability of the data and forecasts that do not account for this issue. Finally, the predictive ability for recession forecasts will be assessed.

### 4.1 Predictive content for industrial production

Table 5 displays the predictive accuracy of the benchmark model for IP (first row) and the relative gains and losses of the indicator-augmented models subsequently. The FLUC indicators by HB12 have been suppressed from the table as they do not find any bubble periods until late 2008. Overall, the findings are ambiguous. First it should be noted, that this conclusion holds in particular for the recursive HP-filter as applied by AWG10. For short-run forecast up to h = 6, the findings of AWG10 are contradicted with small yet significant forecast gains of the bubble augmented model. For larger horizons, however, their findings seem to be supported as the benchmark model performs better. Nonetheless, there are a non-neglectable number of models that perform significantly better for both short- and long-run forecasts. Most interestingly, this applies foremost to the PSY13 indicator applied to individual series that finds both the 1987 crash and the dot-com bubble, yet signals some intermediate collapse during the course of the second bubble. The best short-run forecast up to h = 9 are obtained by the PWY11 indicator with rolling estimation applied to the individual series and by the combination indicator with  $\kappa = 5$  that detect the 1987 pre-crash and the dot-com bubble period. Both indicators are extremely accurate in detecting the collapse date, hence the gains potentially stem from the period of lower output growth in the succession of the crisis. Importantly, one can conclude, that these indicators do not only detect plausible bubble periods, but also help significantly in forecasting output growth for all forecast horizons. For indicators that detect either too few or too many bubble periods (such as the combinations with  $\kappa \leq 2$  and the HP indicators) the predictive ability deteriorates significantly compared to the benchmark model.

Table 6 displays the results for house price bubble indicators. Here, the forecasts are overall more similar to the benchmark model and often slightly worse, in particular, for the short-run. Only in the very long-run ( $h \ge 6$ ), significant gains can be obtained. As for stock price bubbles, the PWY13 indicator applied to individual series is particularly successful. In general, the indicators that detect the prominent house price bubble and only few other bubble periods, also provide superior medium- to long-run forecasts. The poor short-run forecast performance of the augmented models can be due to several issues. First, it is important to emphasize that house prices, in contrast to stock prices, are only available with a lag of two periods and are thus lagging even the real variables. Second, the inferior forecast performance can be due to the nature of house price bubbles which might disinflate slower than fast crashing stock price bubbles. Also, the rare occurrence of house price bubbles poses difficulties for a proper estimation of the model.

In case stock and house price bubbles share some common feature, it might be suitable to combine both asset classes and explore the predictive content of an indicator that signals a bubble as soon as either a stock or house price bubble is detected. These results are displayed in Table 7. Compared to the results in tables 5, the forecasts up to h = 12 are often improved further, especially for the combination indicator with  $\kappa = 5$  and the rolling-window PWY11 indicator applied to individual series. Regarding the longer forecast horizons, the results are ambiguous but indicate a poorer forecast performance for most joint indicators compared to individual asset price bubble indicators. This might in part be due to different long-run effects of stock and house price bubbles. Here, it has been suggested that recessions following house price bubbles are deeper and longer lasting than recessions following stock market crashes, as housing represents an asset class of higher importance to a large share of households.

In order to assess whether the real-time dimension of stock and house price bubble indicators and real variables matters and to compare the findings of this paper to the ones of AWG10, the forecast exercise is carried out for revised data. The results are depicted in Table 8 for stock price bubbles and Table 9 for house prices. For both asset classes, the changes from real-time to revised data leave the pattern of forecast gains largely unchanged. Overall, stock price bubbles improve short-run prediction more than house price bubbles, and vice versa. Also the same indicators remain superior. However, the forecast gains for stock prices are now smaller as the overall forecast performance of the benchmark model also improves. For house prices, the opposite holds. As these are published with a longer lag, their predictive power is now improved relative to the benchmark. In summary, it is decisive that the real-time dimension is considered in evaluating the forecast performance of asset price bubble indicators.

Finally, the sensitivity of the results with regard to the benchmark model shall be assessed. For this, a specific-to-general (SPEC) model selection approach has been applied to each forecast model, allowing for a flexible selection of predictors and their lags up to  $p_{max} = 3$ . The results for forecasting IP growth with stock price bubbles are displayed in Table 10. The first thing to notice is that SPEC modeling improves the forecast performance of the benchmark for short horizons up to h = 9. For these periods, the forecast gains of bubble augmented models decrease, yet largely the same indicators perform better than the benchmark model. However, for h = 3 and h = 6, no gains can be achieved. For medium horizons  $9 \le h \le 18$ , the relative forecast gains remain largely in the same range. Beyond that, forecast gains even increase. Similar results hold for SPEC modeling with house price bubbles and the joint indicator of stock and house price bubbles. Hence, it can be concluded, that bubble indicators add predictive content even to models that allow for autoregressive components and additional lags of standard predictors.

#### 4.2 Predictive content for inflation

Analogous to the previous section, Table 11 displays the predictive accuracy of stock price bubbles for CPI inflation. In contrast to IP growth, the results here seem to support the finding of AWG10 that bubble indicators do not help to predict inflation. Again, this holds for the recursive HP-filter indicator that has been employed by AWG10 and that provides significantly worse forecasts especially in the long-run ( $h \ge 12$ ). However, there are again some indicators that feature significant predictive content in the short and medium term. These include the PSY13 indicator when applied to the price-to-dividend ratio and the combination indicators when setting a low threshold of  $\kappa = 1$  or  $\kappa = 2$ . Interestingly, these indicators differ with respect to the identified bubble periods, such that consistent conclusions are difficult to draw from inspecting the RMSPE onlys.

Table 12 provides the results for house price indicators. Here, the forecasts are overall very similar to the benchmark model and slightly worse for most indicators for the short and medium prediction horizon. Again, the recursive HP-filter applied by AWG10 does not perform well. The best forecasts are frequently obtained by combination indicators, especially with medium thresholds of  $\kappa = 3$  and  $\kappa = 4$ . Here it seems that house price bubbles particular matter for forecasting in the medium- and long-term. Raising the threshold leaves only the most recent housing price bubble, which impedes estimation and forecast evaluation. Yet, those indicators and the rolling window PWY11 indicator for the individual series provide relatively large and partially significant gains for the very long-run of h = 48 and  $h = 60.^{28}$ 

The results for the joint indicator of stock and house price bubbles are displayed in Table 13. Against what could be expected, the forecasts generally deteriorate significantly. This might argue for an offsetting between the predictive content in stock and house prices, possibly due to different short- and long-run effects.

Regarding the implications of considering real-time information when forecasting, the same holds true as for IP forecasts. Evaluating forecasts obtained from revised data of real variables improves the benchmark and cuts down on the predictive gains obtained by including stock price bubble indicators when being cognizant about the real-time dimension. Similarly, the predictive content of housing price indicators is exacerbated when revised data is employed. The results described above are also not sensitive to the choice of the benchmark as evaluated by the SPEC modeling approach. This is due to the fact, that the benchmark with SPEC modeling performs worse than the benchmark with fixed lag length for all horizons. Hence there are larger gains possible by including bubble indicators than by a flexible variable and lag length selection without bubble indicators.

