The housing price boom of the late '90s: did inflation targeting matter?*

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7 May 2009 - Preliminary version

Abstract

The unprecedented boom in housing markets of most developed economies over the last decade has spurred criticism that the (successful) inflation targeting strategies followed by many central banks could have contributed, for various reasons, to the build-up of financial imbalances. This paper aims at providing a formal empirical test of such claims, using a standard program evaluation methodology in order to disentangle the impact of the choice of the monetary policy strategy from the consequences of other plausible determinants of housing price dynamics. We consider 17 industrial economies over the period 1980-2006, among which nine countries have targeted inflation at some dates. Using different propensity score matching methods, we find robust evidence of significantly higher growth rates of real housing prices in targeting countries.

JEL classification: E4; E52; E58.

Keywords: Inflation targeting; Housing market; Treatment effect; OECD countries.

*We thank Hubert Kempf, Stefan Krause, Benoît Mojon and Xavier Ragot for useful discussions and comments. The opinions expressed here are the authors' own and do not necessarily reflect the views of the Banque de France.

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1 Introduction

The credible anti-inflationist monetary policies conducted in major developed economies since the mid 1980s have been identified as one plausible factor behind the Great moderation episode over the last two decades. However, as the dotcom boom and bust of the early 2000s and the subprime mortgage crisis that began in 2007 amply proved it, financial crises associated with boom and bust episodes in asset prices are not merely a relic of the twentieth century. This unpleasant diagnosis has recently prompted a debate about the role of monetary policies that have a narrow focus on inflation stabilization in the build-up of imbalances that eventually led to such episodes of financial turmoil. Indeed, some central bank watchers have regularly contended over the recent years that monetary policy strategies that aim primarily at stabilizing inflation over a 2-3 years horizon would actively contribute to damaging financial stability at longer horizons, as they notably tend to neglect monetary and financial developments because these are irrelevant for future inflation in the short to medium term.[1] As for instance Leijonhufvud (2007) provocatively put it: "suppose you conduct a very expansionary monetary policy, and for a reason or another you do not experience inflation? Then what do you get? The answer is, on the one hand, inflation on asset prices and on the other, a general deterioration of credit standards. (...) Inflation targeting might mislead you into pursuing a policy that is actively damaging to financial stability".

While the consensus is broad in the economic profession that a policy focused at maintaining price stability is a necessary condition for maintaining also financial stability, opinions are much more contrasted as to whether it is a sufficient one.[2] Two lines of reasoning highlight how a restrictive view of the inflation targeting agenda could lead to a destabilizing outcome on the financial side.

First, an inflation targeting central bank may neglect important information about

[1] See notably a series of contributions by Claudio Borio, William White and their coauthors at the BIS (Borio et al., 2003, Borio and White, 2003, White, 2006). Bean (2003) claims on the contrary that inflation targets may be enough provided the central bank is sufficiently forward-looking.

[2] See for instance Bordo and Wheelock (1998) and Bordo et al. (2003) regarding the detrimental effect of episodes of monetary instability on financial stability from an historical perspective.

the build-up of financial imbalances which do not materialize rapidly into consumer price pressure. Many reasons may account for this disconnection between financial and price developments. The impact of globalization may be one. Indeed, falling import prices from emerging market economies that pursued policies of exchange rate pegs to major currencies have contributed to dampening inflation pressures and flattening the Phillips curve. Structural changes that have affected the functioning of labour and financial markets over the last two decades may be another cause. As labour markets get more flexible, second-round effects of inflationary supply shocks into wages remain contained. As financial markets are widely deregulated and witness a bout of innovative products like securitization (this is part of what Borio et al., 2003, call the "new environment hypothesis"), households and firms have an easier access to credit and their demand for debt is all the more stronger than the benign inflationary outlook warrants that interest rates are kept at a low level.

