OECD Economics Department Working Papers No. 772

Can Emerging Asset Price Bubbles be Detected?

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https://dx.doi.org/10.1787/5kmdfmztmqtj-en

OECD

Unclassified **ECO/WKP(2010)28**

Organisation de Coopération et de Développement Économiques
Organisation for Economic Co-operation and Development **01-Jun-2010**

English - Or. English

ECONOMICS DEPARTMENT

ECO/WKP(2010)28
Unclassified

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JT03284551

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Abstract/Résumé

Can emerging asset price bubbles be detected?

Bayesian Model Averaging techniques are used to analyse how robustly it is possible to identify factors that may lead to the bursting of asset price bubbles in OECD economies. A large set of variables put forward in the literature is assessed, as well as interactions of these variables with estimates of asset price misalignments to evaluate the importance of the different channels postulated by theory. The results indicate that asset price misalignments are not robust determinants of house price reversals unless their interaction with other characteristics of the economy (credit growth, population growth and interest rate developments) is taken into account. On the other hand, stock price reversals are affected by misalignments, as well as other real and monetary variables. Out-of-sample prediction exercises provide evidence that dealing explicitly with model uncertainty using Bayesian model averaging techniques leads to better forecasts of reversals in asset prices than relying on model selection. Conclusions regarding the importance of dealing quantitatively with model uncertainty are drawn to improve the anticipation of asset price reversals.

Keywords: Asset prices; house prices; stock prices; model uncertainty; model averaging
JEL classification: C11; C23; G12

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Peut-on détecter les bulles naissantes des prix des actifs ?

Des techniques de modèle bayésien en moyenne ont été utilisées pour analyser dans quelle mesure il est possible d'identifier de façon robuste les facteurs qui peuvent provoquer l'éclatement de bulles des prix des actifs dans les économies de l'OCDE. Un large ensemble de variables mises en avant par les spécialistes a été évalué, de même que les interactions de ces variables avec les estimations des désalignements des prix des actifs, le but étant de déterminer l'importance des différents canaux retenus sur le plan théorique. Les résultats montrent que les désalignements des prix des actifs ne constituent pas un déterminant fiable des retournements des prix immobiliers, sauf si l'on prend en compte leur interaction avec d'autres caractéristiques de l'économie (croissance du crédit, croissance démographique et évolution des taux d'intérêt). En revanche, les retournements des cours des actions subissent les effets des désalignements ainsi que ceux d'autres variables réelles et monétaires. Des exercices de prévision hors échantillon montrent qu'en traitant expressément l'incertitude du modèle par des techniques bayésiennes en moyenne, on obtient des prévisions des retournements des prix des actifs qui sont meilleures qu'en sélectionnant un modèle. Ce document tire une série de conclusions quant à l'importance d'un traitement quantitatif de l'incertitude liée à la modélisation, afin de pouvoir mieux anticiper les retournements des prix des actifs.

Mots clés : prix des actifs ; prix immobiliers ; cours des actions ; incertitude des modèles ; moyenne des modèles
Mots clés : C11; C23; G12

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CAN EMERGING ASSET PRICE BUBBLES BE DETECTED?[1]

By Jesús Crespo Cuaresma

1. Introduction

1. Recently, economists have shown an increased interest in the boom-bust dynamics of asset prices. The sub-prime crisis in the United States in 2007 and the effects of the 2008 financial crisis have put asset price developments at the center of attention of the economics profession.

2. Despite the large amount of research carried out on the topic, there is no widely accepted set of robust determinants of asset price misalignments. The potential complexity of the links between asset prices and other economic variables implies that the existing studies tend to concentrate on particular channels. Several financial and macroeconomic variables have been proposed in the literature as explanatory variables when it comes to the specification of econometric models aimed at explaining turning points in asset prices. Developments in money aggregates, credit markets and investment dynamics are put forward by Borio and Lowe (2002, 2004) as relevant factors affecting the probability of busts in asset prices. Adalid and Detken (2007) and Gerdesmeier *et al.* (2009) emphasize the role of credit aggregates and variables related to monetary policy as factors affecting the occurrence of busts in asset prices. Agnello and Schuknecht (2009) stress the role of institutional factors, such as mortgage market regulation, in addition to monetary policy variables. Goodhart and Hofmann (2008), on the other hand, find empirical evidence that the effect of monetary policy as an instrument to smooth boom-bust cycles in asset and credit markets is limited.

3. Although the empirical literature concentrates on the occurrence of busts, similar methods can be used to evaluate the determinants of the building up of bubbles in asset prices. The measurement of the birth of price bubbles can be carried out by monitoring the estimated probabilities of a turning point, as well as modeling directly the underlying continuous series from which the turning points are extracted.

4. This study contributes to the literature in several respects. On the one hand, for the first time a fully-fledged analysis of the determinants of asset price misalignments taking model uncertainty explicitly into account is presented. Using Bayesian Model Averaging (BMA) techniques for limited dependent variable models, makes it possible to assess the relative importance of particular covariates within a large set of potential explanatory factors for the occurrence of turning points. On the other hand, the importance of non-linearities in the relationships is evaluated by allowing for general interaction terms in the

1. Jesús Crespo Cuaresma is Professor of Economics at Vienna University of Economics and Business. This is one of the background papers for the OECD's project on counter-cyclical economic policy. The main paper was issued as the *OECD Economics Department Working Paper* No. 760. The author is indebted to Balázs Égert, Peter Hoeller, Oliver Röhn and Douglas Sutherland for their invaluable input to this paper and Susan Gascard for excellent editorial support.

specifications considered. The results of the BMA exercise with interactions will shed light on whether the predictive content of misalignment estimates differs in time or across countries depending on the value of other explanatory factors. Such a systematic analysis has not yet been carried out in the literature on asset price dynamics. In particular, dealing with interaction terms in the BMA framework allows answering questions such as: Why do large asset price misalignments lead to busts in certain countries, while in other countries they are maintained for long periods? Which conditions must prevail for misalignments to correct themselves? The results of the analysis provide for the first time a quantification of the relative robustness of different determinants of asset price misalignments, and sheds light on the recent discussion concerning the importance of monetary variables for asset price developments.

5. The paper is structured as follows. Section 2 presents the methodological framework which is used in the econometric analysis, which is based on the assessment of model uncertainty using Bayesian Model Averaging. Section 3 presents potential determinants of asset price dynamics and introduces the data, and section 4 shows the results for house and stock prices. Section 5 presents some conclusions related to model uncertainty for out-of-sample prediction and policy advice concerning asset price reversals. Section 6 concludes and puts forward potential paths for future research.

2. Assessing determinants of asset price dynamics under model uncertainty

6. The aim of this paper is to study the robustness of determinants of the boom-bust dynamics of asset prices. In particular, bubble-building and bust periods are identified and the characteristics of macroeconomic, financial and asset market variables leading to such phenomena are assessed.

7. The concept of model uncertainty which has received most interest in the statistical literature refers to uncertainty about the number and nature of covariates to be included in the model which explains asset price dynamics. Model uncertainty is a prominent feature of the literature on asset price misalignments. Most studies concentrate on particular transmission mechanisms between macroeconomic developments and asset price dynamics, but these do not tend to be mutually exclusive. The fact that an economic phenomenon may be explained by different (possibly many and complementary) theoretical models implies that the choice of a single specification to carry out inference underestimates the degree of uncertainty of the estimated parameters by disregarding model uncertainty. An example of the scope of the problem associated with model uncertainty on the issue of asset price determinants can be obtained by analyzing the specifications in Gerdesmeier *et al*. (2009). Gerdesmeier *et al*. (2009) use 45 different variables to explain asset price corrections empirically and present 78 complementary specifications where turning points in asset prices are explained by sub-groups of that set of potential determinants.

8. BMA and Bayesian Averaging of Classical Estimates (BACE, see Sala i Martin *et al*., 2004) have often been used to account for such uncertainty inherent in the model selection process. BMA copes with model uncertainty by averaging over many different specifications and has been used extensively in empirical research on economic growth (see for example Fernández *et al.*, 2001*b*, Sala-i-Martin *et al*., 2004 or Crespo Cuaresma and Doppelhofer, 2007). Recently, the technique has been applied to other economic research questions such as the determinants of currency crises (Crespo Cuaresma and Slacik, 2009).[2] The basic idea behind BMA is to obtain weighted average estimates of the parameters of interest across potential models using the posterior probability that the model is the true one as a weight. The estimates are thus computed from the full set of models, instead of single specifications.

9. In considering the problem of predicting the turning point in asset prices, the binary variable (y) takes value one at bust periods ($y=1$) and zero in the rest of the sample ($y=0$). Assume a set of

2. A thorough account of the statistical details of model uncertainty and BMA can be found in Leamer (1978), Raftery (1995) and Hoeting *et al.* (1999).

regressors $\mathbf{X} = \{x_1, \ldots, x_K\}$ which have been proposed as potential explanatory factors for triggering a bust in asset prices. In principle, any combination of these K variables may be considered as covariates in a model and let $\mathbf{X}_k$ denote a group of $k \leq K$ variables in the set **X**. A typical model explaining busts in asset prices with this group of covariates is given by

$$\mathrm{P}(y = 1 \,|\, \mathbf{X}_k) = F(\mathbf{X}_k \beta), \tag{1}$$

where $F(z)$ will typically be a logistic function ($F(z) = (1 + e^z)^{-1}$) or the Gaussian distribution function ($F(z) = \Phi(z)$), leading to a logit or probit model, respectively. There are thus 2^K possible linear models (we will denote each model M_j, for $j = 1 \ldots 2^K$) which can be considered. Bayesian model averaged estimates of a parameter of interest (θ) in this setting can be obtained by weighting each (model-specific) estimate of the parameter with the posterior probability of the model it comes from and summing over the whole model space, which is composed by all 2^K specifications,

$$\mathrm{P}(\theta \,|\, y) = \sum_{m=1}^{2^K} \mathrm{P}(\theta \,|\, y, M_m) \mathrm{P}(M_m \,|\, y). \tag{2}$$

10. The posterior model probability is, in turn, a function of the prior probability of the model and its marginal likelihood, so that $\mathrm{P}(M_k \,|\, y) \propto \mathrm{P}(y \,|\, M_k) \mathrm{P}(M_k)$. A choice needs to be made on the prior probability over the model space, as well as over the parameters of each specific model. A flat prior probability over models is the preferred choice in the literature, leading to a 0.5 prior probability of inclusion for the K variables considered. A problem relating to this choice of model space prior is that it leads to a mean prior model size of $K/2$ and assigns a relatively high prior probability to models which may be considered "too large" for many econometric applications. Recently, Ley and Steel (2009) proposed using a hyper-prior on model size and show that this approach leads to more robust inference when applying BMA.

11. The usual choice of prior distribution over the parameters of a given model is given by Zellner's g-prior (Fernández *et al*., 2001*a*), which implies $\mathrm{P}(\beta_k \,|\, M_j) \approx N(0, g(\mathbf{X}_k' \mathbf{X}_k)^{-1})$, a prior which is elicited by the choice of g. Raftery (1995), Kass and Raftery (1995) and Clyde (2000) propose the use of Laplace approximations for determining posterior model probabilities, which simplifies the computational burden for limited dependent variable models considerably. The Bayes factor comparing two models ($B_{jk} = \mathrm{P}(y \,|\, M_j)/\mathrm{P}(y \,|\, M_k)$) can thus be approximated using the Bayesian information criterion (Schwarz, 1978) as

$$-2 \log B_{jk} \approx BIC_k - BIC_j,$$

where BIC_i is the Bayesian information criterion of model i. Different penalties to the inclusion of new parameters in the model can be achieved by changing the BIC above by the Risk Inflation Criterion (RIC, Foster and George, 1994) or the Akaike Information Criterion (AIC, Akaike, 1973). In these cases, one departs from the purely Bayesian case and averages over models using weights which are justified using non-Bayesian approaches to inference, but that have often been used in BMA exercises (see Clyde, 2000 for a theoretical discussion and applications).

12. An extra computational problem is caused by the cardinality of the model space, which can be large enough as to make the expression in (2) intractable. Several methods have been proposed for approximating the sum in (2). The leaps and bounds algorithm, the use of Markov Chain Monte Carlo Model Composite (MC^3) methods or the use of Occam's window are methods of setting bounds to the number of models to be evaluated when computing (2) (see Raftery, 1995, Fernández *et al*., 2001*b*, or Koop, 2003 for descriptions of these methods).

13. The BMA technique allows computing statistics such as the *posterior inclusion probability* of the different potential determinants of asset price misalignments. This statistic is the sum of the posterior probability of models including a given variable, and can be interpreted as the probability that this variable belongs to the true model determining busts in asset prices. The posterior inclusion probability is routinely interpreted as the robustness of a variable as a determinant of the phenomenon under investigation. Similarly, weighted averages of the parameter estimates and its variance are interpreted as the estimated effect of the covariate and its precision once model uncertainty has been taken into account. The method is thus able to deliver a full account of the relative importance of the different mechanisms put forward in the literature, as well as estimates of the size of their effect.