### 4.3 Predictive content for recession periods

The last section has provided evidence for potential gains for practitioners to improve upon forecasts for output and inflation by including asset price bubble indicators. To investigate the predictive content of asset price bubble indicators on recession events, this section presents the results of the probit model forecasts. Here, the focus will rest solely on the indicators that have shown the largest predictive content for IP growth, namely the combination indicator with  $\kappa = 5$  for stock, and stock and house prices jointly, as well as the PSY13 indicator applied to the S&P 500 and house prices.

Table 14 presents the RMSPE for the benchmark probit and the augmented models. First, it should be noted that the benchmark model performs relatively poorly with RM-SPE's around 0.4 to 0.45. Second, two of the indicators (the combination indicator applied

<sup>&</sup>lt;sup>28</sup>The indicator based on the rolling HP-filter also appears to provide good forecasts in the long-run. However, these are most likely due to different parameter estimates only, as the indicator does not detect a bubble in the out-of-sample-forecasting window except for the very last periods. Hence, no additional information is employed for forecasting.

to both stock and house prices and the PSY13 indicator on stock prices) offer substantial improvements for horizons up h = 12. In contrast to the findings for OLS forecasts, the joint indicator of stock and house prices performs best for very short horizons. This might, however, also be due to the few recession and bubble events in the sample and accounting for the last house price bubble improves the model's forecasts. The PSY13 indicator applied to house prices only performs worse than the benchmark, which might also be due to the infrequent occurrence of house price bubbles and recessions. In contrast to the findings for OLS forecasts, the augmented models do not predict recessions more accurately at longer horizons. Yet, the differences are generally not substantial.

To see if bubble indicators can help to provide more accurate recession alarms, Table 15 evaluates the signal quality when a cut-off threshold of 30% is used. The top panel confirms the finding on the accuracy measure and shows that the joint combination indicator with  $\kappa = 5$  provides more correct signals than the benchmark for short forecast horizons up to h = 12. The other indicators do not improve the overall signal quality. This also holds for all indicators in the longer run, where all models perform almost equally poorly. The encouraging findings for short horizons could, however, reflect that recession events are rare and that the augmented models generally signal fewer recessions than the benchmark. Hence, the second panel displays the number of correctly signaled recessions to the total number of recession periods. Again, it can be seen that the combination indicator on both stock and house price bubbles signals more recession events correctly than the benchmark model for short horizons. For the nowcast and the one month horizon, the detection frequency can be more than doubled. Also, the PSY13 indicator on stock prices outperforms the benchmark. Nonetheless, all models perform very poorly beyond the six month horizon. For horizons longer than two years, none of the models signals a recession. Related to the above criticism, these findings might, however, also reflect that models including bubble indicators issue too many signals and hence also too many false alarms. Therefore, the bottom panel displays the number of correct recession alarms to total alarms. Again, the positive findings above are confirmed and the indicator accounting for stock and house price bubbles provides the best signals for  $h \leq 12$ .

Overall, the results indicate that bubble indicators can improve recession forecasts especially in the short-run. These results should, however, be taken with a grain of caution as the forecast accuracy of all models is rather poor and there might be other options of improving recession forecasts than relying on asset price bubble indicators. The poor results potentially also reflect the rare occurrence of recessions and asset price bubbles.

## 5 Conclusion

This paper contributes to the discussion around the role of monetary policy in influencing asset price cycles. In particular, there is an ongoing debate on whether central banks should stronger "lean against the wind" of emerging bubbles. For this to be feasible, asset price bubbles need to be detected in real-time, and they should carry predictive content for real variables of interest to central banks.

This paper shows that, following the seminal contribution of Phillips et al. (2011), there is now a promising battery of monitoring tests for detecting asset price bubbles. However, the detection and precise dating of asset price bubbles is highly sensitive to the exact specification of the tests. Frequently, tests fail to detect commonly accepted bubble episodes or indicate bubbles when there is no strong narrative evidence for such events. Also, these indicators often miss the collapse date of bubbles or signal an end of the bubble prior to the ultimate peak. To account for the uncertainty around those dates, this paper suggests to employ combinations of a large set of available indicators. Conducting a first-step sensitivity analysis, it is found that meaningful stock and house price bubbles can be detected when relying on tests that can detect multiple bubbles such as the newly suggested combinations or the generalized test by Phillips et al. (2013).

In a second step, this paper then shows that several of these asset price bubble indicators are also useful for forecasting output growth, inflation and recession events. Indicators that perform well in predicting output and inflation are foremost the most recently proposed indicator by Phillips et al. (2013) and the combinations suggested in this paper. By this, the paper highlights that previous results obtained by Assenmacher-Wesche & Gerlach (2010) are sensitive to several important changes. First, the choice of the bubble indicator is decisive. Second, considering the real-time dimension of all variables is crucial. As stock prices and dividends are available in real-time, they may particularly add to the information set of central banks. House price bubble indicators that are available with a lag of two months only, suffer from that limitation. Nonetheless, this paper finds that indicators for both asset classes can significantly improve the forecasts obtained from a standard forecast model. Stock prices are particularly useful in horizons of up to 24 months, while house prices are useful for even longer horizons. Forecasts for industrial production can benefit more from the inclusion of asset price bubble information than predictions of inflation. Finally, the paper tentatively indicates that also recession forecasts can be improved, particularly for horizon of up to one year.

In sum, these findings suggest that central banks should closely monitor asset price developments for patterns commonly found during bubble episodes. This can then also enrich the information set of central banks and other practitioners for forecasting. The paper does not answer the question whether central banks can and should pursue an active, leaningagainst-the-wind policy as it remains unclear if monetary policy with it's standard tools can effectively contain bubbles without hampering real economic growth in the short-run.

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## A Figures



Figure 1: Bubbles in the S&P 500.

The top five panels show the bubble periods (grey areas) detected by unit root tests. The left panel shows the indicators applied to the price and dividend series individually. The right panel shows the indicators applied to the price-dividend (PtD) ratio. The bottom panel shows the indicators based on the HP-filter (left: recursive, right: rolling). The solid line plots the PtD ratio.



Figure 2: Bubbles in the U.S. housing market. See figure 1 for further notes. The solid line displays the ratio of average house prices to disposable income per capita.



Figure 3: Bubbles in the S&P 500 as detected by the combination indicators for different threshold levels  $\kappa$ .



Figure 4: Bubbles in the U.S. housing market. See figure 3 for further notes.



Figure 5: Recession events as defined by the business cycle turning point algorithm by Harding & Pagan (2002) applied to the industrial production series smoothed by a moving average (MA(3)) process.