Second, the mere success of inflation targeting strategies could have contributed to hampering a proper risk assessment by inflation fighting central banks, what Borio et al. (2003) labelled the "paradox of credibility". Since the anti-inflationary commitment of the central bank becomes more credible, and long-run inflation expectations get more firmly anchored around the central bank's objective, the macroeconomic consequences of "cheap money" -including credit booms that sustain a rise in some asset prices- may take more time to show up into higher inflation. As a conclusion, policy rates may fail to rise sufficiently promptly to help restrain the build-up of financial imbalances (Borio and White, 2003).[3]

The housing price boom of the last decade in many developed economies was probably one of the most striking developments of the recent period and certainly the symptom of accumulated financial imbalances. In line with the "paradox of credibility" hypothesis, we may suspect that expectations of low and stable inflation over the medium term have been an ingredient of the rise of housing prices in countries where the central bank is committed to a credible inflation targeting strategy. Let us for example suppose that a positive shock

[3] A more formal presentation of a similar argument has been put forward by Amato and Shin (2005). In their model, where private agents have diverse private information about the true state of the economy, the public signal provided by the central bank has a disproportionate effect on agents' decisions, is likely to crowd out their private information and then tends to lower the information value of prices.

hits households'income or their capacity to borrow (due e.g. to financial innovation). As households are confident that the central bank will not need to raise short term interest rates in a foreseeable future because they think that inflation is on check, they will tend to believe that observed and projected growth rates in housing prices are sustainable. Since their expectations of low future interest rate should increase mechanically their assessment of the present value of houses considered as assets, they will be more willing to buy housing property at high current prices (compared to historical records). Finally, they will be less reluctant to finance their home acquisition through mortgage contracts with adjustable rates, which are generally cheaper than fixed rate mortgages. Other things being equal, this last effect would contribute to making access to mortgage credit easier under a credible inflation targeting monetary policy regime.[4]

We aim in this paper to bring this hypothesis to the data and evaluate whether inflation targeting actually mattered as regards housing price inflation in developed OECD economies. Over the last decade, an abundant empirical literature has tried to quantify the macroeconomic performance of countries that adopted inflation targeting.[5] Most studies focus on inflation performance, in absolute or in relative terms, while some also examine whether adopting an inflation targeting strategy could be made responsible for a more volatile output. However, to our knowledge, there is no comparative empirical work about the consequences of inflation targeting policies for financial stability. We thus aim at filling this gap, using a program evaluation methodology that has been recently transposed to macroeconomic issues (see notably Persson, 2001 and Lin and Ye, 2007) in order to circumvent some self-selection bias that is likely to plague previous studies on the consequences of adopting inflation targeting. Our study encompasses 17 industrial economies over the period 1980-2006, among which nine countries have targeted inflation at some dates.

Our results show that the average effect of inflation targeting on house price inflation is positive and statistically significant. These results are robust to various specifications

[4] On the optimal choice between fixed and adjustable rate mortgages by indebted households, see Campbell and Coco (2003).

[5] See for instance Ball and Sheridan (2004), Lin and Ye (2007), Vega and Winkelried (2005) and the studies collected in Bernanke and Woodford (2004).

and options of the evaluation procedure. On average, the adoption of inflation targeting has led to an increase in the level of house price inflation by some 2.1 percentage points in targeting countries. Note that the estimated effect is even larger when the control sample is restricted to the most recent sub-period (from 1990 to 2006).

In the rest of the paper, section 2 provide a summary view of the recent housing price boom in developed OECD economies. Section 3 presents our econometric methodology. Section 4 presents the dataset and discusses several empirical issues. Section 5 comments on the results and section 6 concludes.

2 The housing price boom of the last decade

Since 1970, nominal housing price growth has fluctuated widely in developed economies, with four expansionary phases -in the early and late 1970s, in the mid to late 1980s and from the late 1990s to the mid-2000s- and three slowing phases -in the mid 1970s, the early 1980s and the early 1990s.[6]. Note that, while housing price busts are normally characterized by a significant drop in real house prices, nominal house price deflation is rare and was associated in the past with episodes of severe economic downturns, such as the recessions in the early 1990s in Finland, Norway and Sweden[7].