3. Mechanisms, variables and models

14. The analysis of robust determinants of asset price misalignments is carried out using a set of potential covariates for 18 OECD countries at quarterly periodicity and spanning (in the best cases) the period 1975-2009 for house prices and 1989-2009 for stock prices.[3] The determinants are chosen based on several theoretical approaches. On the one hand, the importance of monetary policy and credit variables as signaling devices for asset price misalignments has been highlighted in the recent empirical literature (see in particular Gerdesmeier *et al*., 2009). Variables summarizing developments in the real economy have also been put forward as covariates in models estimating the probability of busts in asset prices, as well as variables summarizing demographic dynamics.

15. Turning points in asset price dynamics need to be defined. The starting point is to compute the deviation cycle using the Hodrick-Prescott (HP) filter, which eliminates the permanent component from the series.[4] Then a variant of the Bry-Boschan procedure (Bry and Boschan, 1971) is used to identify peaks and troughs in the series. As in Avouyi-Dovi and Matheron (2005) and Everts (2007), the peaks and troughs are coded using a 3-step procedure. Let z_t denote the HP-detrended component of the original data on asset prices. An observation $z_{m,t}$ is defined to be a peak if it is a local maximum ($z_{m,t-j}<z_{m,t} >z_{m,t+j}$ for j=1,…,w), and a local minimum is defined in a similar fashion. In the occurrence of multiple consecutive peaks or troughs, the highest peak or lowest trough is selected and the rest eliminated. Then, a minimum length is imposed for peak-to-trough and trough-to-peak phases (*p*) and for full peak-to-peak and trough-to-trough cycles (*c*). In this analysis, based on quarterly data, we set *w*=2, *p*=1 and *c*=3, although the robustness of the results to changes in the turning-point identification process is checked. The dependent variable in the models is defined as the turning point corresponding to a downward correction in asset prices. A corrective period is defined as the observation corresponding to a peak, as well as the previous and following quarter. In the Appendix the turning points are presented together with the asset price gap variables, which form the basis of the turning point identification procedure. The reversal estimates for house prices are shown in the Appendix from 1975 (the earliest period for which misalignment estimates

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3. The countries are Australia, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Ireland, Italy, Japan, Korea, New Zealand, Sweden and the United States. The choice is based solely on data availability.

4. In order to avoid peaks and troughs being identified due to noise, the HP-filtered series is smoothed using a 5-quarter moving average filter.

exist) to the end of the sample, and for stock prices starting in 1989. Some features of the turning points deserve comment. On the one hand, the smoothing procedure, together with the conditions imposed on the characteristic of the phases implies that the observations at the beginning and at the end of the sample are not used in the identification procedure, so in some countries the last bust in house prices is not included in the dataset to which the BMA is applied. Below, the end of the sample is used to check the quality of bust probabilities. Furthermore, the relatively liberal choice of parameters used to identify price reversals implies that some countries have a large number of (small) price reversals.

16. A central variable of interest in the analysis is the measure of *misalignment in asset prices*. The empirical literature on the determinants of asset prices postulates the existence of a long-run equilibrium relationship between asset prices and several other variables. Country-specific estimates of misalignments may give a richer assessment than adopting a common approach across countries. However, in order to remain tractable and exploit the experiences across countries, some simplification was needed in identifying asset price misalignments.

- For house prices, the long-run equilibrium tends to be modeled in terms of a cointegration relationship between house prices and the set of explanatory variables mentioned above, and the deviations from the equilibrium level are interpreted as a measure of the degree of misalignment. In this contribution, a recursive dynamic OLS (DOLS) is estimated based on simple cointegration relationships estimated with information up to the time period where each observation is measured. In particular, simple recursive cointegration relationships are estimated between the (log) real house price index, (log) income per capita and the real interest rate using the Stock and Watson (1993) DOLS method. At each period in time, long-run elasticities of real prices to changes in GDP per capita and real interest rates (long-term interest rates deflated by CPI inflation) are estimated using a cointegration relationship enhanced with leads and lags of the right-hand-side variables. Data for the estimation of the cointegration relationship range back to 1970 for all countries except Germany and Korea, and the first misalignment estimate is obtained for the observation corresponding to the first quarter of 1975 (1990 for Korea and 1995 for Germany). The sample is then expanded quarter by quarter to obtain misalignment estimates based exclusively on past information. The estimates of the country-specific parameters of the cointegration relationship for the full sample are presented in the Appendix. With the exception of Germany and Korea, for which only a shorter sample is available, all countries show the expected sign of the long-run elasticities, although there are large differences in the absolute value of the parameters attached to the interest rate variable across countries.

- For the case of stock prices, there is not such an evident choice of long-run determinants. For the main set of results the deviation of the (logged) stock price index from its historical linear trend is used as a measure of misalignment. The trend is estimated recursively so that the observation for a given period is exclusively based on past observations.

Table 1. Potential determinants of asset price busts and bubbles

Variables	Source
Misalignment	
Asset price misalignment estimate	Own calculation a) as residual from a cointegration relationship between real house prices, income per capita and the real interest rate. b) as deviation from the long-run trend in stock prices.
Demographic and real economy variables	
Population growth	OECD
Share of working age to total population	OECD
Real effective exchange rate	BIS
Current account balance as % of GDP	OECD
GDP per capita growth	OECD
Labor productivity growth	OECD
Private credit growth	OECD
Real short-term interest rate	OECD
Monetary variables	
Growth in M1 monetary aggregate	OECD
Long-term nominal interest rate	OECD
Short-term nominal interest rate	OECD
Financial/asset market variables	
Housing investment as % of GDP	OECD
Stock market returns	Datastream
Dividend yield	OECD
Price/earnings ratio	OECD
House price-income ratio	OECD

17. The variables that are used in the BMA exercise as covariates are presented in Table 1. All variables enter the model as linear covariates as well as interaction terms between each variable and the misalignment in asset prices. This implies that 33 variables can be used to form potential specifications and therefore the model space is composed by 2^{33} (over 8.5 billion) models. For this empirical study Markov Chain Monte Carlo Model Composite (MC^3) methods are used to overcome the problem of the intractability of the model space and compute the necessary statistics.[5] The results are presented based on model designs where the covariates are lagged one quarter, as well as models where the covariates are lagged one and two years, so as to examine the differences between short and medium-term predictors of turning points in asset prices. For each design we will concentrate on the interpretation of the posterior inclusion probability of each covariate and the mean (PM) and standard deviation (PSD) of the posterior distribution of the corresponding parameter (all variables enter the models in standardized form, so that the parameters are comparable across covariates). The variables which have a posterior inclusion probability above 0.5 are labeled "robust determinants". In all cases we average over logit regressions[6] and the approximation based on the RIC is used to compute posterior model probabilities.

5. The results reported are based on 2 million Markov Chain draws, computed after discarding 1 million burn-in draws.

6. The results are qualitatively unchanged if the BMA exercise is conducted using probit instead of logit regressions.

18. Ley and Steel's (2009) hyperprior over the model space is employed with a prior expected model size of 17.5 (thus leading to an expected prior inclusion probability of 0.5). While the posterior inclusion probability indicates the relative importance of a variable as a robust explanatory factor of corrective dynamics in asset prices, it does not give information about how well the quantitative effect of such a variable on the probability of a turning point is estimated. For this purpose, the ratio of PM to PSD is used, in the spirit of the t-statistic corresponding to a regression parameter in the frequentist paradigm. Raftery (1995) proposes the use of a threshold of unity in the ratio to consider a variable effective, while Masanjala and Papageorgiou (2008) put forward a value of 1.3 for the threshold, roughly equivalent to a 90% confidence interval in frequentist hypothesis testing. The robustness of the variables in this study will thus be interpreted both in terms of posterior inclusion probability and effectiveness.

4. The determinants of asset price reversals: a BMA analysis

4.1. Empirical results

19. Table 2 presents descriptive statistics for the potential determinants of house and stock price reversals. The mean and standard deviation of observations over the full sample are presented, for the periods which are coded as reversal periods and for the "quiet" periods. Surprisingly, misalignments in house prices do not tend to be significantly larger in bust periods, although they are higher on average than in quiet times. In the case of stock prices, the misalignment measure does appear much higher during busts, although its dispersion is sizable across countries. The current account balance is on average lower in bust periods, independently of whether house or stock price busts are considered, and busts in asset prices tend to take place, when GDP per capita growth is relatively high. The empirical complexity of the mechanisms under study here is clearly exemplified by the fact that the dispersion of the variables across countries and over time considered as determinants does not allow for clear-cut conclusions on the differences in these variables between corrective and non-corrective periods. Furthermore, strong qualitative differences appear across asset prices, with long-term interest rates, for instance, being more stable (in terms of the size of yearly changes) on average during corrective periods in house prices but the opposite being true for stock prices.

20. In Table 3 the BMA results for house prices are presented for three designs: a) using a lag of a quarter in the explanatory variables, b) using a lag of a year and c) using a lag of two years.[7] All variables have been standardized prior to the BMA analysis, which implies that the posterior means of the parameters are partly comparable across covariates.

21. Several factors appear robust in explaining corrections in house prices in the short and medium run. Changes in the house price–income ratio, which are highly correlated with inflation dynamics of house prices, appears as a relevant indicator of misalignments in the market, with increases of the ratio being related to higher correction probabilities. This term captures the short-run persistence of house price dynamics. In the medium run (as defined by the results based on one-year lags) the house price-income ratio has better predictive characteristics than in the short term, where the quantitative effect of changes in the ratio is not well estimated for countries with a large misalignment in house prices (as measured by deviations from the cointegrating long-run equilibrium). External disequilibria, measured by current account deficits, are also robust determinants of house price bubbles in both the short and medium term. The results for the interaction of the misalignment proxy and population growth show that large misalignments can be sustainable in economies whose population is growing at a faster path.

7. The single best models in terms of maximal posterior inclusion probability are shown in the Appendix for house and stock prices.

Table 2. Descriptive statistics, potential determinants of asset price reversals

Variable	Full sample Mean	Full sample Std. Dev.	Corrective periods Mean	Corrective periods Std. Dev.	Non-corrective periods Mean	Non-corrective periods Std. Dev.
a) House prices						
House price corrections	0.1733	0.3787	-	-	-	-
Misalignment	0.0299	0.1654	0.0312	0.1551	0.0297	0.1676
Current account balance	0.0115	0.0434	0.0087	0.0437	0.0121	0.0433
Working age share	0.6851	0.0310	0.6853	0.0322	0.6851	0.0308
Population growth	0.0062	0.0041	0.0062	0.0038	0.0062	0.0042
Housing investment	0.0501	0.0134	0.0503	0.0123	0.0501	0.0136
Labor productivity growth	0.0157	0.0150	0.0165	0.0126	0.0155	0.0155
GDP growth	0.0194	0.0199	0.0249	0.0174	0.0182	0.0202
Long-term interest rate (y-o-y change)	-0.3626	1.1503	-0.0106	1.2524	-0.4364	1.1146
House price-income ratio (y-o-y change)	0.0023	0.0750	0.0112	0.0461	0.0004	0.0797
Short-term nominal interest rate (y-o-y change)	-0.0042	0.0168	-0.0004	0.0137	-0.0050	0.0173
Short-term real interest rate (y-o-y change)	-0.0027	0.0177	-0.0014	0.0150	-0.0030	0.0182
Credit growth	0.0381	0.0700	0.0373	0.0943	0.0383	0.0639
Real exchange rate (y-o-y change)	-0.0015	0.0608	0.0012	0.0538	-0.0021	0.0621
M1 growth	0.0602	0.0453	0.0546	0.0388	0.0613	0.0465
Price-earnings ratio	20.2505	11.2970	21.2395	9.1186	20.0432	11.6975
Dividend yield	2.3222	1.0421	2.2248	0.8875	2.3426	1.0712
Stock returns	0.0716	0.2070	0.0620	0.1747	0.0736	0.2132
Observations	830		144		686	
b) Stock prices						
House price corrections	0.1686	0.3747	-	-	-	-
Misalignment	-0.0003	0.2458	0.1245	0.1374	-0.0256	0.2552
Current account balance	0.0120	0.0435	0.0056	0.0351	0.0132	0.0449
Working age share	0.6843	0.0301	0.6854	0.0300	0.6840	0.0301
Population growth	0.0060	0.0040	0.0058	0.0038	0.0061	0.0041
Housing investment	0.0503	0.0135	0.0493	0.0131	0.0505	0.0136
Labor productivity growth	0.0160	0.0147	0.0199	0.0170	0.0152	0.0140
GDP growth	0.0204	0.0190	0.0277	0.0193	0.0189	0.0186
Long-term interest rate (y-o-y change)	-0.3490	1.1277	-0.4953	1.0738	-0.3194	1.1368
House price-income ratio (y-o-y change)	0.0094	0.0679	-0.0003	0.0514	0.0113	0.0707
Short-term nominal interest rate (y-o-y change)	-0.0039	0.0168	-0.0042	0.0175	-0.0039	0.0166
Short-term real interest rate (y-o-y change)	-0.0026	0.0165	-0.0025	0.0191	-0.0026	0.0159
Credit growth	0.0417	0.0711	0.0429	0.0698	0.0415	0.0714
Real exchange rate (y-o-y change)	0.0001	0.0604	-0.0072	0.0508	0.0016	0.0621
M1 growth	0.0602	0.0437	0.0576	0.0431	0.0608	0.0438
Price-earnings ratio	19.8335	9.4854	24.0542	16.1765	18.9775	7.1520
Dividend yield	2.2590	1.0150	2.0380	1.0034	2.3038	1.0123
Stock returns	0.0825	0.2088	0.1556	0.1441	0.0677	0.2167
Observations	769		129		640	