# **B** Tables

Notation	$r_0$	Estimation windows	Specifications
$PWY11_s$	0.1	recursive	$J^{max} = 12$ , selection of J by AIC
$PWY11_l$	0.2	rolling	$J^{max} = 12$ , selection of J by AIC
$FLUC_s$	0.1	recursive	Pre-detrending of time series on constant
			and linear trend
$FLUC_l$	0.2	recursive	Pre-detrending of time series on constant
			and linear trend
PWY13	$0.01 + \frac{1.8}{T}$	forward recursive,	J = 1
	1	backward rolling	
$HP_{rec}$	0	recursive	$\lambda = 100,000 * 3^4$
$HP_{rol}$	0	rolling	$\lambda = 100,000 * 3^4,  \omega = 96$

Table 1: C	Overview o	n bubble	tests
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	Controo	Table 2: Ov Identifier	erview on real-time dat: Adimetment	a and regressors Dublication lag	Ratricione	Trancformation
eries	Source	Identiner	Adjustment	Fublication lag	Kevisions	Iransformation
onsumer price index	FRED	CPIAUCSL	Seasonally adjusted	1 month	Recalculations of seasonal	log-diff
					factors dating back several	
					years	
ndustrial production	RTDS	IPT	Seasonally adjusted	1 month	Revisions of	log-diff
					past 5 months	
Jnemployment rate	RTDS	RUC	Seasonally adjusted	1 month	Recalculations	None
					of seasonal	
					factors dating	
					back several	
					years	
Effective federal funds	FRED	FEDFUNDS	I	ı	I	None
ate						
-Month treasury bill:	FRED	TB3MS	I	I	I	10V 3M Chrond
econdary market rate						npathe the-tot
.0-Year government	FRED	GS10	I	I	I	
oond: constant matu-						
ity rate						
stock price bubble in-	I	I	ı	I	I	None
licator						
House price bubble in-	I	I	ı	2 months	I	None
licator						

				Vint	ages			
Date	M1	Q1 = M2	M3	M4	Q2 = M5	M6	M7	
M1	-	$U_{M1}(Q1)$	$U_{M1}(Q1)$	$U_{M1}(Q1)$	$U_{M1}(Q2)$	$U_{M1}(Q2)$	$U_{M1}(Q2)$	
M2	-	-	$U_{M2}(Q2)$	$U_{M2}(Q2)$	$U_{M2}(Q2)$	$U_{M2}(Q2)$	$U_{M2}(Q2)$	
M3	-	-	-	$U_{M3}(Q2)$	$U_{M3}(Q2)$	$U_{M3}(Q2)$	$U_{M3}(Q2)$	
M4	-	-	-	-	$U_{M4}(Q2)$	$U_{M4}(Q2)$	$U_{M4}(Q2)$	
M5	-	-	-	-	-	$U_{M5}(Q3)$	$U_{M5}(Q3)$	
M6	-	-	-	-	-	-	$U_{M6}(Q3)$	

Table 3: Constructing monthly vintages for unemployment data

The subscript denotes the observation date, the term in bracket denotes the vintage.

Table 4: Recession signal evaluation and type I and II errors

		Obser	vation
		$r_{\tau+h} = 1$	$r_{\tau+h} = 0$
Signal	$r_{\tau+h} = 1$	А	B (type II)
Signai	$r_{\tau+h} = 0$	C (type I)	D

Table 5: Relative RMSE: IP + Stock Prices

						Horizon					
Model	0	1	33 S	9	6	12	18	24	36	48	60
Benchmark	0.007	0.012	0.022	0.035	0.044	0.054	0.078	0.101	0.119	0.133	0.197
PWY11 <sub>s</sub> : individual	0.995*	$0.986^{*}$	$0.970^{*}$	$0.976^{*}$	$0.996^{*}$	1.003	$0.993^{*}$	$0.959^{*}$	$0.953^{*}$	0.991	$1.080^{*}$
PWY11 <sub>s</sub> : ratio	0.999	$0.994^{*}$	$0.988^{*}$	1.003	$1.018^{*}$	$1.024^{*}$	1.036	1.047	1.094	1.173	1.238
PWY11 <sub>1</sub> : individual	$0.979^{*}$	$0.959^{*}$	$0.942^{*}$	$0.955^{*}$	$0.981^{*}$	0.996	1.001	0.996	1.000	$1.062^{*}$	$1.104^{*}$
$PWY11_1$ : ratio	1.021	1.032	1.042	$1.056^{*}$	$1.057^{*}$	$1.041^{*}$	$1.012^{*}$	1.000	$1.014^{*}$	$1.065^{*}$	$1.128^{*}$
PSY13: individual	$0.994^{*}$	$0.988^{*}$	$0.976^{*}$	$0.974^{*}$	$0.977^{*}$	$0.972^{*}$	$0.952^{*}$	$0.924^{*}$	$0.888^{*}$	$0.928^{*}$	$0.991^{*}$
PSY13: ratio	1.024	1.036	1.041	1.046	$1.043^{*}$	$1.030^{*}$	0.999	0.979	0.977	1.007	1.038
$\mathrm{HP}_{\mathrm{rec}}$	$0.982^{*}$	$0.971^{*}$	$0.963^{*}$	$0.981^{*}$	1.007	$1.007^{*}$	1.000	0.982	1.013	$1.043^{*}$	$1.007^{*}$
$HP_{rol}$	$0.994^{*}$	$0.984^{*}$	$0.979^{*}$	$0.995^{*}$	$1.022^{*}$	$1.035^{*}$	$1.061^{*}$	$1.080^{*}$	$1.034^{*}$	$0.978^{*}$	$0.957^{*}$
<b>Combination:</b> $\kappa = 1$	1.013	1.018	1.018	1.025	$1.036^{*}$	$1.029^{*}$	$1.017^{*}$	$1.018^{*}$	$0.999^{*}$	$1.021^{*}$	0.997
<b>Combination:</b> $\kappa = 2$	1.016	1.021	1.023	1.028	$1.038^{*}$	$1.029^{*}$	$0.992^{*}$	$0.965^{*}$	1.000	$1.056^{*}$	$1.053^{*}$
<b>Combination:</b> $\kappa = 3$	1.003	1.014	1.006	$1.011^{*}$	$1.023^{*}$	$1.021^{*}$	1.004	$0.988^{*}$	0.997	$1.049^{*}$	$1.100^{*}$
<b>Combination:</b> $\kappa = 4$	1.004	1.014	1.006	$1.013^{*}$	$1.024^{*}$	$1.021^{*}$	1.003	$0.990^{*}$	1.000	$1.049^{*}$	$1.120^{*}$
<b>Combination:</b> $\kappa = 5$	$0.975^{*}$	$0.958^{*}$	$0.940^{*}$	$0.959^{*}$	$0.986^{*}$	0.996	1.002	0.996	1.010	$1.081^{*}$	$1.132^{*}$
<b>Combination:</b> $\kappa = 6$	$0.994^{*}$	$0.983^{*}$	$0.973^{*}$	$0.982^{*}$	0.996	0.996	0.987	0.971	0.970	$1.019^{*}$	$1.053^{*}$
<b>Combination:</b> $\kappa = 7$	$0.992^{*}$	$0.980^{*}$	$0.975^{*}$	$0.984^{*}$	0.997	0.995	0.986	0.969	0.964	1.016	1.047
<b>Combination:</b> $\kappa = 8$	$0.996^{*}$	$0.989^{*}$	$0.981^{*}$	$0.985^{*}$	0.996	0.995	0.992	0.985	0.975	1.006	1.023
Rows 2 and following dis	splay the ]	RMSPE o	f the stoc	k price bu	ubble augi	nented m	odels rela	tive to th	e RMSPE	of the be	nchmark
given in the first row. Va.	lues less t	han 1 indi	icate that	the augm	ented mo	del is sup	erior to th	ie benchm	ark. Fore	casts den	ted by $*$
are significantly different.	at the $5\%$	-level fron	n the bend	chmark as	indicated	by the te	est for equ	al predict	ive ability	r for real-t	ime data
by Clark & McCracken ( $\hat{z}$	2009). Bol	d values s	show the l	pest forec	ust for a g	iven horiz	ion. Value	s in italic	s indicate	that the	indicator

does not detect a bubble period for the respective model's training sample and hence the benchmark forecast has been applied at

least to some part. The test for equal predictive ability does not apply for that model and forecast horizon.