Most developed economies have experienced rapidly rising house prices since the mid-1990s.[8] Taken by its magnitude, length and geographical coverage, the latest boom has been quite exceptional. In the 17 OECD countries of our sample[9], the rate of growth of nominal housing prices has reached a yearly average of almost 7.5% (5.5% in real terms)

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[6] See for instance Lecat and Mésonnier (2005).

[7] For a description of past housing booms and busts and the size of associated recessions in developped OECD economies, see for instance Claessens, Kose and Terrones (2008).

[8] An exception is Germany whose nominal house prices have been gradually declining since they reached a modest peak in 1994. Japan is another obvious exception, the country being stuck over the whole 1990s in the slump consecutive to the housing price and stock market bust of the beginning of that decade. The Japanese case being quite special, we excluded Japan from our database. Note that since Japan did not target inflation over the period under review, excluding Japan tends to minimize the probability of rejecting the null of no-impact of IT on house price growth.

[9] Countries are listed in section 4 below

between 1996 and 2006, to be compared with only 5.4% over the 1980-1995 period (0.5% in real terms). In addition, the recent boom lasted for almost ten years in most countries, which is roughly twice as long as the duration of past episodes.

An abundant literature has investigated the reasons why this housing boom was so pronounced and in particular decoupled that much from normal business cycle fluctuations. Demographic trends such as changes in the composition of households, the impact of financial deregulation affecting mortgage markets via a credit boom (Cardarelli et al., 2008), the loosening of credit standards (Dell'Ariccia et al., 2008) and the declining trend in real interest rates (Girouard et al., 2006) have been proposed as possible factors explaining this phenomenon. To our knowledge however, no empirical study so far tests the impact of the monetary policy regime and in particular of inflation targeting strategies.

We appreciate in the following the buoyancy of the housing market according to the annual rate of growth of housing prices in real terms (denoted RHOPG).[10] Arguably, real housing price growth is a very rough measure of possible imbalances in housing markets. Other measures, like the gap between real housing prices housing price inflation to their respective one-sided HP trend or even a rent to price ratio, could have been considered here as well. However, reliable information on rent to price ratios is very difficult to obtain for a large number of countries over the last two decades. Besides, since we see no reason to suspect that inflation targeting as such could induce any substantive shift in the equilibrium or long run real housing price growth, it seems that detecting any extra-growth in housing price inflation would be enough to signal a contribution of inflation targeting per se on the build-up of a positive housing price gap.

Figure 1 shows real house price growth developments for each country of the panel. The shaded area indicates whenever the central bank follows an explicit inflation targeting strategy (see section 4 for details). Most economies experienced a sharp rise in residential property prices in the second half of the 1980s, that often followed on a deregulation of the housing finance sector. In the 1990s, house prices slowed down or fell, following the US

[10]Note that we also considered nominal housing price growth as a dependent variable, adding lagged inflation to the conditioning variables listed below in section 4. Results ar qualitatively unchanged. We nevertheless preferred to focus on real growth (1) for comparability with other studies and (2) to limit the risk of having conditioning variables that are endogenous to the adoption of formal inflation targeting.

recession in 1990-1991 and the episode of high interest rates in Europe after the ERM crisis in 1992-93. Finally, housing price inflation accelerated in the second half of the 90s for most countries, apparently irrespective of their monetary policy strategy. However, what this graphical evidence cannot tell is whether this surge in housing price inflation was stronger in targeting countries, other things else being equal. This is what our empirical exercise aims to clarify.

3 Methodology

Let us first consider equation (1) where we regress housing price inflation Y_{it} on a dummy variable D_{it} standing for the adoption of inflation targeting and on relevant control variables X_{it} using a panel of countries i over T periods:

$$Y_{it} = \gamma D_{it} + \beta X_{it} + \varepsilon_{it} \tag{1}$$

Estimating equation (1) using some standard regression technique, may yield biased estimates of the policy regime coefficient γ if countries that choose to follow inflation targeting strategies are systematically different in terms of X_{it} from countries that do not. For instance, it may well be that countries with more liberalized and more developped financial markets, and notably more deregulated mortgage markets, which may imply for instance a stronger impact of interest rate variations on housing price developments, are also countries that opt for an inflation targeting strategy. Indeed, a high degree of financial develoment is often seen as one pre-requisite for successful inflation targeting. In that case, we then face a problem of selectivity on the observables. Note that this problem cannot be solved by simply instrumenting the IT variable. The point at stake here is the possibility of non-linearities in the relationship between the control variables in X_{it} and the dependent variable Y_{it}.