Table 3. BMA results, house prices

	1-quarter lag				4-quarter lag				8-quarter lag			
	PIP	PM	PSD	PM/PSD	PIP	PM	PSD	PM/PSD	PIP	PM	PSD	PM/PSD
Misalignment	0.001	0.000	0.006	-0.007	0.000	0.000	0.005	-0.011	0.030	-0.009	0.054	-0.162
Current account balance	**0.697**	**-0.268**	**0.207**	**-1.295**	**0.999**	**-0.521**	**0.136**	**-3.826**	0.001	0.000	0.006	-0.022
Working age share	0.001	0.000	0.004	-0.013	0.001	0.000	0.005	-0.017	0.000	0.000	0.001	-0.001
Population growth	0.001	0.000	0.006	0.015	0.000	0.000	0.004	-0.014	0.000	0.000	0.004	0.014
Housing investment	0.066	0.029	0.119	0.246	0.001	0.000	0.007	0.019	0.001	0.000	0.006	0.014
Labor productivity growth	0.003	-0.001	0.023	-0.047	0.000	0.000	0.004	0.014	0.000	0.000	0.002	0.005
GDP growth	**0.828**	**0.417**	**0.241**	**1.731**	0.002	0.000	0.012	0.039	0.000	0.000	0.000	0.000
Long-term interest rate	**0.998**	**0.520**	**0.147**	**3.531**	0.000	0.000	0.002	-0.003	0.001	0.000	0.005	-0.019
House price-income ratio	**1.000**	**0.888**	**0.211**	**4.210**	**1.000**	**1.161**	**0.191**	**6.087**	0.014	0.005	0.045	0.108
Short-term nominal interest rate	0.000	0.000	0.005	0.011	0.000	0.000	0.003	-0.005	0.000	0.000	0.000	0.000
Short-term real interest rate	0.003	0.001	0.019	0.049	0.001	0.000	0.005	0.016	0.000	0.000	0.003	0.010
Credit growth	0.002	0.000	0.010	0.028	0.001	0.000	0.005	-0.022	0.000	0.000	0.000	0.000
Real exchange rate	0.003	0.000	0.011	0.042	0.001	0.000	0.006	-0.024	**0.887**	**-0.305**	**0.144**	**-2.125**
M1 growth	0.000	0.000	0.003	0.006	0.000	0.000	0.001	0.000	0.000	0.000	0.001	-0.003
Price-earnings ratio	0.001	0.000	0.005	0.025	0.008	0.001	0.018	0.081	0.000	0.000	0.000	0.000
Dividend yield	0.000	0.000	0.002	0.002	0.000	0.000	0.002	-0.004	0.000	0.000	0.002	0.009
Stock returns	0.001	0.000	0.004	0.011	0.011	0.003	0.027	0.094	0.000	0.000	0.002	0.008
Misalignment × Current account balance	0.089	-0.026	0.092	-0.288	0.001	0.000	0.005	-0.019	0.000	0.000	0.000	0.000
Misalignment × Working age share	0.001	0.000	0.005	-0.009	0.000	0.000	0.005	-0.011	0.036	-0.011	0.061	-0.180
Misalignment × Population growth	**0.999**	**-0.910**	**0.249**	**-3.662**	**1.000**	**-1.216**	**0.225**	**-5.414**	0.376	-0.173	0.243	-0.710
Misalignment × Housing investment	0.000	0.000	0.005	-0.001	0.000	0.000	0.005	-0.003	0.017	-0.006	0.051	-0.120
Misalignment × Labor productivity growth	0.001	0.000	0.005	0.011	0.000	0.000	0.003	-0.006	0.000	0.000	0.004	-0.015
Misalignment × GDP growth	0.000	0.000	0.003	0.002	0.001	0.000	0.006	0.018	0.002	0.001	0.016	0.036
Misalignment × Long-term interest rate	0.181	-0.104	0.235	-0.440	**1.000**	**0.789**	**0.204**	**3.874**	0.023	-0.008	0.055	-0.143
Misalignment × House price-income ratio	**0.812**	**-0.403**	**0.247**	**-1.632**	0.002	-0.001	0.015	-0.041	0.000	0.000	0.003	0.013
Misalignment × Short-term interest rate	0.125	0.103	0.288	0.358	0.001	0.000	0.015	0.017	0.002	-0.001	0.016	-0.042
Misalignment × Short-term real interest rate	0.086	0.057	0.203	0.283	**0.740**	**-0.491**	**0.348**	**-1.412**	0.000	0.000	0.004	-0.010
Misalignment × Credit growth	**0.971**	**0.515**	**0.173**	**2.983**	0.000	0.000	0.004	0.011	0.053	-0.021	0.094	-0.218
Misalignment × Real exchange rate	0.033	0.009	0.051	0.169	0.000	0.000	0.002	-0.002	0.002	0.000	0.009	0.038
Misalignment × M1 growth	0.000	0.000	0.003	-0.003	0.000	0.000	0.004	0.009	0.050	-0.025	0.115	-0.214
Misalignment × Price-earnings ratio	0.000	0.000	0.003	0.000	0.000	0.000	0.002	-0.001	0.001	0.000	0.007	-0.020
Misalignment × Dividend yield	0.000	0.000	0.003	0.000	0.000	0.000	0.002	0.001	0.039	-0.014	0.075	-0.188
Misalignment × Stock returns	0.000	0.000	0.002	0.002	0.000	0.000	0.003	0.013	0.000	0.000	0.003	-0.005
Observations		830				796				736		

"PIP" stands for "Posterior inclusion probability", "PM" stands for "Mean of the posterior distribution of the parameter", "PSD" stands for "Standard deviation of the posterior distribution of the parameter". All results based on Markov Chain Monte Carlo Model Composite with 2 million replications after 1 million burn-in rounds.

22. The results for short-term signals of house price turning points (based on a one quarter lag) indicate that large misalignments lead to higher correction probabilities in economies with relatively high credit growth. Increases in long-term interest rates further increase the probability of busts in house prices, which tend to happen also more often during high-growth periods.

23. For the case of variables lagged four quarters, short-term real interest rates appear also as a robust determinant in its interaction with the misalignment measure. The implication is that misalignments are less sustainable in economies with decreasing real interest rates, and act as a signal for house price reversals if real interest rates are increasing. The results are largely in line with the analysis carried out by the IMF (2009). Based on the analysis of descriptive statistics prior, during and after a house price bust,

IMF (2009) proposes using credit measures, the current account balance, residential investment, stock prices and inflation to predict house price busts.

24. The results concerning longer-term determinants indicate that there are no robust long-run predictors of busts in house prices. At this horizon only exchange rate appreciation trends tend to be linked with higher house price reversal probabilities. The measure of misalignment, as well as its interaction with other variables, does not turn out to be a robust factor in explaining house price busts.

25. In Table 4 the results of the BMA exercise for stock price reversals are presented, in the same fashion as the BMA estimates for house prices were presented above. In general, the estimates show less continuity of the importance of different determinants of asset price misalignments at different horizons than the results for house prices. This may reflect a more complex relationship.

Table 4. BMA results, stock prices

	1-quarter lag				4-quarter lag				8-quarter lag			
	PIP	**PM**	**PSD**	**PM/PSD**	**PIP**	**PM**	**PSD**	**PM/PSD**	**PIP**	**PM**	**PSD**	**PM/PSD**
Misalignment	0.006	0.003	0.051	0.053	**0.739**	**1.558**	**0.990**	**1.574**	0.060	0.028	0.135	0.211
Current account balance	0.168	-0.060	0.145	-0.416	0.001	0.000	0.005	-0.016	0.000	0.000	0.002	-0.008
Working age share	0.000	0.000	0.003	0.008	0.000	0.000	0.003	0.007	0.000	0.000	0.002	-0.001
Population growth	0.000	0.000	0.005	0.007	0.002	0.000	0.010	0.031	0.000	0.000	0.003	0.009
Housing investment	0.000	0.000	0.005	-0.012	0.000	0.000	0.003	-0.003	0.000	0.000	0.002	-0.003
Labor productivity growth	0.003	0.001	0.022	0.052	**1.000**	**1.415**	**0.286**	**4.940**	0.002	-0.001	0.015	-0.043
GDP p.c. growth	0.005	0.003	0.046	0.063	**1.000**	**-1.410**	**0.255**	**-5.531**	0.000	0.000	0.002	-0.001
Long term interest rate	0.001	0.000	0.006	-0.023	**1.000**	**0.633**	**0.151**	**4.195**	**1.000**	**-0.910**	**0.180**	**-5.051**
House price-income ratio	0.000	0.000	0.004	-0.008	0.000	0.000	0.002	-0.004	0.000	0.000	0.002	-0.003
Short-term nominal interest rate	0.000	0.000	0.001	-0.002	0.001	0.000	0.011	-0.017	0.079	0.070	0.252	0.279
Short-term real interest rate	0.000	0.000	0.003	-0.008	**1.000**	**-0.920**	**0.182**	**-5.047**	**0.933**	**0.736**	**0.260**	**2.827**
Credit growth	0.002	-0.001	0.014	-0.043	**0.999**	**0.683**	**0.188**	**3.627**	0.000	0.000	0.004	0.013
Real exchange rate	0.053	-0.015	0.070	-0.219	0.000	0.000	0.002	-0.002	0.002	0.000	0.010	-0.041
M1 growth	0.000	0.000	0.003	-0.009	0.001	0.000	0.004	0.014	0.000	0.000	0.005	-0.016
Price-earnings ratio	0.164	0.080	0.189	0.420	0.002	0.000	0.006	0.031	0.000	0.000	0.002	-0.010
Dividend yield	0.000	0.000	0.002	0.005	0.000	0.000	0.003	0.009	0.000	0.000	0.002	0.005
Stock returns	**0.960**	**0.788**	**0.320**	**2.466**	**0.978**	**-0.632**	**0.206**	**-3.068**	0.064	-0.025	0.103	-0.241
Misalignment × Current account balance	0.000	0.000	0.004	-0.009	0.000	0.000	0.007	0.010	0.001	0.000	0.009	0.021
Misalignment × Working age share	0.003	0.001	0.032	0.020	0.262	0.556	0.975	0.570	0.040	0.017	0.106	0.156
Misalignment × Population growth	0.119	0.088	0.250	0.353	0.026	0.018	0.122	0.146	0.071	0.030	0.115	0.258
Misalignment × Housing investment	0.000	0.000	0.011	-0.001	0.001	0.001	0.027	0.021	0.024	0.009	0.065	0.141
Misalignment × Labor productivity growth	0.000	0.000	0.003	-0.004	**0.634**	**-0.500**	**0.427**	**-1.170**	0.041	-0.018	0.094	-0.191
Misalignment × GDP p.c. growth	0.010	-0.007	0.080	-0.089	0.302	-0.187	0.316	-0.591	0.001	0.000	0.007	-0.020
Misalignment × Long term interest rate	0.000	0.000	0.002	-0.001	0.001	0.000	0.005	-0.018	0.000	0.000	0.002	-0.002
Misalignment × House price-income ratio	0.004	0.002	0.028	0.058	0.000	0.000	0.004	-0.009	0.002	0.000	0.013	0.037
Misalignment × Short-term interest rate	0.000	0.000	0.003	-0.008	0.008	-0.002	0.022	-0.080	0.000	0.000	0.002	-0.005
Misalignment × Short-term real interest rate	0.000	0.000	0.001	-0.002	0.001	0.000	0.008	-0.029	0.002	0.000	0.010	-0.034
Misalignment × Credit growth	0.000	0.000	0.004	-0.014	0.021	0.011	0.082	0.136	0.000	0.000	0.003	-0.006
Misalignment × Real exchange rate	0.001	0.000	0.009	0.022	0.000	0.000	0.003	0.006	**1.000**	**0.444**	**0.099**	**4.465**
Misalignment × M1 growth	0.001	0.000	0.011	-0.022	0.001	0.000	0.014	0.027	0.004	0.001	0.021	0.054
Misalignment × Price-earnings ratio	**0.865**	**0.839**	**0.416**	**2.016**	0.000	0.000	0.006	0.006	0.001	0.000	0.012	0.012
Misalignment × Dividend yield	0.010	0.008	0.091	0.093	0.000	0.000	0.008	-0.006	**0.701**	**0.362**	**0.288**	**1.255**
Misalignment × Stock Returns	0.284	-0.318	0.549	-0.578	0.047	-0.029	0.144	-0.204	0.005	-0.001	0.025	-0.060
Observations		769				758				724		

"PIP" stands for "Posterior inclusion probability", "PM" stands for "Mean of the posterior distribution of the parameter","PSD" stands for "Standard deviation of the posterior distribution of the parameter". All results based on Markov Chain Monte Carlo Model Composite with 2 million replications after 1 million burn-in rounds.