						Horizon					
Model	0	1	c,	9	6	12	18	24	36	48	09
Benchmark	0.007	0.012	0.022	0.035	0.044	0.054	0.078	0.101	0.119	0.133	0.197
PWY11 <sub>1</sub> : individual	1.005	1.007	1.013	1.036	1.061	$1.079^{*}$	1.048	1.049	$1.070^{*}$	$0.913^{*}$	$0.886^{*}$
PWY11 <sub>1</sub> : ratio	1.028	1.038	1.043	1.055	1.064	1.051	1.034	1.033	$1.085^{*}$	$1.035^{*}$	0.996
FLUC <sub>s</sub> : individual	1.006	1.004	1.014	1.049	1.110	$1.129^{*}$	$1.130^{*}$	$1.119^{*}$	$1.111^{*}$	$0.893^{*}$	$0.949^{*}$
FLUC <sub>s</sub> : ratio	1.005	1.002	1.000	0.999	0.995	0.993	0.995	1.017	1.065	1.024	1.000
FLUC <sub>1</sub> : individual	1.001	1.002	1.013	1.040	1.073	$1.093^{*}$	$1.100^{*}$	$1.116^{*}$	$1.112^{*}$	$0.935^{*}$	$0.967^{*}$
FLUC <sub>1</sub> : ratio	1.005	1.003	0.999	1.000	0.997	0.995	0.997	1.023	1.070	1.027	1.000
<b>PSY13:</b> individual	$1.004^{*}$	1.007	1.012	$1.026^{*}$	1.026	1.033	1.033	$1.052^{*}$	$1.086^{*}$	$0.876^{*}$	$0.850^{*}$
PSY13: ratio	0.995	0.994	0.988	1.000	1.001	$0.993^{*}$	0.975	0.989	$1.052^{*}$	$1.057^{*}$	1.004
$\mathrm{HP}_{\mathrm{rec}}$	$1.015^{*}$	$1.033^{*}$	$1.060^{*}$	$1.100^{*}$	$1.133^{*}$	1.128	1.081	1.083	$1.073^{*}$	$1.013^{*}$	$1.023^{*}$
$\mathrm{HP}_{\mathrm{rol}}$	0.998	0.998	0.999	0.995	0.996	0.998	0.997	1.002	1.027	1.010	0.948
<b>Combination:</b> $\kappa = 1$	$0.992^{*}$	0.993	0.990	1.007	$1.011^{*}$	$1.007^{*}$	1.011	$1.030^{*}$	$1.043^{*}$	$1.024^{*}$	1.000
Combination: $\kappa = 2$	1.015	1.017	1.021	1.030	1.032	1.031	1.054	$1.079^{*}$	$1.091^{*}$	$0.950^{*}$	$0.949^{*}$
<b>Combination:</b> $\kappa = 3$	1.015	1.017	1.026	1.048	1.064	1.066	1.052	$1.077^{*}$	$1.116^{*}$	$1.019^{*}$	1.021
<b>Combination:</b> $\kappa = 4$	1.004	1.009	1.022	1.040	1.053	1.057	1.035	1.058	$1.101^{*}$	$1.040^{*}$	1.021
Combination: $\kappa = 5$	1.004	1.009	1.018	1.040	1.061	1.068	1.050	1.070	1.124	1.065	1.013
<b>Combination:</b> $\kappa = 6$	1.006	1.012	1.018	1.039	1.055	1.060	1.045	1.063	1.126	1.067	1.012
<b>Combination:</b> $\kappa = 7$	1.005	1.005	1.001	1.000	0.995	0.992	0.993	1.013	1.073	1.027	1.000
<b>Combination:</b> $\kappa = 8$	1.003	1.003	1.000	1.000	0.994	0.988	0.991	1.007	1.072	1.027	1.000
Rows 2 and following di	isplay the	RMSPE	f of the	house pr	ice bubb	ole augme	inted mo	dels rela	utive to t	the RMSP	E of the
benchmark given in the fi	rst row. S	ee table	5 tor turt	ther com	nents.						

 Table 6: Relative RMSE: IP + House Prices

						Horizon					
Model	0	1	က	9	6	12	18	24	36	48	60
Benchmark	0.007	0.012	0.022	0.035	0.044	0.054	0.078	0.101	0.119	0.133	0.197
PWY11 <sub>s</sub> : individual	$0.995^{*}$	$0.986^{*}$	$0.970^{*}$	$0.976^{*}$	$0.996^{*}$	$1.003^{*}$	0.993	$0.959^{*}$	$0.953^{*}$	0.991	$1.080^{*}$
PWY11 <sub>s</sub> : ratio	$0.994^{*}$	$0.987^{*}$	0.986	0.994	1.004	1.015	$1.032^{*}$	$1.032^{*}$	$1.058^{*}$	$1.157^{*}$	$1.198^{*}$
PWY11 <sub>1</sub> : individual	$0.977^{*}$	$0.952^{*}$	$0.936^{*}$	$0.941^{*}$	$0.949^{*}$	0.968	0.991	0.993	$1.031^{*}$	$0.948^{*}$	$0.923^{*}$
$PWY11_1$ : ratio	0.999	0.999	0.998	0.993	0.980	0.982	0.995	0.994	$1.038^{*}$	$0.991^{*}$	$0.984^{*}$
FLUC <sub>s</sub> : individual	1.003	1.010	1.026	1.056	1.099	1.130	1.123	1.135	1.109	0.857	0.931
FLUCs: ratio	1.006	1.006	$1.005^{*}$	$1.007^{*}$	$1.002^{*}$	$0.998^{*}$	$0.996^{*}$	$1.018^{*}$	$1.045^{*}$	$1.010^{*}$	$1.000^{*}$
FLUC <sub>1</sub> : individual	0.998	1.000	1.018	1.049	1.077	1.114	1.116	1.141	1.124	0.921	0.979
FLUC <sub>1</sub> : ratio	1.011	1.007	$1.012^{*}$	$1.005^{*}$	$1.003^{*}$	$0.999^{*}$	$0.997^{*}$	$1.021^{*}$	$1.043^{*}$	$1.009^{*}$	0.998
<b>PSY13:</b> individual	1.000	$0.994^{*}$	$0.983^{*}$	0.989	$0.986^{*}$	0.986	0.977	1.002	$1.106^{*}$	$1.051^{*}$	$0.982^{*}$
PSY13: ratio	0.998	1.000	1.002	1.006	$1.004^{*}$	0.986	0.965	0.983	$1.043^{*}$	$1.038^{*}$	$1.001^{*}$
$\mathrm{HP}_{\mathrm{rec}}$	$0.988^{*}$	$0.979^{*}$	0.977	0.985	0.994	1.009	1.025	1.038	$1.113^{*}$	$0.955^{*}$	$0.872^{*}$
$HP_{rol}$	$0.994^{*}$	$0.984^{*}$	$0.979^{*}$	$0.994^{*}$	$1.020^{*}$	$1.033^{*}$	$1.057^{*}$	$1.077^{*}$	$1.034^{*}$	$0.976^{*}$	$0.949^{*}$
<b>Combination:</b> $\kappa = 1$	1.003	$1.007^{*}$	$1.008^{*}$	$1.007^{*}$	$0.997^{*}$	$0.987^{*}$	1.008	$1.033^{*}$	$1.056^{*}$	$1.018^{*}$	0.994
<b>Combination:</b> $\kappa = 2$	$0.995^{*}$	$0.989^{*}$	$0.986^{*}$	$0.991^{*}$	0.990	0.996	1.036	$1.081^{*}$	$1.114^{*}$	$0.990^{*}$	$0.959^{*}$
<b>Combination:</b> $\kappa = 3$	$0.979^{*}$	$0.964^{*}$	$0.950^{*}$	$0.946^{*}$	$0.941^{*}$	0.958	0.978	1.008	$1.052^{*}$	$0.970^{*}$	$0.968^{*}$
<b>Combination:</b> $\kappa = 4$	$0.988^{*}$	$0.982^{*}$	$0.967^{*}$	$0.960^{*}$	$0.957^{*}$	0.971	0.981	1.005	$1.051^{*}$	$0.951^{*}$	$0.941^{*}$
<b>Combination:</b> $\kappa = 5$	$0.970^{*}$	$0.946^{*}$	$0.930^{*}$	$0.941^{*}$	0.954	0.973	0.995	1.016	$1.049^{*}$	$0.914^{*}$	$0.900^{*}$
<b>Combination:</b> $\kappa = 6$	$0.994^{*}$	$0.984^{*}$	$0.981^{*}$	0.983	0.982	0.987	0.994	$1.024^{*}$	$1.103^{*}$	$0.972^{*}$	$0.903^{*}$
<b>Combination:</b> $\kappa = 7$	$0.994^{*}$	$0.985^{*}$	$0.976^{*}$	$0.971^{*}$	$0.968^{*}$	0.970	0.981	1.015	1.094	0.988	0.951
<b>Combination:</b> $\kappa = 8$	1.005	1.002	$0.991^{*}$	$0.980^{*}$	$0.973^{*}$	0.972	0.988	1.013	1.112	0.998	0.958
Rows 2 and following displementation benchmark given in the fit	play the F rst row. S	MSPE of ee table 5	the stoch for furth	s and hous er commer	se price b nts.	ubble aug	gmented	models re	lative to 1	the RMSI	•E of the