Following recent work (Persson, 2001, Vega and Winkelried, 2005, Lin and Ye, 2007), we solve this problem by applying to our macroeconomic dataset a microeconometric technique borrowed from the program evaluation literature. The intuition is to consider the adoption of IT as a natural experiment and to mimic the conditions of a randomized experiment where adopting officially an IT strategy is equivalent to receiving randomly a "treatment". Our objective is thus to assess the average effect of the "treatment" on the treated (ATT) in terms of some dependant variable Y_{it} (here real house price growth). Formally, we have:

$$ATT = E\left[Y_{it}^{1}|D_{it} = 1\right] - E\left[Y_{it}^{0}|D_{it} = 1\right] \quad (2)$$

where $Y_{it}^{1}|D = 1$ denotes the value of the dependant variable in period t for a country that adopted IT $(D = 1)$ and $Y_{it}^{0}|D = 1$ is the value of the outcome that would had obtain the same IT country if it had not adopted IT at the same date. Of course, the latter is unobservable, so we cannot measure the ATT directly. If IT adoption were a purely random decision, one could nevertheless obtain an accurate estimate of the ATT by comparing the mean of the dependant variable over all targeters (the treatment group) and its mean over all non-targeters (the control group). However, it is very likely that IT countries did not adopt IT randomly but instead waited for some preconditions to be met. In turn, some of these preconditions can be expressed in terms of macroeconomic variables that may also play a role in determining the dependant variable (house prices). Assuming that these variables are not altered in turn by the treatment, a solution is then to condition the outcome on these explaining variables. Hence, we have :

$$ATT = E\left[Y_{it}^{1}|D_{it} = 1, X_i\right] - E\left[Y_{it}^{0}|D_{it} = 1, X_i\right] \quad (3)$$

If, conditionally on X_i, the dependant variable is independent of the strategy variable[11], $E\left[Y_{it}^{0}|D = 1, X_i\right]$ is then equivalent to $E\left[Y_{it}^{0}|D = 0, X_i\right]$, which is observable.

The intuition of the matching procedure is thus to find for each observation taken from an IT country a counterfactual equivalent observation that is taken from a non-targeter country. Conditioning on the X_i allows us to attribute the difference in the value of Y_{it} between both observations to the impact of the "treatment" alone. In practice, when the dimension of X_i is superior to one, matching treated units with control units that share the same values of X_i becomes rapidly a tricky task (aka. the "curse of dimensionality"). A solution initially developed by Rosenbaum and Rubin (1983) consists in summarizing the information in X_i into a single one-dimensional index, called the propensity score

[11] This assumption is called CIA (conditionnal independance assumption) in evaluation literature.

$p(X_i)$ and matching treated and control observations on the basis of a comparison of their respective score. The propensity score is the probability of getting the treatment conditional on X_i:

$$p(X_i) = P(D_{it} = 1|X_i) = E\left[D_{it}|X_i\right] \tag{4}$$

It can here be estimated in a straightforward way using a simple logit or probit regression. Importantly, one has then to check that we compare things that do indeed compare, i.e. that the control units used for the matching procedure share the same support as the treated units. In our application, we only keep control units $Y_{it}^0|D_{it} = 0$ such that their propensity score $p(X_{it})$ is superior or equal to the minimum of the distribution of the scores of the treated units, $min\left\{p(X)|D_{it} = 1\right\}$, and discard the remaining observations. Finally, estimating equation 2 amounts to computing:

$$E\left[Y_{it}^1|D_{ii} = 1, p(X_{it})\right] - E\left[Y_{it}^0|D_{it} = 0, p(X_{it})\right] \tag{5}$$