26. In the very short run, represented by the results corresponding to the 1-quarter horizon, busts tend to occur at times of large stock returns, in particular for countries or periods which present simultaneously large stock price misalignments and high price-earnings ratios. At the horizon of one year, a much larger set of covariates appears important as robust predictors of stock price reversals. The probability of stock price reversals is positively affected by credit growth and negatively related to changes in the short-term real interest rate, which implies that a loose monetary policy stance contributes to the building and bursting of stock price bubbles. The role of monetary policy in stock market boom-bust cycles has been the focus of many recent theoretical contributions to the literature on the dynamics of stock prices. Christiano *et al.* (2008), for instance, present a theoretical setting in which agents receive a signal of improved future technology which leads to a rise in the real wage and downward pressures in inflation. Under a standard Taylor rule, the central bank cuts the interest rate, thus inflating the bubble further and precipitating the bust phase. The empirical implications of this model are backed up by the results in Table 4 for the one-year horizon.

27. The results on the effects of labor productivity and GDP per capita growth at the 1-year horizon may seem intriguing at first sight, since they point in opposite directions, with labor productivity growth increasing stock price bust probabilities and income growth decreasing them. This result is however driven by the experience of Finland and Sweden in the first half of the 1990s. The deep crisis and recession experienced in these countries ran in parallel with a rapid fall in stock prices and with an increase in labor productivity due to sectoral restructuring. These features are thus interpreted by the econometric models as positive effects of labor productivity growth on the probability of an asset price correction and a negative effect of GDP per capita growth.

28. The results for variables lagged 8 quarters are puzzling compared to those of the 1-year horizon. Long-term nominal interest rate changes and short-term interest rate changes appear robustly related to the probability of stock price reversals. However, the estimate of their effect (the mean of the posterior distribution of their corresponding parameter) is of the opposite sign of that found for the 4-quarter lag setting. The cyclical dynamics of these variables may be responsible for this result, in which case the signals which appear robust in the longer horizon would just be mirroring those found using models with explanatory variables lagged 4 quarters. Apart from these variables, economies with large misalignments coupled with real depreciations and/or high dividend yields appear more prone to stock price reversals.

4.2 Robustness of the results[8]

29. The results concerning the importance of the interaction between population growth and misalignment estimates may be interpreted as indicating that population should belong to the long-run determinants of house prices and thus be included in the cointegration relationship. We also performed the analysis using misalignment estimates based on cointegration relationships between house prices and (log) population levels, in addition to the real interest rate and income per capita variables included in the prior analysis. The results based on this misalignment measure do not differ strongly from those presented in Table 3, although the only misalignment measure that appears robustly related to corrective price behavior is the interaction between the deviation of the cointegration relationship and the house price-income ratio.

30. It should be noted that the results indicate that misalignment measures by themselves do not appear to be robust determinants of house price busts, but their interaction with other variables do appear as important factors to explain corrective house price dynamics. This implies that not all asset price misalignments are equally dangerous and that other variables (in particular population and credit growth) mediate this relationship. Different ways of modeling the parameter heterogeneity implied by such results were also tried. Variables based on the extent and duration of the misalignments and these covariates (interacted with the deviation from the long-run relationship) were calculated and included as potential determinants of price reversals both instead of the interactions shown in Table 3 and as additional variables to those in the table. In particular, a variable measuring the duration of positive misalignments (number of quarters up to the observation) was created and a set of dummy variables defining periods with large misalignment, based on the percentiles of the distribution of observed misalignments. None of these variables turned out to be robust determinants of house price busts, thus emphasizing the fact that it is other covariates (the degree of credit growth and the growth rate of population for the one-lag setting) which affect the role of misalignments as determinants of house price busts.

31. Concerning the dependent variable, the method identifies price busts using HP-filtered asset price data as the underlying series, as is often done in the literature (see for example Detken and Smets, 2004, Adalid and Detken, 2007 and Agnello and Schuknecht, 2009) and thus implicitly accounts for the long-run driving forces (observable and unobservable) of real house prices. Results were also obtained based on the

8. The results presented in this section are based on estimations which are not shown in detail here, but are available from the author upon request.

original series of house and stock price data without prior HP-filtering. The results for house prices based on this coding when the explanatory variable is lagged 4 quarters lead to a robust and negative effect of the misalignment measure on the probability of a price reversal. For the case of stock prices, no variable was found to be robust at the one-year horizon, most probably due to the small number of busts identified if the original asset price data is not previously filtered. This implies that obtaining turning points from data which ignore secular trends in house and stock price data may lead to inference which may not be very sensible from a theoretical perspective.

32. As already noted, the parameters used to extract turning points lead to small price reversals to be considered turning points. BMA was also applied to the same dataset using a turning point procedure based on w=3, p=2 and c=12. The results are qualitatively unchanged for stock prices, but some differences are worth mentioning for the case of house prices. The BMA results for house prices in the setting where the explanatory variables are lagged one quarter indicate that only two covariates are robust determinants of corrective price dynamics in this setting: changes in long-term interest rates (with a powerful positive effect) and the interaction of the misalignment measure with credit growth (also with a powerful positive effect). When four-quarter lags are used, only the growth rate of GDP per capita is a robust determinant of price corrections in house prices. At eight lags of the explanatory variables, no single variable is robust. In this case, the specification implying constant price reversal probabilities has the highest posterior model probability. These results complement the estimates in Table 3 by emphasizing the importance of the joint short-run dynamics of credit aggregates and misalignments in house prices as one of the most relevant factors signaling price reversals.

33. For the case of stock prices, estimates were also obtained after eliminating the data for Finland and Sweden, in order to check the hypothesis put forward in the previous section concerning the reason for the puzzling results on labor productivity. The robustness of the productivity variable, as well as that of GDP per capita growth, was considerably reduced after excluding these economies from the sample.

5. Monetary policy, model uncertainty and asset price bubbles: How informative is model averaging?

5.1. The out-of-sample information content of model averaged predictions

34. It has been often emphasized that asset price bubbles represent an important challenge for policymakers, particularly for central bankers (see Trichet, 2005, as an example of the problems that monetary policymakers face concerning asset price bubbles). The theoretical literature on policy responses to asset price developments is however ambiguous when it comes to delivering clear-cut recommendations in terms of the optimal degree of monetary policy activism in the presence of asset price bubbles (see Bernanke, 2002 and Cecchetti *et al*. 2003, for opposite views on the issue). On the other hand, many studies deal with the role of monetary policy as a determinant of asset price dynamics in the light of the developments observed during the recent crisis. In a nutshell, the overall conclusion of these contributions can be summarized as follows: a loose monetary policy stance tends to precede asset price busts but this association is just one of many factors leading to asset price bubbles and not necessarily the most important one (see IMF, 2009, for a thorough evaluation and Ahearne *et al*., 2005, for a view on the issue prior to the last crisis).

35. Concentrating on the monetary policy response to asset price dynamics, Gruen *et al*. (2005) study possible policy responses to bubbles in asset prices in a theoretical setting where the policymaker may not possess full information about the characteristics of the asset price bubble process. Gruen *et al*. (2005) conclude that the optimal degree of activism of monetary policy confronted with an asset price bubble depends on knowledge about the process underlying asset price dynamics. In this framework, active monetary policy is only feasible if enough information about the bubble process is available, so unveiling

the robust determinants of asset price corrections is a key element to enable policy responses to emerging asset price bubbles. The importance of understanding the underlying nature of asset price dynamics when reacting with monetary policy tools to the forming of bubbles is also studied in Fukunaga and Saito (2009). Using a dynamic general equilibrium model with financial market imperfections, Fukunaga and Saito (2009) show that fractionary information about the source of asset price movements strongly limits the benefits from active monetary policy in the presence of asset price bubbles.

36. The theoretical literature thus concludes that model uncertainty sets important limits to the effectiveness of monetary policy when reacting to asset price developments. From an empirical point of view, the question arises whether methods aimed at exploiting large model spaces, such as the one used in this paper, are able to provide better predictions of the development of asset prices. A natural question that arises is whether policymakers can profit from exploiting model uncertainty in a systematic way in terms of the efficient anticipation of asset price bubbles and their bursting. The importance of model uncertainty for policy evaluation has been highlighted in recent research on macroeconomic policy (see Brock *et al*., 2003, 2007), which reaches the conclusion that (single) model selection is not necessarily appropriate for policy evaluation. Furthermore, ignoring the dimension of model uncertainty by conditioning policy on a single model may lead to economic policy choices which are not robust when confronted by uncertainty.

37. The results presented above indicate that abstracting from uncertainty about the econometric specification may lead to overconfident results concerning the nature of the determinants of busts in asset prices. For the case of house prices, for instance, inference based on the best model for the predictive horizon of one quarter (see the appendix for the specification with the highest posterior probability) would lead to the conclusion that the interaction between the misalignment variable and long-term interest rates exerts a very significant effect on bust probabilities, while information concerning external imbalances is not important for explaining downward price corrections. After a deeper analysis of the model space spanned by all potential determinants of house price bubbles, however, the researcher would conclude that the importance of this interaction term is restricted to a relatively small group of models, and that information on the current account balance helps explain asset price corrections in many other specifications.

38. The question arises, whether averaging across models with weights based on the BMA setting can lead to better informed policy advice by improving out-of-sample predictions of asset price corrections. In the prediction exercise model averaged forecasts are averaged against those which would have been obtained from the single best specification supported by the data. For this purpose, we assume a policymaker whose loss function depends on predicting asset price corrections accurately, so that

$$L(y \mid \hat{y}) = f(\{y = 1 \cap \hat{y} = 1\}, \{y = 0 \cap \hat{y} = 0\}),$$

where $\hat{y}$ are the predicted events (asset price bust is predicted to take place - $\hat{y} = 1$ - or not - $\hat{y} = 0$) given data prior to *y*. The loss function given by *L(•)* depends thus on the correctly predicted turning points in asset prices, as well as on the correctly predicted "quiet times". The relative importance of these two components of the loss function is in principle arbitrary and may change over time. A policymaker may consider a false alarm (which can affect expectation formation mechanisms of economic agents very strongly) just as harmful as (or more harmful than) missing a turning point in certain environments, while the opposite may be true at other times or for other policymakers.

39. In this sense, a simple loss function is assumed such as

$$L(y \mid \hat{y}) = \alpha_1 \left(1 - \frac{card\{y = 1 \cap \hat{y} = 1\}}{card\{y = 1\}} \right) + \alpha_0 \left(1 - \frac{card\{y = 0 \cap \hat{y} = 0\}}{card\{y = 0\}} \right),$$

where *card{X}* refers to the cardinality of the set *X*. The loss function assumed is therefore a weighted average of the proportions of bubble-burst and non-bubble burst observations which are incorrectly predicted. The weights depend on the preferences of the policymaker concerning type I and type II errors in prediction. The literature on the evaluation of out-of-sample prediction of binary variables tends to use the standard approach (see for example Berg *et al.*, 2005) of choosing as a loss function the (unweighted) average of incorrectly predicted busts as a percentage of the total number of out-of-sample busts and incorrectly predicted non-bust periods as a percentage of non-bust periods. This setting corresponds to setting $\alpha_0 = \alpha_1$. In our case, we evaluate the usefulness of model averaging for predicting asset price bubbles based also on two other types of loss function: $\alpha_0 = 0.75$, $\alpha_1 = 0.25$ and $\alpha_0 = 0.25$, $\alpha_1 = 0.75$.

40. In the framework of model uncertainty put forward above, a forecast of the probability of a reversal in asset prices is given by

$$P(y_h = 1 | \mathbf{X}_k) = \sum_{m=1}^{2^K} P(y_h = 1 | y, M_m, \mathbf{X}_k) P(M_m | y), \tag{3}$$

where y_h is the h-step ahead forecast of y. The predictive density of y_h is thus given by the weighted average of predictive densities of the specifications in the model space.[9] In our setting, the benchmark for BMA predictions is given by the predictive ability of the single model with highest posterior probability for each one of the samples used in the forecasting exercise.

41. The evaluation of predictive ability for binary variables requires the definition of a probability threshold which defines "alarms", such that predicted probabilities above the threshold imply that a price correction is actually predicted. Predictions in terms of probability are thus coded into alarm signals for a given probability threshold as follows,

$$A_h | \mathbf{X}_k = \begin{cases} 1 & \text{if } P(y_h = 1 | \mathbf{X}_k) > \mu \\ 0 & \text{otherwise} \end{cases},$$

where μ should be chosen so as to minimize the corresponding loss function of the policymaker.

42. The quality of model averaged forecasts is evaluated as follows. Using data ranging until 1999/4, a model-averaged prediction of the probability of a bust in asset prices is obtained (independently for house and stock prices) for the observation corresponding to 2000/1. The BMA method is applied to all potential models containing explanatory variables which are lagged 4 quarters, and can thus be interpreted as one-year-ahead predictions. The prediction corresponding to the single model with the highest posterior probability (the "best" model for the in-sample period) is also shown. A new observation (the one corresponding to 2000/1) is included in the in-sample period and predictions are obtained for 2000/2. This procedure is repeated until the end of the dataset is reached.[10]

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9. In terms of implementation in the framework of MC^3, the probability of a turn in house prices is thus predicted as the average of bust probabilities implied by the set of models chosen in the Markov Chain, which implies that the weights in (3) are approximated by the relative frequencies with which models are visited.