Table 7: Relative RMSE: IP + Stock & House Prices

						Horizon					
Model	0	Н	3 C	9	6	12	18	24	36	48	60
Benchmark	0.007	0.011	0.022	0.037	0.045	0.053	0.075	0.097	0.124	0.132	0.182
PWY11 <sub>s</sub> : individual	1.001	0.995	0.981	0.987	1.008	1.020	1.016	1.000	1.023	1.019	1.043
PWY11 <sub>s</sub> : ratio	1.009	1.010	1.004	1.016	1.035	1.050	1.049	1.068	1.092	1.140	1.186
PWY11 <sub>1</sub> : individual	0.991	0.972	0.960	0.969	0.992	1.008	1.012	1.013	1.004	1.046	1.087
PWY11 <sub>1</sub> : ratio	1.016	1.029	1.045	1.056	1.071	1.067	1.037	1.033	1.033	1.047	1.099
PSY13: individual	0.995	0.987	0.975	0.974	0.975	0.974	0.957	0.939	0.933	0.937	0.981
PSY13: ratio	1.021	1.032	1.038	1.043	1.046	1.044	1.016	0.996	1.004	1.010	1.031
$\mathrm{HP}_{\mathrm{rec}}$	0.989	0.976	0.970	0.981	1.002	1.008	1.002	0.992	1.003	1.018	1.017
$HP_{rol}$	0.999	0.997	0.988	0.995	1.020	1.034	1.053	1.062	1.020	0.982	0.973
Combination: $\kappa = 1$	1.008	1.021	1.021	1.029	1.047	1.046	1.030	1.046	1.031	1.023	1.005
Combination: $\kappa = 2$	1.015	1.027	1.031	1.037	1.050	1.048	1.017	0.996	1.011	1.041	1.040
<b>Combination:</b> $\kappa = 3$	1.009	1.020	1.017	1.022	1.035	1.039	1.026	1.014	1.015	1.037	1.082
<b>Combination:</b> $\kappa = 4$	1.008	1.019	1.014	1.021	1.036	1.041	1.027	1.019	1.021	1.037	1.089
Combination: $\kappa = 5$	0.987	0.973	0.957	0.972	0.999	1.012	1.015	1.020	1.013	1.058	1.109
<b>Combination:</b> $\kappa = 6$	1.005	0.992	0.981	0.985	1.000	1.005	0.986	0.980	0.981	1.017	1.041
Combination: $\kappa = 7$	1.000	0.987	0.980	0.987	1.001	1.006	0.986	0.978	0.982	1.016	1.040
<b>Combination:</b> $\kappa = 8$	1.002	0.992	0.983	0.984	0.993	0.997	0.988	0.985	0.984	1.007	1.020
Rows 2 and following displayed	play the	RMSPE	of the st	ock pric	e bubble	augmen	ted mod	els relati	ive to the	e RMSPI	E of the
each forecast horizon.	MOT DOT		MD DOGTA		manne	тт · бтт			nto Aprile		

Table 8: Relative RMSE: IP + Stock Prices: No real-time data

						Horizon					
Model	0	1	က	9	6	12	18	24	36	48	60
Benchmark	0.007	0.011	0.022	0.037	0.045	0.053	0.075	0.097	0.124	0.132	0.182
PWY11 <sub>1</sub> : individual	0.991	1.001	1.008	1.026	1.049	1.062	1.039	1.034	1.067	0.919	0.847
PWY11 <sub>1</sub> : ratio	1.020	1.028	1.033	1.045	1.061	1.054	1.036	1.035	1.087	1.043	0.993
FLUC <sub>1</sub> : individual	0.989	0.994	0.998	1.013	1.038	1.080	1.103	1.102	1.074	0.958	1.003
FLUC <sub>1</sub> : ratio	0.992	0.995	0.994	0.995	0.992	0.986	0.997	1.009	1.004	1.029	1.002
FLUC <sub>s</sub> : individual	0.991	0.997	1.001	1.017	1.059	1.107	1.148	1.125	1.076	0.923	0.993
$FLUC_s$ : ratio	0.992	0.996	0.994	0.995	0.991	0.985	0.997	1.007	1.005	1.026	1.001
PSY13: individual	0.997	1.007	1.015	1.033	1.041	1.051	1.043	1.055	1.091	0.922	0.840
PSY13: ratio	0.993	0.995	0.992	1.005	1.009	0.999	0.975	0.977	1.026	1.040	1.017
$\mathrm{HP}_{\mathrm{rec}}$	0.994	1.007	1.035	1.063	1.096	1.093	1.067	1.075	1.061	1.013	1.019
$\mathrm{HP}_{\mathrm{rol}}$	0.996	0.995	0.998	0.993	0.990	0.990	0.996	1.002	1.027	1.020	0.964
Combination: $\kappa = 1$	0.991	0.993	0.995	1.009	1.016	1.007	1.006	1.029	1.043	1.019	0.988
Combination: $\kappa = 2$	1.001	1.006	1.013	1.023	1.029	1.028	1.049	1.077	1.117	0.985	0.935
Combination: $\kappa = 3$	1.000	1.005	1.010	1.027	1.039	1.049	1.049	1.064	1.103	1.036	1.016
<b>Combination:</b> $\kappa = 4$	0.992	1.000	1.009	1.019	1.028	1.041	1.039	1.045	1.060	1.058	1.024
Combination: $\kappa = 5$	0.991	1.001	1.006	1.017	1.036	1.054	1.057	1.065	1.068	1.064	1.017
<b>Combination:</b> $\kappa = 6$	0.994	1.002	1.009	1.017	1.035	1.047	1.050	1.058	1.067	1.065	1.015
Combination: $\kappa = 7$	0.992	0.997	0.996	0.997	0.993	0.984	0.994	1.012	1.018	1.029	1.002
Combination: $\kappa = 8$	0.992	0.998	0.999	1.002	0.996	0.984	0.990	1.011	1.038	1.029	1.002
Rows 2 and following dis	splay the	RMSPE	of the	house pr	ice bubł	ole augm	ented m	odels re	lative to	the RN	ISPE of