For robustness, we consider in the following a variety of propensity score matching methods. The first one are the nearest-neighbours matching with replacement, where a treated unit is matched to the n control units which have the closest propensity score. We apply this method for $n = 1$ and $n = 3$. The second one is radius matching, which matches a treated unit to the control units with estimated propensity scores falling within radius r. We use a relatively large radius ($r = 0.05$) and a smaller one ($r = 0.01$). The third method is local linear matching. The fourth one is kernel matching, which means that each treated unit is matched to all control units weighted in proportion to the closeness between the treated unit and the control unit[12].

[12] All matching procedures have been implemented using the Stata routine PSMATCH2 developped by Leuven and Sianesi (2003). See the technical appendix for some discussions about the methods.

4 Empirical issues

4.1 Data and definition of variables

Our data set includes 17 industrial countries, namely Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, the United Kingdom and the United States. The database covers the period from 1980 to 2006 with annual frequency. Nine countries—Australia, Canada, Finland, New Zealand, Norway, Spain, Sweden, Switzerland and the United Kingdom—adopted inflation targeting during our sample period. Note that two targeting countries, Finland and Spain, joined the Euro in 1999, thus switching from IT to non-IT in our sample. This notwithstanding, the within variability of the IT variable remains obviously very low, which makes usual panel regression methods less relevant, as stated in section 3 above.

Whatever the targeting country, the date of IT adoption is not always clear-cut and depends on how inflation targeting is defined. Several choices occur in the empirical literature. While some authors consider the first year when the turn to an IT-like strategy was mentioned or announced by monetary authorities, others adopt a stricter view and date IT adoption to the year when an explicit or fully fledged IT scheme was implemented, including the publication of a quantified inflation objective by the central bank.[13] For robustness, we considered both definitions in the following, that we labelled IT1 for soft inflation targeting and IT2 for the adoption of a fully fledged targeting scheme. Table 1 shows the adoption dates according to both definitions. Depending on the definition, adoption dates differ for four countries in our sample: Canada (by three years), New Zealand (one year), Spain (one year) and Sweden (two years). In others cases both definitions converge.

Commenting on Ball and Sheridan (2004), Gertler (2004) argues that a host of countries that these authors classified as non-targeters did actually run monetary policies that proved to be close in practice to formal inflation targeting. He concludes that classifying countries according to what they say (their official strategy), not what they do, is probably

[13] For details about dates of IT adoption, see Vega and Winkelried (2005) and references therein.

misleading when assessing the relative performance of countries in terms of inflation stabilization. In particular, this issue could be raised regarding the classification of two major non-targeting central banks, the US Federal Reserve of the Greenspan-Bernanke era as well as the ECB, which have been frequently described as implicit targeters by commentators.[14] Nonetheless, we preferred not to introduce any arbitrariness in our classification scheme and stuck to official statements about the prevailing monetary policy strategies in both economies.

4.2 Propensity scores estimation

We estimate the propensity scores using a pooled probit where the dependent variable is the targeting dummy (i.e. either IT1 for soft targeting or IT2 for fully fledged targeting) and the RHS variables are the factors deemed to influence the choice of an inflation targeting strategy and the dynamics of house prices. Remember that the purpose of the probit regression is to reduce the dimensionality of the matching problem, not to provide any plausible model of IT adoption. We must select all regressors that we would expect to have an impact on the ultimate variable of interest, here RHOPG, and could impinge on the IT status, thus implying a bias if we had computed the ATT without correction. Meanwhile, for the CIA to be valid, all conditioning variables should be chosen so that they are not influenced by the adoption of the IT regime.

Having this in mind, we finally selected seven conditioning variables for our baseline specification with reference to standard empirical models of housing price dynamics. These conditioning variables are : the lagged short and long interest rates in real terms (RIRS_1 and RIRL_1), the lagged net household disposable income in real terms (NDIG_1), a fixed exchange rate regime dummy (FER), a dummy variable indicating the degree of sophistication of the national mortgage market (MS) and the lagged ratio of the private credit to GDP (CREGDP_1) as a proxy for national financial development[15].