10. The computational requirements of the prediction exercise are large, so we base BMA inference for each step of the forecasting exercise on 20 000 replications of the Markov chain, after a burn-in phase of 10 000 runs. For the whole sample, the results obtained with 20 000 replications are very similar to those with 2 million replications.

43. Using all predictions, the threshold value, μ, is calculated, which minimizes the loss function chosen and in Table 5 statistics corresponding to the predictive performance of BMA and "best" models are reported. Although the posterior model probabilities tend to be concentrated on few specifications and there are only small qualitative differences in the predictions obtained from the best models and the model averaged forecasts, BMA forecasts perform better on average independently of the loss function used to evaluate the predictive ability of the models. For both asset prices, BMA forecasts beat those of the best model for all loss functions. For house prices, model averaged forecasts tend to be less conservative than those of the single best model, thus delivering a relatively high number of false alarms, although they achieve better overall predictive power as measured by the different loss functions.

44. The results of the prediction exercise give a clear result concerning the benefits of exploiting multiple specifications to improve the predictive ability for turning points in asset prices. To the extent that monetary policy activism in the framework of asset price bubbles depends on the ability of the policymaker to anticipate the development of asset prices, inference based on model selection may be counterproductive. On the other hand, acknowledging the uncertainty attached to model specification and dealing with it within the BMA framework leads to improvements in the predictive information available to the policymaker at a given period in time.

5.2. Anticipating asset price busts during the recent crisis: the role of model uncertainty

45. The recent global financial crisis has increased the interest of economists in the role that monitoring asset prices should play in setting monetary policy. In this section some evidence on the predictive gains are reported, which would have been obtained from the use of model averaging techniques to forecast corrective behavior in asset prices in recent years.

46. A question that needs to be addressed before drawing conclusions concerns the relevance of our results for the last wave of asset price busts. We thus analyse whether the determinants of the latest crisis have been systematically different from those of previous busts in house prices. For that purpose, the BMA estimation presented above is repeated using data exclusively up to 2005 and thus not including the latest bust episodes captured by the turning-point identification procedure. The results were not qualitatively different from those reported for the full sample, and only deviated from those in that population growth and current account balance differences appeared relatively less important as determinants of price reversals in house prices. In this sense, demographic differences across countries appear to have played a particularly important role in the latest episodes of house price busts by determining the sustainability of house price misalignments in terms of housing demand pressures. On the other hand, to the extent that they are captured by the current account balance, external imbalances have been a particularly relevant factor explaining house price busts since 2005.

Table 5. Out of sample prediction exercise results

House prices

	BMA	Best model	BMA	Best model	BMA	Best model
Busts correctly predicted divided by total busts (a)	0.647	0.595	0.059	0.051	0.824	0.772
Non-busts correctly predicted divided by total non-bust obs. (b)	0.602	0.620	0.983	0.983	0.345	0.378
False alarms divided by total alarms	0.391	0.384	0.164	0.154	0.578	0.564
Value of loss function	0.375	0.393	0.248	0.250	0.296	0.326
Cut-off threshold (μ)	0.200	0.220	0.650	0.650	0.100	0.100
Loss function	(1-a)+(1-b)		0.75×(1-a) + 0.25× (1-b)		0.25× (1-a) + 0.75× (1-b)	

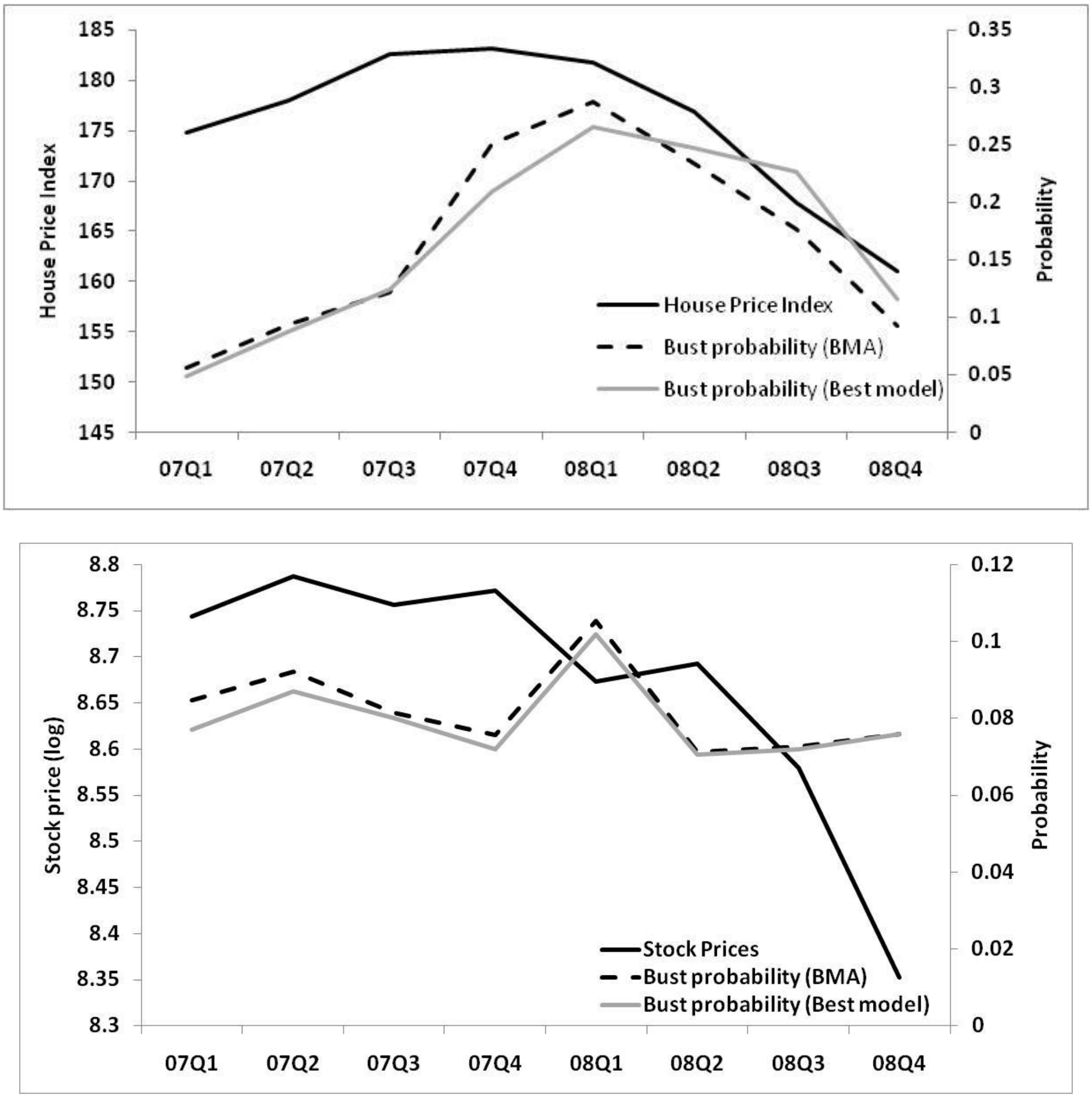
Stock prices

	BMA	Best model	BMA	Best model	BMA	Best model
Busts correctly predicted divided by total busts (a)	0.945	0.709	0.945	0.963	0.145	0.509
Non-busts correctly predicted divided by total non-bust obs. (b)	0.328	0.558	0.328	0.241	0.817	0.663
False alarms divided by total alarms	0.816	0.796	0.816	0.795	0.887	0.806
Value of loss function	0.726	0.733	0.209	0.217	0.351	0.376
Cut-off threshold (μ)	0.205	0.200	0.205	0.195	0.250	0.230
Loss function	(1-a)+(1-b)		0.75×(1-a) + 0.25× (1-b)		0.25× (1-a) + 0.75× (1-b)	

47. As a representative example of the predictive ability of BMA forecasts, Figure 1 shows the out-of-sample one-year ahead predicted probabilities of a house/stock price corrections for the United Kingdom for the period 2007-08, which was not included in the estimation sample or in the forecast exercise presented above. We present the model averaged predicted probabilities together with those implied by the best model based on in-sample information. The figure for house prices exemplifies the source of the gains of using model-averaged predictions: while both start the period assigning similar bust probabilities of around 0.05, the BMA predictions reach higher probabilities than those forecast by the best model prior to the recent bust in house prices, and the probabilities decrease at a speedier pace than those of the best model once the bust occurs. Model-averaged forecasts would thus have sent a stronger (correct) alarm signal before the best model would, and would have also signaled the end of the turning point earlier. The possibilities of policy reacting to the anticipation of corrective dynamics in house prices would have thus been better based on predictions emanating from the model-averaging technique. For the case of stock prices, the predicted probabilities are significantly lower and there are smaller differences between best model and BMA forecasts, with BMA predictions indicating slightly higher probabilities of corrective

dynamics. Both predictions indicate an increase of reversal probability for the first quarter of 2008, which is the period which marks the beginning of a steep fall in UK stock prices.[11]

Figure 1. House prices, stock prices and out-of-sample bust probability predictions, UK 2007-08



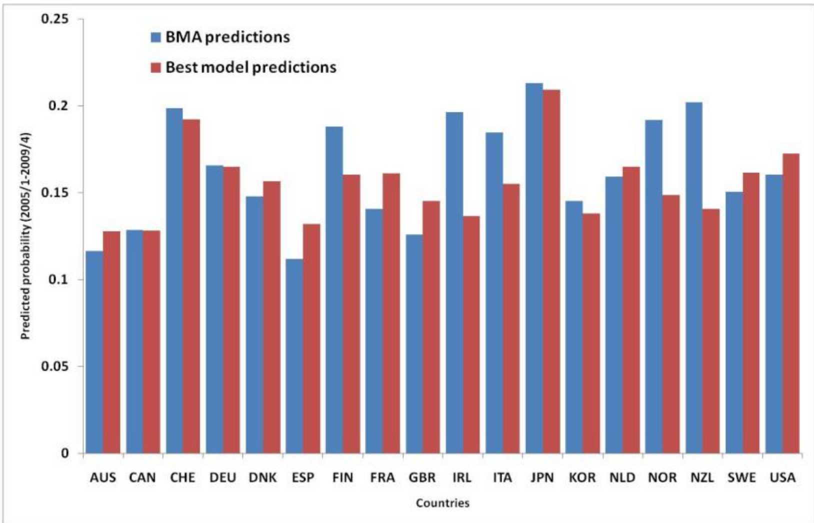
48. While Figure 1 gives evidence of good predictive capabilities for Bayesian model averaging methods in the time dimension for a given country, the results are not that favorable when comparisons across countries are carried out. In Figure 2 we present the average out-of-sample correction probabilities for house and stock prices predicted by the BMA procedure and those implied by the model with the highest posterior probability for the countries in the sample in the period ranging from 2005 to 2009. The

11. A first feature of the results in Figure 1 that deserves comment is the fact that the difference between best-model and BMA results is relatively modest in terms of predicted probabilities. This implies that, at least when considering differences across countries, the posterior model probability tends to be very concentrated in single specifications. This feature has been dubbed the *supermodel effect* by Feldkircher and Zeugner (2009) and calls for the use of different prior structures if mixing over larger subsets of the model space is desired.

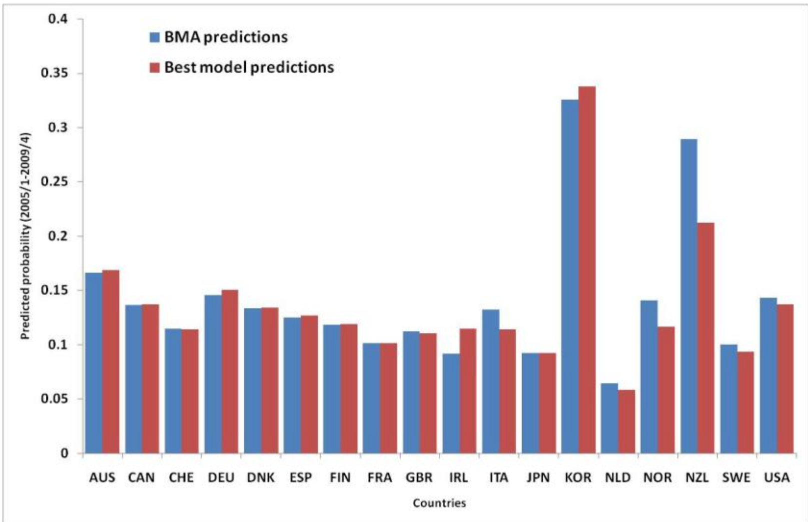
figure reveals different patterns across countries for the two asset prices. For the case of house prices, the probabilities do not tend to differ strongly across countries although interesting differences across methods can be observed for some countries: the probabilities predicted by BMA for Ireland and New Zealand, for instance, appear significantly higher than those from the best model. Stock price reversal probabilities, on the other hand, show more cross-country variation, with New Zealand and especially Korea being assigned sizable probabilities of a stock price reversal. A further check of the quality of prediction can be obtained by evaluating whether the correlation in predicted probabilities across asset prices conforms to the stylized facts supported by the data. The data used in our study present no significant correlation between busts in house and stocks prices (the correlation is positive but below 0.1). Forecasts based on best models, however, are negatively correlated between house and stock prices, with a correlation of around -0.4, while BMA predictions are practically uncorrelated (the correlation equals -0.02).