the benchmark given in the first row when revised data is considered only. The bold values display the best model for each forecast horizon.

Table 9: Relative RMSE: IP + House Prices: No real-time data

						Horizor	I				
Model	0	1	n	9	6	12	18	24	36	48	60
Benchmark without SPEC	0.007	0.012	0.022	0.035	0.044	0.054	0.078	0.101	0.119	0.133	0.197
Benchmark with SPEC	0.007	0.011	0.018	0.030	0.043	0.055	0.081	0.105	0.097	0.167	0.265
PWY11 <sub>s</sub> : individual	0.975	0.970	1.008	1.009	0.983	0.999	1.042	0.969	1.017	1.045	1.004
$PWY11_s$ : ratio	0.997	1.002	1.019	1.009	1.010	1.027	1.061	1.082	1.131	1.112	1.027
PWY11 <sub>1</sub> : individual	0.966	0.972	1.016	1.027	1.020	0.996	1.007	1.011	1.027	0.901	0.983
$PWY11_1$ : ratio	0.983	1.000	1.079	1.084	1.048	1.025	1.027	1.013	1.057	1.009	0.986
PSY13: individual	0.987	0.980	1.020	1.017	0.974	0.957	0.949	0.876	0.950	1.016	0.992
PSY13: ratio	0.996	1.003	1.056	1.053	1.036	1.022	1.020	0.977	1.020	0.998	0.995
HPrec	0.957	0.964	1.004	1.035	1.011	1.005	1.013	0.966	1.010	0.884	0.934
HP <sub>rol</sub>	0.981	0.986	1.026	1.031	1.022	1.057	1.097	1.074	1.001	0.784	0.890
Combination: $\kappa = 1$	0.962	1.000	1.040	1.051	1.044	1.034	1.013	1.028	0.997	0.971	0.944
Combination: $\kappa = 2$	0.989	0.996	1.044	1.055	1.034	1.033	0.986	0.951	1.043	0.941	0.993
<b>Combination:</b> $\kappa = 3$	0.983	1.005	1.057	1.069	1.020	1.018	0.997	1.002	1.044	0.945	0.985
<b>Combination:</b> $\kappa = 4$	0.989	1.007	1.059	1.064	1.026	1.018	1.004	1.001	1.055	0.950	0.984
<b>Combination:</b> $\kappa = 5$	0.964	0.961	1.024	1.042	1.013	0.999	1.022	1.028	1.061	0.977	0.987
<b>Combination:</b> $\kappa = 6$	0.980	0.997	1.011	1.025	1.015	0.995	0.984	0.983	1.007	0.975	0.999
<b>Combination:</b> $\kappa = 7$	0.982	0.986	1.009	1.008	1.007	0.990	0.985	0.982	1.005	0.987	0.994
<b>Combination:</b> $\kappa = 8$	0.983	0.992	1.006	1.004	1.004	1.001	0.996	0.986	1.010	1.000	1.000
Rows 3 and following display the	he RMS	PE of th	ne stock	t price	bubble a	ugmente	ed model	s relativ	e to the	RMSPE	of the
benchmark given in the second 1	row whe	n a spec	ific-to-g	general	(SPEC)	model se	election a	approach	has be	en applie	d. The
first row shows the benchmark	of table	5. The	v blod v	alues d	isplay th	ie best i	nodel fo	r each fe	orecast 1	norizon.	As the

model potentially changes in the recursive out-of-sample forecast exercise, the test for equal predictive ability by Clark &

McCracken (2009) is not feasible.

Table 10: Relative RMSE: IP + Stock Prices: SPEC-Model Selection

						Horizon					
Indicator	0		e.	9	6	12	18	24	36	48	60
Benchmark	0.004	0.007	0.010	0.012	0.013	0.014	0.019	0.021	0.026	0.039	0.046
PWY11 <sub>s</sub> : individual	0.999	1.000	$1.007^{*}$	0.997	$0.981^{*}$	$0.973^{*}$	$0.974^{*}$	1.010	$1.181^{*}$	$1.208^{*}$	$1.169^{*}$
$PWY11_s$ : ratio	1.001	1.002	1.007	1.001	0.993	0.994	1.012	1.010	0.982	1.080	1.103
PWY11 <sub>1</sub> : individual	1.001	$1.001^{*}$	$1.012^{*}$	$1.011^{*}$	1.008	$1.021^{*}$	$1.057^{*}$	$1.076^{*}$	$1.361^{*}$	$1.157^{*}$	$1.157^{*}$
$PWY11_1$ : ratio	$0.995^{*}$	$1.009^{*}$	$1.022^{*}$	1.022	1.009	1.006	$1.019^{*}$	$1.051^{*}$	$1.283^{*}$	$1.108^{*}$	$1.165^{*}$
<b>PSY13:</b> individual	$1.001^{*}$	1.000	$1.004^{*}$	$1.004^{*}$	1.001	1.001	$1.012^{*}$	$1.060^{*}$	$1.146^{*}$	$1.085^{*}$	$1.030^{*}$
PSY13: ratio	0.987	0.993	$1.000^{*}$	$0.994^{*}$	$0.971^{*}$	$0.957^{*}$	$0.972^{*}$	1.021	1.021	1.026	1.022
$\mathrm{HP}_{\mathrm{rec}}$	$0.998^{*}$	$0.996^{*}$	$0.999^{*}$	$0.998^{*}$	$0.994^{*}$	1.000	1.003	$1.043^{*}$	$1.274^{*}$	$1.088^{*}$	$1.177^{*}$
$\mathrm{HP}_{\mathrm{rol}}$	1.000	0.997	0.998	0.996	$1.006^{*}$	$1.016^{*}$	$1.023^{*}$	$1.071^{*}$	$1.222^{*}$	$1.068^{*}$	$1.106^{*}$
<b>Combination:</b> $\kappa = 1$	$0.988^{*}$	$0.993^{*}$	$0.995^{*}$	$0.984^{*}$	$0.982^{*}$	$0.968^{*}$	$0.933^{*}$	$0.954^{*}$	$1.105^{*}$	$1.096^{*}$	$1.219^{*}$
<b>Combination:</b> $\kappa = 2$	0.989	0.995	0.997	$0.992^{*}$	$0.969^*$	$0.961^{*}$	$0.962^{*}$	1.011	$1.232^{*}$	$1.211^{*}$	$1.295^{*}$
Combination: $\kappa = 3$	0.996	$1.004^{*}$	$1.015^{*}$	$1.015^{*}$	1.005	1.006	$1.007^{*}$	$1.051^{*}$	$1.272^{*}$	$1.147^{*}$	$1.183^{*}$
<b>Combination:</b> $\kappa = 4$	$0.996^{*}$	$1.003^{*}$	$1.017^{*}$	1.018	1.008	1.007	$1.012^{*}$	$1.053^{*}$	$1.283^{*}$	$1.140^{*}$	$1.149^{*}$
Combination: $\kappa = 5$	1.000	1.000	$1.012^{*}$	$1.011^{*}$	1.011	$1.036^{*}$	$1.082^{*}$	$1.105^{*}$	$1.412^{*}$	1.142	$1.171^{*}$
<b>Combination:</b> $\kappa = 6$	$1.000^{*}$	$0.997^{*}$	$1.003^{*}$	$0.996^{*}$	$0.978^{*}$	$0.998^{*}$	$1.057^{*}$	$1.102^{*}$	$1.228^{*}$	$1.064^{*}$	$1.066^{*}$
<b>Combination:</b> $\kappa = 7$	$1.001^{*}$	$0.997^{*}$	$1.004^{*}$	0.998	$0.977^{*}$	0.981	1.015	1.057	1.028	1.033	1.035
<b>Combination:</b> $\kappa = 8$	$1.003^{*}$	$1.001^{*}$	$1.006^{*}$	$1.005^{*}$	$0.994^{*}$	0.995	1.009	1.039	1.019	1.019	1.019
Rows 2 and following disp	play the F	IMSPE of	the stock	price bul	oble augm	nented mo	dels relati	ve to the	RMSPE (	of the be	nchmark