Figure 2. Price reversal probability predictions (average 2005-09)

House prices



Stock prices

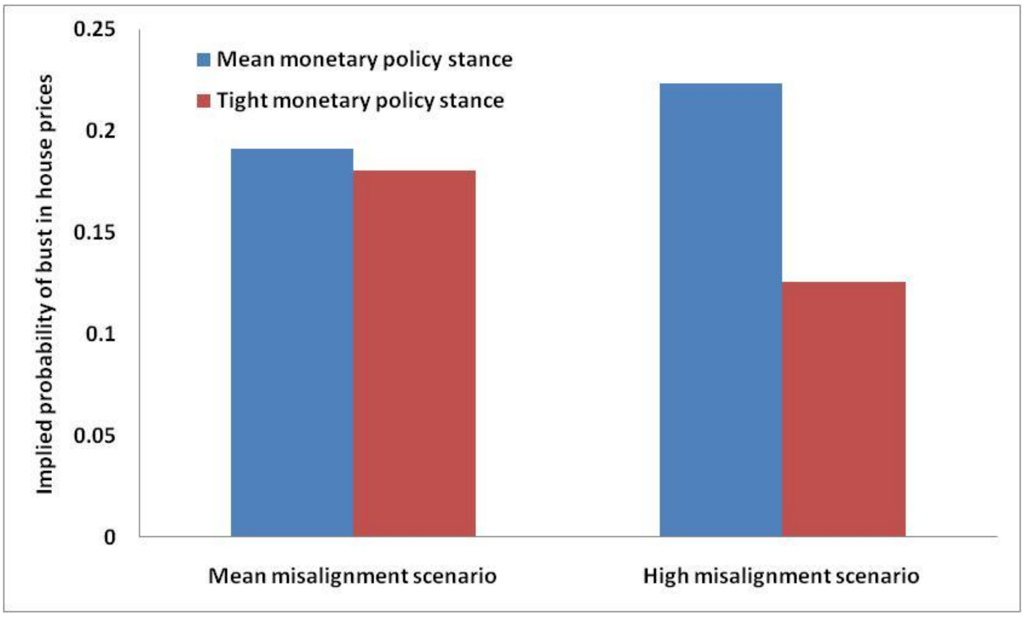


49. Combining the results presented in Table 3 for the one-quarter-lag and one-year-lag time horizons, one can gain a clearer picture about the association between the monetary policy stance and busts

in house prices which is, furthermore, consistent with the links put forward in the empirical literature (see Ahearne *et al*., 2005, and references therein). The estimation results, for instance, indicate that house price busts tend to be preceded by periods of monetary loosening and credit growth coupled with house price misalignments. Furthermore, increases in long-term interest rates tend to happen prior to the house price correction. All these features have been documented in the empirical literature, but their robustness to model uncertainty had not been analyzed hitherto.

50. In Figure 3 the quantitative importance of monetary policy as a potential catalyst of house price corrections is illustrated. Using data for the period 2000-07, the implied bust probabilities for four hypothetical scenarios are presented, which highlight the possible interaction between price misalignments and the monetary policy stance. The four hypothetical scenarios present the combinations of two misalignment scenarios (mean value of the misalignment variable for the subsample – mean misalignment – and a scenario corresponding to a misalignment equal to the subsample mean plus one standard deviation – high misalignment) and two monetary policy stance scenarios based on short-term real interest rates (mean monetary policy stance versus tight monetary policy stance, where the latter corresponds to the mean value plus one standard deviation based on the 2000-05 subsample).

Figure 3. House price bust probabilities: mean vs. high misalignment and mean vs. tight monetary policy stance



51. The results in Figure 3 give an indication of the sensitivity of bust probabilities to the monetary policy stance at different levels of misalignment, holding other things equal. All probabilities correspond to the specification with a lag of one year. The reduction in bust probability implied by a tighter monetary policy is much more sizable when misalignments are relatively large, and further measures of monetary policy tightening related to credit growth would widen the effect further at shorter horizons (Table 3). These results support the view that monetary policy factors may have played a role in the formation and bust of the recent house price bubble.

52. The results shed new light on two different issues related to asset prices and economic policy. On the one hand, a practical conclusion that can be drawn from the results implies that the detailed treatment of model uncertainty on the determinants of asset price reversals leads to improvements in the quality of predictions of asset price busts. This in turn implies that policy measures related to asset price bubbles can be taken more efficiently if model uncertainty in asset price determinants is assessed by the policymaker.

On the other hand, the results emphasise the role played by monetary policy in the process of birth and burst of asset price bubbles highlighting the interaction of misalignments and the monetary stance. A broader discussion on whether the monetary authorities should consider asset price dynamics when conducting monetary policy falls outside the scope of this paper.

6. Conclusions

53. This contribution presents the first empirical assessment of the robust determinants of asset price reversals in the presence of model uncertainty. BMA methods are used to study the relative importance of different factors which have been put forward in the literature to explain asset price busts and the role of model uncertainty for out-of-sample predictive performance is evaluated.

54. The results indicate that the mechanisms underlying the bursting of asset prices are complex and require the evaluation of potentially many models emphasizing different channels. In spite of the difficulties underlying the interpretation of many of the empirical results linking macroeconomic variables and asset price dynamics, several conclusions can be drawn.

55. For the case of house prices, the analysis indicates that misalignment variables built from long-run relationships between house prices and fundamental macroeconomic variables are not by themselves good predictors of the probability of price reversals. Misaligned house prices can be very persistent and only tend to lead to price corrections in environments of loose monetary policy and high credit growth. Our results for house prices also emphasize the importance of external imbalances as catalysts of house price reversals.

56. In the case of stock prices, on the other hand, simple measures of misalignments do serve as good predictors of price reversals, although the interaction between monetary variables, stock returns and corrective price dynamics appears more intriguing than for house price busts. Measures of the monetary policy stance also appear as good predictors of stock price reversals, and in particular countries with a loose interest rate policy and high credit growth also tend to be more at risk of stock price corrections.

57. The results of the paper support the importance of considering model uncertainty when obtaining out-of-sample predictions of asset price busts. Averaged forecasts of turning point probabilities based on weights obtained using BMA appear superior to those based on single specifications chosen using model selection criteria and thus should be preferred when exploiting information for policymaking.

58. Several paths of further research appear natural. The importance of non-linearities in the form of interaction terms in models of asset price reversals calls for improvements of the technique when averaging over model spaces formed by specifications with interactive terms (see Chipman, 1996, and Crespo Cuaresma, 2010, for developments in this direction). The explicit comparison (and mixing) of structural models which highlight specific transmission channels to asset prices may also give valuable insights and open new avenues of both theoretical and empirical research. Models including contagion and correlation across price dynamics in different countries can also be modeled in the framework proposed here, albeit with increased complexity if uncertainty about contagion links is assumed (see Crespo Cuaresma and Feldkircher, 2010, for such methods applied to spatially auto-correlated data).

REFERENCES

Adalid, R. and C. Detken (2007), "Liquidity Shocks and Asset Price Boom/Bust Cycles", *ECB Working Paper,* No. 732.

Agnello L. and L. Schuknecht (2009), "Booms and Busts in Housing Markets: Determinants and Implications", *ECB Working Paper,* No. 1071.

Ahearne, A.G., J. Ammer, B.M. Doyle, L.S. Kole and R.F. Martin (2005), "House Prices and Monetary Policy: A Cross-country Study", *International Finance Discussion Paper,* No. 841.

Akaike, H. (1973), "Information Theory and an Extension of the Maximum Likelihood Principle", in: Petrov and Csaki (eds.), *Second International Symposium on Information Theory,* Akademiai Kiado: pp. 267-281, Budapest.

Avouyi-Dovi, S. and J. Matheron (2005), "Interactions between Business Cycles, Financial Cycles and Monetary Policy: Stylised Facts", *BIS Papers,* No. 22.

Bernanke, B.S. (2002), "Asset Price Bubbles and Monetary Policy", Speech at the New York Chapter of the National Association for Business Economics, New York, October 15.

Borio, C. and P. Lowe (2002), "Asset Prices, Financial and Monetary Stability: Exploring the Nexus", *BIS Working Paper,* No. 114.

Borio, C. and P. Lowe (2004), "Securing Sustainable Price Stability: Should Credit Come Back from the Wilderness?", *BIS Working Paper,* No. 157.

Boucher, M., B. Maillet and T. Michel (2008), "Do Misalignments Predict Aggregated Stock Market Volatility?", *Economics Letters,* No. 100.

Brock, W., S. N. Durlauf, and K. West (2003), "Policy Analysis in Uncertain Economic Environments", *Brookings Papers on Economic Activity,* 1: 235-322.

Brock, W., S. N. Durlauf and K. West (2007), "Model Uncertainty and Policy Evaluation: Some Theory and Empirics", *Journal of Econometrics,* No. 136: 629-664.

Bry, G. and C. Boschan (1971), "Cyclical Analysis of Time Series: Selected Procedures and Computer Programs", NBER.

Cecchetti, S.G., H. Genberg and S. Wadhwani (2003), "Asset Prices in a Flexible Inflation Targeting Framework", In: W. C. Hunter, G. G. Kaufman and M. Pomerleano (eds.), *Asset Price Bubbles: The Implications for Monetary, Regulatory, and International Policies,* MIT Press, Cambridge, Mass.

Chipman, H.A. (1996), "Bayesian Variable Selection with Related Predictors", *Canadian Journal of Statistics*, 24: pp. 17-36.

Christiano, L. J., C.L. Ilut, R. Motto and M. Rostagno (2008), "Monetary Policy and Stock Market Boom-Bust Cycles", *ECB Working Paper,* No. 955.

Clyde, M. (2000), "Model Uncertainty and Health Effect of Studies for Particulate Matter", *Environmetrics,* No. 11.

Crespo Cuaresma, J. and T. Slacik (2009), "Predicting Currency Crises: The Role of Model Uncertainty", *Journal of Macroeconomics*, forthcoming.

Crespo Cuaresma, J. and G. Doppelhofer (2007), "Nonlinearities in Cross-Country Growth Regressions: A Bayesian Averaging of Thresholds (BAT) Approach", *Journal of Macroeconomics,* No. 29.

Crespo Cuaresma, J. and M. Feldkircher (2010), "Spatial Filtering, Model Uncertainty and the Speed of Income Convergence in Europe", *Working Paper,* No. 160, Oesterreichische National Bank.

Crespo Cuaresma, J. (2010), "How Different is Africa? A Comment on Masanjala and Papageorgiou", *Journal of Applied Econometrics,* forthcoming.

Detken C. and F. Smets (2004), "Asset Prices Booms and Monetary Policy", *ECB Working Paper,* No. 364.

Everts, M. (2007), "Duration of Business Cycles", *MPRA Paper,* No. 1219.

Feldkircher, M. and S. Zeugner (2009), "Benchmark Priors Revisited: On Adaptive Shrinkage and the Supermodel Effect in Bayesian Model Averaging", *IMF Working Papers 09/202,* International Monetary Fund.

Fernández, C., E. Ley and M.F. Steel (2001*a*), "Benchmark Priors for Bayesian Model Averaging", *Journal of Econometrics,* No. 100.

Fernández, C., E. Ley and M.F. Steel (2001*b*), "Model Uncertainty in Cross-Country Growth Regressions", *Journal of Applied Econometrics,* No. 16.

Foster, D.P. and E.I. George (1994), "The Risk Inflation Criterion for Multiple Regression", *Annals of Statistics,* 22: pp. 1947-1975.

Fukunaga, I. and M. Saito (2009), "Asset Prices and Monetary Policy", *Discussion Paper,* No. 2009-E-21, Institute for Monetary and Economic Studies, Bank of Japan.

Gerdesmeier, D., H.E. Reimers and B. Roffia (2009), "Asset Price Misalignments and the Role of Money and Credit", *ECB Working Paper,* No. 1068.

Goodman, C. and B. Hofmann (2008), "House Prices, Money, Credit and the Macroeconomy", *ECB Working Paper,* No. 888.

Gruen, D., M. Plumb and A. Stone (2005), "How Should Monetary Policy Respond to Asset Price Bubbles?", *International Journal of Central Banking,* 1: pp. 1-31.

Hoeting, J.A., D. Madigan and A.E. Raftery (1997), "Bayesian Model Averaging for Regression Models", *Journal of the American Statistical Association*, No. 92.

IMF (2009), *World Economic Outlook: Sustaining the Recovery,* October 2009, International Monetary Fund, Washington DC.

Kass, R.E. and A.E. Raftery (1995), "Bayes Factors", *Journal of the American Statistical Association*, No. 90.

Koop, G. (2003), *Bayesian Econometrics*, John Wiley and Sons, Chichester.

Leamer, E.E. (1978), *Specification Searches*, John Wiley and Sons, New York.

Ley, E. and M.F. Steel (2009), "On the Effect of Prior Assumptions in Bayesian Model Averaging with Applications to Growth Regression", *Journal of Applied Econometrics*, No. 24.