Table 11: Relative RMSE: CPI + Stock Prices

given in the first row. See table 5 for further comments.

						Horizor	I				
Model	0	1	3	9	6	12	18	<b>24</b>	36	48	60
Benchmark	0.004	0.007	0.010	0.012	0.013	0.014	0.019	0.021	0.026	0.039	0.046
PWY11 <sub>1</sub> : individual	$1.005^{*}$	$1.009^{*}$	$1.006^{*}$	0.998	0.992	$1.049^{*}$	$1.085^{*}$	$1.111^{*}$	$1.164^{*}$	$0.824^{*}$	$0.881^{*}$
PWY11 <sub>1</sub> : ratio	1.000	1.006	1.005	0.997	0.999	1.033	1.042	1.012	1.037	1.016	1.010
FLUC <sub>s</sub> : individual	$1.006^{*}$	$1.009^{*}$	$1.011^{*}$	0.997	0.995	0.998	1.020	$1.016^{*}$	$1.019^{*}$	$1.108^{*}$	$1.283^{*}$
$FLUC_s$ : ratio	1.013	1.024	1.015	1.009	0.998	1.017	1.022	0.997	0.975	0.981	1.000
FLUC <sub>1</sub> : individual	1.002	$1.008^{*}$	$1.011^{*}$	0.999	0.989	0.997	1.017	1.040	1.007	$1.023^{*}$	$1.189^{*}$
FLUC <sub>1</sub> : ratio	1.007	1.019	1.018	1.006	0.995	1.010	1.021	1.010	0.977	0.979	0.999
<b>PSY13:</b> individual	$1.006^{*}$	$1.013^{*}$	$1.012^{*}$	1.003	0.999	1.010	1.029	$1.075^{*}$	$1.155^{*}$	1.035	$0.933^{*}$
PSY13: ratio	$1.002^{*}$	1.004	1.006	$1.014^{*}$	1.015	1.021	1.062	1.184	1.186	1.036	$0.899^{*}$
$\mathrm{HP}_{\mathrm{rec}}$	1.007	1.019	1.029	1.035	1.066	1.125	1.172	1.251	1.171	0.986	0.977
$\mathrm{HP}_{\mathrm{rol}}$	1.002	1.003	1.003	1.004	0.999	0.996	0.984	0.961	0.942	0.810	0.929
Combination: $\kappa = 1$	$1.002^{*}$	$1.003^{*}$	$1.005^{*}$	1.004	1.008	1.022	1.024	1.045	1.046	$1.072^{*}$	$1.041^{*}$
<b>Combination:</b> $\kappa = 2$	1.001	1.005	$1.007^{*}$	0.997	0.990	0.997	1.005	1.010	0.987	$0.908^{*}$	$0.937^{*}$
<b>Combination:</b> $\kappa = 3$	1.000	$1.003^{*}$	$1.005^{*}$	0.996	0.988	0.987	0.999	0.983	0.973	$0.938^{*}$	0.998
<b>Combination:</b> $\kappa = 4$	$1.006^{*}$	$1.011^{*}$	$1.009^{*}$	0.997	0.988	1.000	1.017	0.973	0.968	$0.914^{*}$	0.987
<b>Combination:</b> $\kappa = 5$	1.007	1.014	1.013	1.004	0.993	1.010	1.024	0.977	0.984	0.975	0.976
<b>Combination:</b> $\kappa = 6$	1.007	1.015	1.015	1.006	0.997	1.012	1.017	0.976	0.988	0.970	0.977
<b>Combination:</b> $\kappa = 7$	1.008	1.021	1.022	1.011	1.003	1.021	1.035	0.994	0.974	0.979	0.999
<b>Combination:</b> $\kappa = 8$	1.003	1.016	1.015	1.012	1.001	1.016	1.045	0.979	0.971	0.979	0.999
Rows 2 and following di	isplay the	RMSPI	E of the	house pr	ice bubl	ole augm	ented mo	odels rel	ative to	the RMSI	E of the
benchmark given in the f	first row.	Note th	at the lo	ng-run fc	recast g	ains of F	$IP_{rol}$ are	probably	r due to	different p	arameter
estimates. As no bubble	is detecte	d in the	forecasti	ng period	l except	for the v	ery last <sub>1</sub>	months (	see figure	$\approx$ 2), these	gains do

not accrue to additional forecast information. See table 5 for further comments.

Table 12: Relative RMSE: CPI + House Prices

(joint)
$\operatorname{Prices}$
z House
Stock &
CPI +
RMSE:
Relative
Table 13:

						Horizon					
Model	0		3 C	9	6	12	18	24	36	48	60
Benchmark	0.004	0.007	0.010	0.012	0.013	0.014	0.019	0.021	0.026	0.039	0.046
PWY11 <sub>s</sub> : individual	0.999	1.000	$1.007^{*}$	0.997	$0.981^{*}$	$0.973^{*}$	$0.974^{*}$	1.010	$1.181^{*}$	$1.208^{*}$	$1.169^{*}$
PWY11 <sub>s</sub> : ratio	$0.999^{*}$	$0.9999^{*}$	1.001	$0.992^{*}$	$0.978^{*}$	$0.974^{*}$	$0.983^{*}$	$0.984^{*}$	0.967	0.982	$0.869^{*}$
PWY11 <sub>1</sub> : individual	1.003	1.005	1.011	1.017	1.036	1.058	1.085	1.079	$1.363^{*}$	$1.327^{*}$	$1.292^{*}$
PWY11 <sub>1</sub> : ratio	$1.001^{*}$	$1.005^{*}$	1.009	1.018	1.039	1.056	1.051	1.023	1.022	$1.093^{*}$	$1.138^{*}$
FLUC <sub>s</sub> : individual	$1.006^{*}$	$1.012^{*}$	$1.015^{*}$	$1.006^{*}$	1.005	1.021	1.034	1.035	1.060	$1.116^{*}$	$1.377^{*}$
FLUCs: ratio	1.013	1.017	1.025	1.013	1.001	1.024	1.038	1.021	0.995	1.004	1.000
FLUC <sub>1</sub> : individual	$1.002^{*}$	$1.010^{*}$	$1.012^{*}$	$1.004^{*}$	1.010	1.015	1.032	$1.048^{*}$	1.038	$1.115^{*}$	$1.331^{*}$
FLUC <sub>1</sub> : ratio	1.014	1.024	1.016	1.013	1.000	1.021	1.044	1.029	0.996	1.005	1.000
PSY13: individual	1.002	1.003	1.006	1.009	1.013	1.023	1.036	1.030	1.045	$1.125^{*}$	1.046
PSY13: ratio	$1.002^{*}$	$1.004^{*}$	$1.008^{*}$	$1.017^{*}$	1.017	1.022	1.071	1.178	1.157	0.999	$0.864^{*}$
$\mathrm{HP}_{\mathrm{rec}}$	$1.001^{*}$	$1.001^{*}$	$1.008^{*}$	1.014	1.022	1.034	1.041	$1.078^{*}$	$1.347^{*}$	$1.055^{*}$	$1.156^{*}$
$HP_{rol}$	0.999	0.996	$0.998^{*}$	0.997	$1.008^{*}$	$1.019^{*}$	$1.033^{*}$	$1.075^{*}$	$1.248^{*}$	$1.069^{*}$	$1.076^{*}$
Combination: $\kappa = 1$	$0.997^{*}$	1.000	1.003	1.012	1.018	1.005	0.996	1.023	$1.072^{*}$	$1.122^{*}$	$1.179^{*}$
<b>Combination:</b> $\kappa = 2$	0.998	$1.001^{*}$	$1.006^{*}$	1.007	1.025	1.032	$1.026^{*}$	$1.059^{*}$	$1.210^{*}$	$1.212^{*}$	$1.273^{*}$
<b>Combination:</b> $\kappa = 3$	1.002	$1.005^{*}$	1.012	1.021	1.031	1.046	1.056	1.041	$1.122^{*}$	$1.206^{*}$	$1.188^{*}$
<b>Combination:</b> $\kappa = 4$	1.003	$1.005^{*}$	1.015	1.027	1.041	1.063	1.079	1.067	$1.195^{*}$	$1.318^{*}$	$1.346^{*}$
Combination: $\kappa = 5$	1.004	$1.005^{*}$	1.014	1.026	1.048	1.085	1.127	1.111	$1.438^{*}$	$1.364^{*}$	$1.443^{*}$
<b>Combination:</b> $\kappa = 6$	$1.005^{*}$	$1.006^{*}$	1.016	1.032	1.052	1.094	1.148	1.125	$1.238^{*}$	$1.267^{*}$	$1.344^{*}$
<b>Combination:</b> $\kappa = 7$	$1.006^{*}$	$1.008^{*}$	1.018	1.035	1.062	1.096	1.123	1.123	1.054	1.187	1.191
<b>Combination:</b> $\kappa = 8$	$1.007^{*}$	$1.010^{*}$	$1.021^{*}$	$1.039^{*}$	1.071	1.100	1.114	1.119	1.054	1.146	1.142
Rows 2 and following di	splay the	RMSPE	of stock	and hous	e price bu	ubble aug	mented m	odel relat	tive to t	he RMSF	E of the
benchmark given in the fi	rst row. S	see table	5 for furtl	ner comme	ents.	)					

				_	Horizon	_			
	0	-	က	9	12	24	36	48	60
Benchmark	0.435	0.424	0.445	0.448	0.424	0.425	0.444	0.395	0.404
Combination $\kappa = 5$ : Stock	1.031	0.990	1.037	1.081	1.002	0.977	1.069	1.001	1.007
Combination $\kappa = 5$ : Stock+House	0.960	0.874	0.950	0.984	1.015	0.990	1.037	0.996	1.007
PSY13: Stock	0.996	0.905	0.966	0.892	0.943	1.040	1.001	1.000	0.997
PSY13: House	1.078	1.024	1.031	1.117	1.025	1.029	0.998	1.000	1.003
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Rows 2 and following display the RMSPE of bubble augmented models relative to the RMSPE of the benchmark given in the first row. Best forecasts are in bold.

				цці,	Iorizon				
	0	1	က	9	12	24	36	48	60
Model			Correct	signals	to tota	l obser	vations		
Benchmark	0.678	0.661	0.712	0.701	0.780	0.825	0.627	0.605	0.633
Combination $\kappa = 5$ : Stock	0.655	0.661	0.678	0.627	0.791	0.757	0.633	0.588	0.695
Combination $\kappa = 5$ : Stock+House	0.763	0.757	0.734	0.706	0.791	0.757	0.525	0.588	0.605
PSY13: Stock	0.661	0.706	0.712	0.791	0.785	0.814	0.627	0.605	0.638
PSY13: House	0.605	0.644	0.684	0.605	0.780	0.650	0.757	0.605	0.638
		Signa	aled rec	essions	to total	recess	ion per	iods	
Benchmark	0.184	0.184	0.342	0.105	0.158	0.316	0.000	0.000	0.000
Combination $\kappa = 5$ : Stock	0.316	0.342	0.395	0.158	0.079	0.316	0.000	0.000	0.000
Combination $\kappa = 5$ : Stock+House	0.395	0.447	0.447	0.132	0.079	0.316	0.000	0.000	0.000
PSY13: Stock	0.211	0.289	0.500	0.237	0.000	0.316	0.000	0.000	0.000
PSY13: House	0.158	0.289	0.395	0.079	0.000	0.158	0.000	0.000	0.000
			Corre	ect alar	ms to te	otal ala	rms		
Benchmark	0.212	0.194	0.333	0.174	0.462	0.706	0.000	0.000	0.000
Combination $\kappa = 5$ : Stock	0.255	0.271	0.306	0.150	0.600	0.414	0.000	0.000	0.000
Combination $\kappa = 5$ : Stock+House	0.441	0.436	0.395	0.208	0.600	0.414	0.000	0.000	0.000
PSY13: Stock	0.211	0.306	0.373	0.529	NaN	0.632	0.000	0.000	0.000
PSY13: House	0.136	0.234	0.313	0.079	0.000	0.167	0.000	0.000	0.000
The first panel displays the signal quality The second panel displays the number o	as measu f signale	ared by t d recessi	the numb ions to t	er of cor otal rece	rect sign: ssion pe	als relati riods. 7	ve to to The third	tal obser d panel	vations. displays
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the number of correct alarms to total alarms. Best signals are in bold.

Table 15: Signal quality: Predicted recession probabilities and recession events