Madigan, D. and J. York (1995), "Bayesian Graphical Models for Discrete Data", *International Statistical Review*, No. 63.

Masanjala, W.H. and C. Papageorgiou (2008), "Rough and Lonely Road to Prosperity: A Reexamination of the Sources of Growth in Africa Using Bayesian Model Averaging", *Journal of Applied Econometrics*, No. 23.

Mishkin, F.S. (2007), "The Role of House Prices in Formulating Monetary Policy", presentation at the Forecasters Club of New York, New York, 17 January 2007.

Raftery, A.E. (1995), "Bayesian Model Selection in Social Research", *Sociological Methodology*, 25: pp. 111-196.

Sala-i-Martin, X., G. Doppelhofer and R. Miller (2004), "Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach", *American Economic Review*, No. 94.

Schwarz, G. (1978), "Estimating the Dimension of a Model", *Annals of Statistics*, No. 6.

Stock, J. and M.W. Watson (1993), "A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems", *Econometrica,* 61: pp. 783-820.

Trichet, J-C. (2005), "Asset Price Bubbles and Monetary Policy", Speech at the Mas lecture, Monetary Authority of Singapore, Singapore, 8 June 2005.

APPENDIX

Figure A1. Turning points and filtered house prices

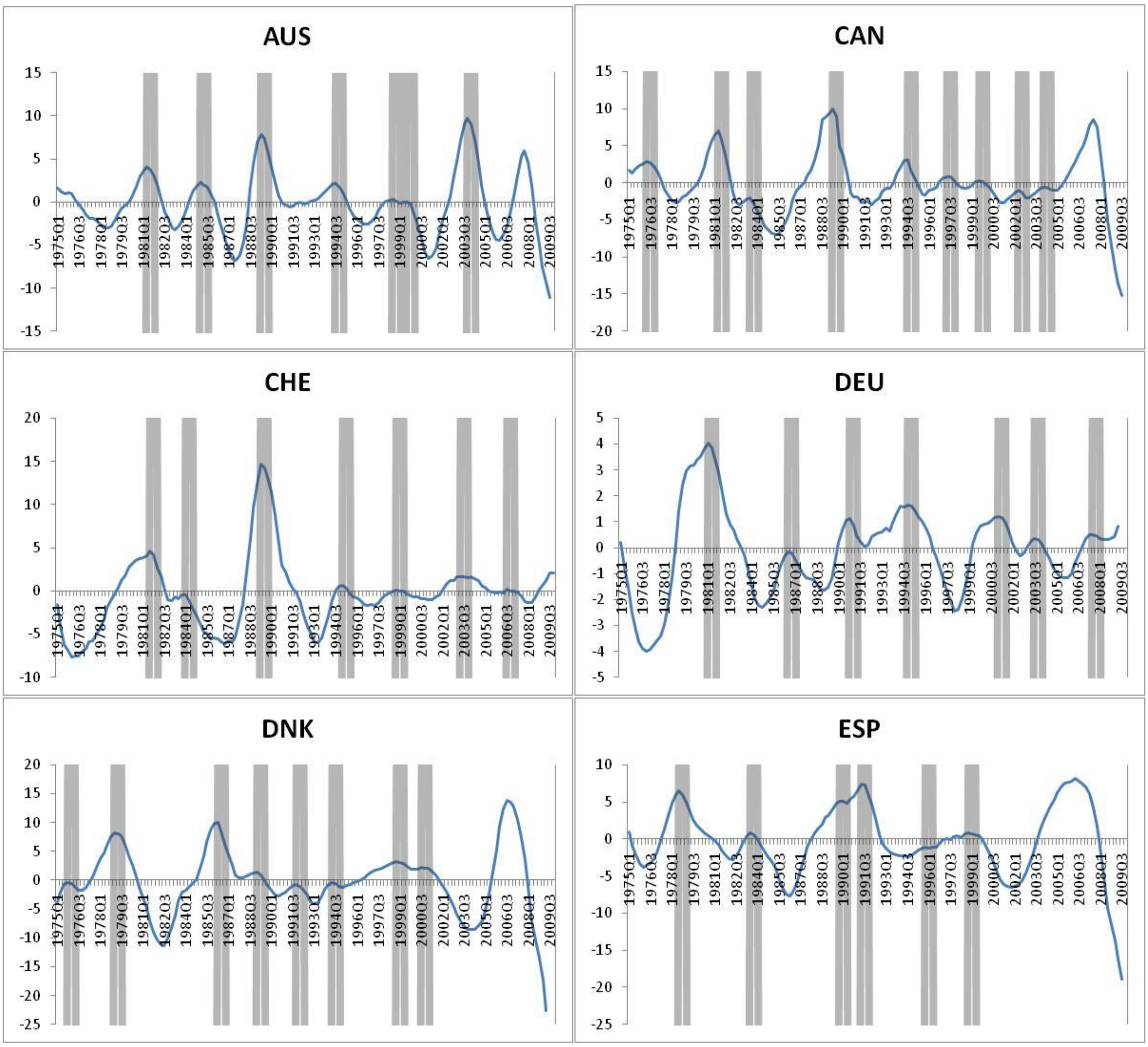


Figure A1. Turning points and filtered house prices (continued)

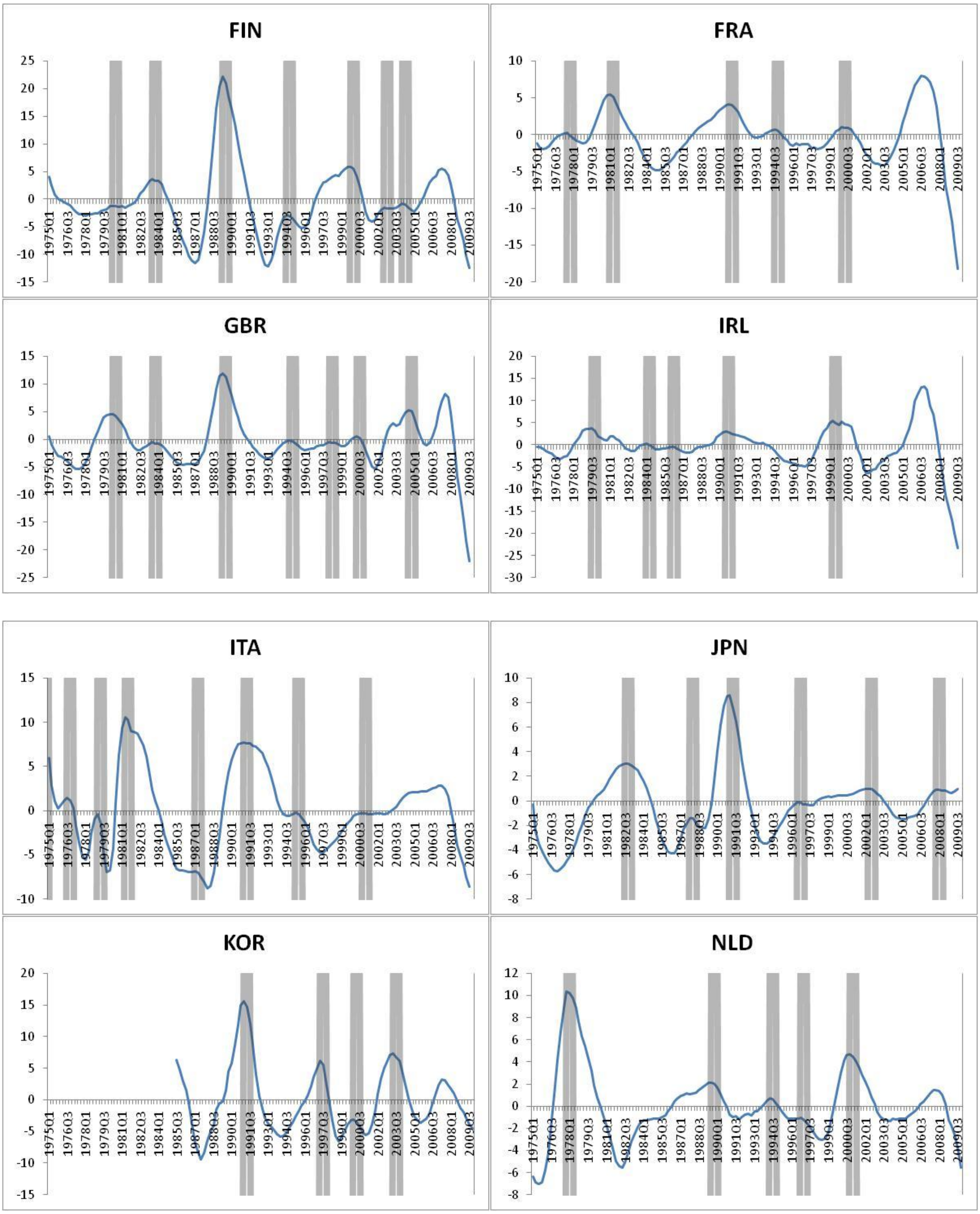


Figure A1. Turning points and filtered house prices (continued)

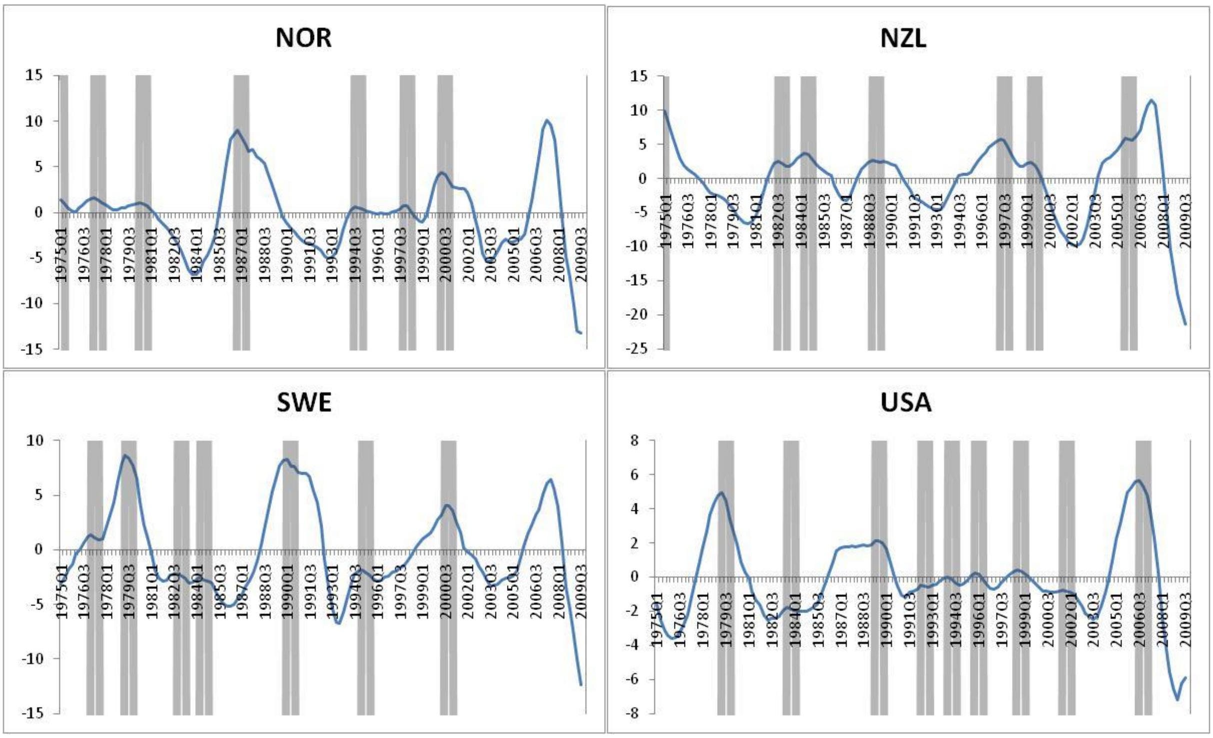


Figure A2. Turning points and filtered stock prices

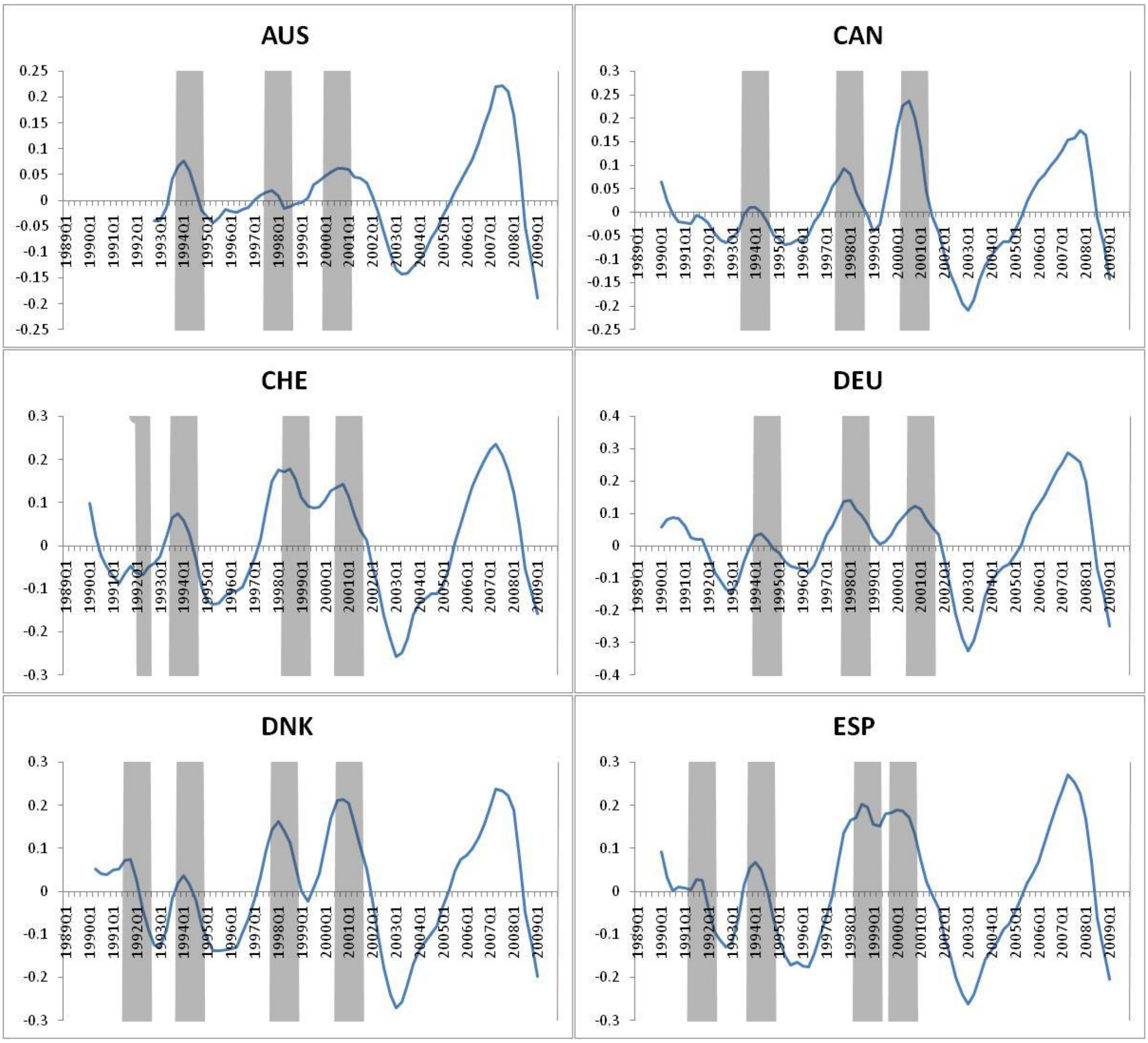


Figure A2. Turning points and filtered stock prices (continued)

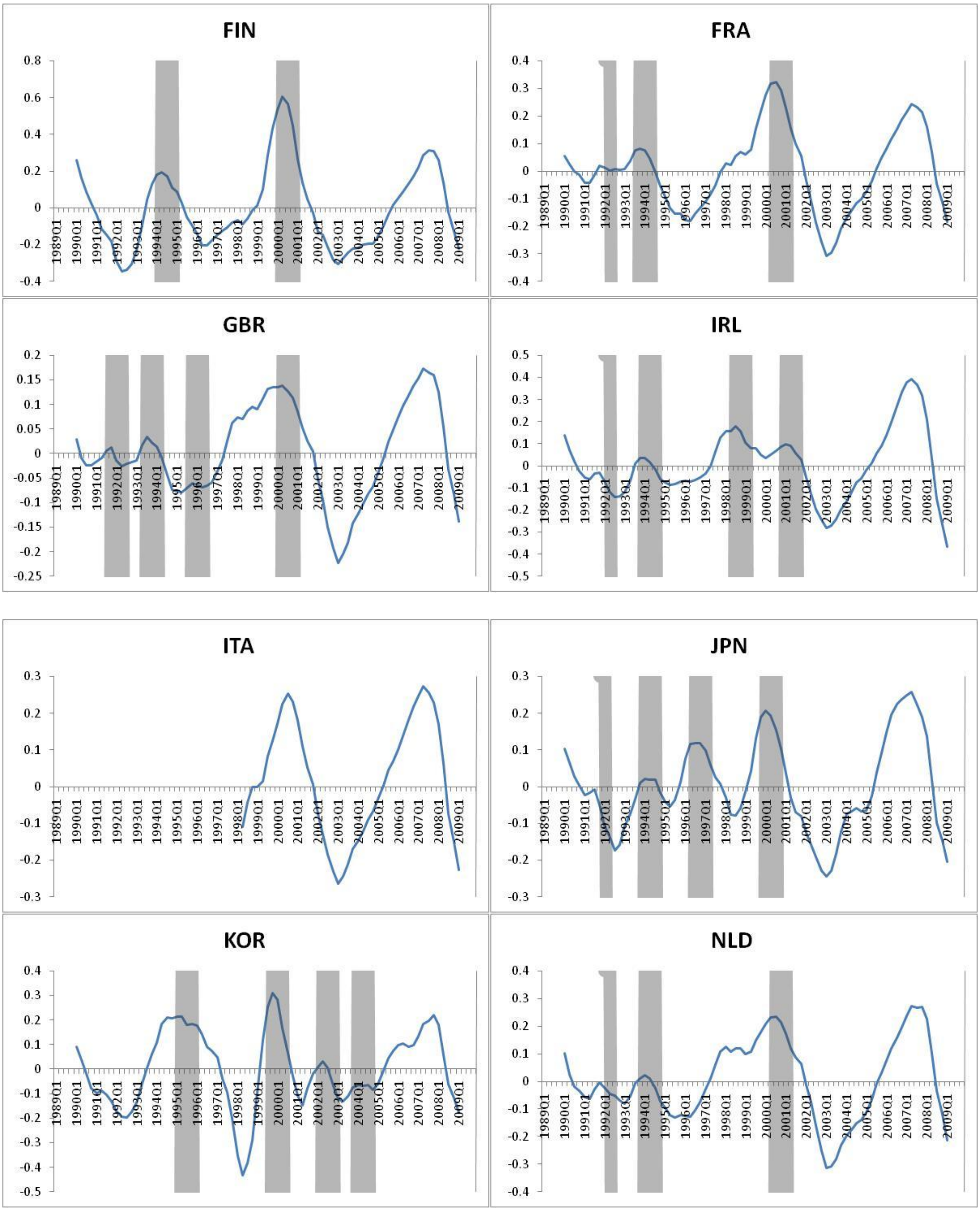


Figure A2. Turning points and filtered stock prices (continued)

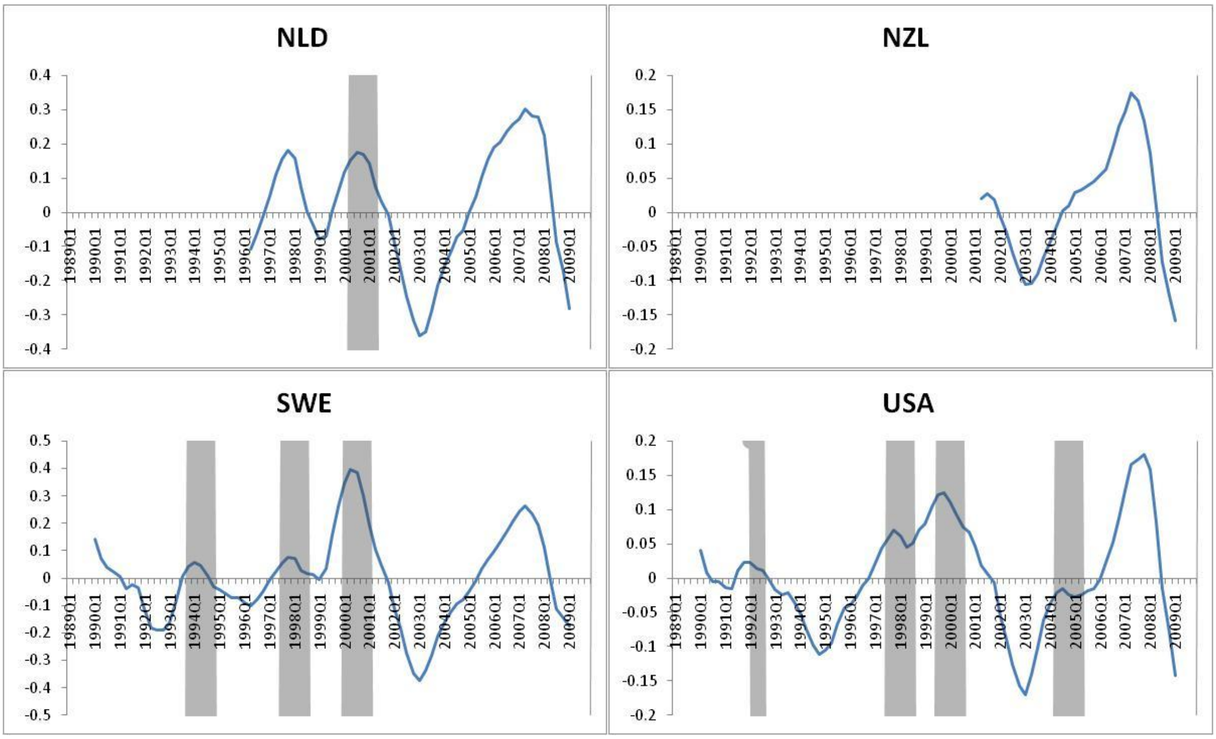


Table A1. Long-run elasticity estimates

Basic equation: $p_t = \alpha_0 + \alpha_1 \log(GDPPC_t) + \alpha_2 lri_t + \varepsilon_t$

Country	α_1	St. dev. α_1	α_2	St. dev. α_2	Obs.
AUS	0.362	0.015	-3.957	0.367	154
CAN	0.287	0.015	-3.651	0.388	154
CHE	0.140	0.034	-1.690	0.805	150
DEU	-0.721	0.034	3.060	0.335	59
DNK	0.134	0.028	-6.215	0.587	154
ESP	0.331	0.027	-3.872	0.480	151
FIN	0.200	0.022	-1.954	0.490	154
FRA	0.290	0.025	-5.514	0.559	154
GBR	0.380	0.029	-5.579	0.814	149
IRL	0.402	0.016	-8.091	0.449	147
ITA	0.219	0.015	-1.670	0.374	154
JPN	0.239	0.037	0.446	0.423	150
KOR	-0.203	0.035	-1.606	0.776	91
NLD	0.630	0.031	-9.624	0.811	150
NOR	0.340	0.019	-4.857	0.561	154
NZL	0.385	0.026	-4.574	0.548	153
SWE	0.202	0.017	-8.134	0.431	153
USA	0.198	0.011	-2.560	0.248	154

Dynamic OLS estimates. Up to two lags and leads of first differenced explanatory variables included in all regressions. Dependent variable: log of house price index; independent variables: log of GDP per capita and real long run interest rate.

Table A2. Models with highest posterior probability: house prices

	Explanatory variables lagged one quarter		Explanatory variables lagged four quarters		Explanatory variables lagged eight quarters	
	Estimate (standard deviation)					
Intercept	-1.4975	(0.1194)	-1.809103	(0.122319)	-1.7129	(0.1117)
GDP p.c. growth	0.6029	(0.1663)				
Long term interest rate	0.5414	(0.1418)				
House price-income ratio	0.6422	(0.1908)	1.143702	(0.192544)		
Misalignment × Long term interest rate	-0.8106	(0.2022)				
Misalignment × House price-income ratio	-0.6269	(0.1761)				
Misalignment × Short-term real interest rate	1.1351	(0.2698)				
Misalignment × Credit growth	0.4491	(0.1247)				
Real exchange rate					-0.3249	(0.0970)
Misalignment × Dividend yield					-0.3445	(0.1362)
Current account balance			-0.483503	(0.133385)		
Misalignment × Population growth			-1.164328	(0.22283)		
Misalignment × Long term interest rate			0.863078	(0.165774)		
Misalignment × Short-term real interest rate			-0.699019	(0.223318)		
Observations	830		796		736	
McFadden R-squared	0.137		0.109		0.032	

Table A3. Models with highest posterior probability: stock prices

	Explanatory variables lagged one quarter		Explanatory variables lagged four quarters		Explanatory variables lagged eight quarters	
	Estimate (standard deviation)					
Intercept	-2.228	(0.149)	-1.778	(0.134)	-2.178	(0.146)
Stock returns	0.876	(0.187)				
Price-earnings ratio	0.512	(0.130)				
Misalignment × Population growth	0.743	(0.197)			0.442	(0.146)
Long term interest rate			0.638	(0.149)	-1.196	(0.196)
Short-term real interest rate			-0.934	(0.181)		
Labor productivity growth			1.519	(0.264)		
GDP p.c. growth			-1.457	(0.250)		
Credit growth			0.662	(0.177)		
Misalignment × Working age share			2.228	(0.328)		
Misalignment × Labor productivity growth			-0.824	(0.250)		
Short-term nominal interest rate					0.976	(0.222)
Misalignment × Real exchange rate					0.441	(0.101)
Observations	769		758		724	
McFadden R-squared	0.174		0.168		0.123	

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