[14] Goodfriend (2005) argues e.g. that the recent successes of US monetary policy "...can be attributed in large part to inflation-targeting policy procedures that the Fed has adopted gradually and implicitly over the last two decades".

[15] Data sources and construction are detailed in Appendix A. In some variants of the baseline specification, we replaced the ratio of credit to GDP with the rate of net houshold savings to their disposable income

We took special care in correcting for cross-country heterogeneity in mortgage structures. Indeed, a few recent studies suggest that those structures matter for housing price dynamics.[16]. They can also have a bearing on the probability to adopt or not an inflation targeting scheme. Indeed, one may argue that monetary authorities are more likely to implement IT when they gauge that the domestic banking and financial systems are developed enough for monetary transmission to work through quickly and efficiently[17]. In practice, controlling for differences in mortgage structures between countries is not an easy task because most available data on the mortgage market characteristics of OECD countries are qualitative, or given as constant for the last two decades (which means that they may actually refer to different periods of time), thus ignoring possible trend changes in market regulations or practices (as the extension of securitization or the decrease in credit standards over the last decade). To bypass these data limitations, we can use some proxies for financial development, such as the private credit-to-GDP ratio[18]. Another possibility is to construct a composite index summarizing institutional aspects of the mortgage markets such as the IMF (2008) recently did it. A quick look at mortgage market characteristics as shown in table 2 suggest that IT countries are predominantly countries where for instance variable rate mortgages prevail, mortgage equity withdrawal is at least legally possible and often used and loan-to-value ratios of mortgages are relatively high. However, it is fair to note that some non-targeters do also share the same strutural characteristics.

That said, we constructed a dummy variable (see data appendix for details) using the results in Calza et al. (2008) and Gerlach and Assenmacher-Wesche (2008). Table 2 details the specific features of mortgage markets that are covered by our dummy variable. Each country is classified as having either a "highly developed" (the dummy variable MS equals

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(SAR), as a proxy of the capacity of housholds to borrow. We also choose a broader indicator of financial development such as liquid liabilities to GDP ratio as in Beck, Demirguc-Kunt, Levine (1999). Finally, we tested the inclusion of a banking crisis dummy (BKCR). None of these changes did affect qualitatively our results. The results are available upon request to the authors.

[16] See Tstatsaronis and Zhu (2004), Gerlach and Assenmacher-Wesche (2008) and Calza et al. (2008).

[17] Mishkin (2004) argues that a sound and well-developed financial system is a necessary condition for the success of an inflation targeting regime.

[18] This measure is widely used in the empirical literature. See Beck, Demirguc-Kunt and Levine (1999).

1) or a “less developed” (the dummy variable MS equals 0) mortgage market. Indeed, significant differences remain in the institutional features of national mortgage markets among OECD countries. Broadly speaking, IT countries (Australia, UK, Sweden and Norway) provide the easiest access to home ownership. In contrast, in non IT countries (France, Italy, Germany, Belgium) the access to housing finance is somewhat constrained. Nevertheless, some exceptions remain such as the US and the Netherlands (both "highly developed" mortgage markets but non IT countries).

Let us turn now to the expected signs of the estimated coefficients in the probit regressions. On the basis of previous studies, we would expect real interest rates and the fixed exchange rate regime to be negatively correlated with the probability of running an inflation targeting strategy. On the contrary, we would expect a positive coefficient for the CREGDP variable and the mortgage structure dummy, since a developed financial system warranting an efficient transmission of monetary policy is often seen as one of the prerequisites for IT adoption.[19]. We would also expect a positive sign for the net disposable income growth.

Table 3 provides summary statistics for housing price growth in real terms and the set of conditioning variables chosen. The comparison of the means of the relevant variables across non-inflation targeting (first two columns for two different periods) and inflation targeting countries reveals that inflation targeters exhibit on average higher real house price inflation, as well as a larger banking credit to GDP ratio and a somewhat stronger net disposable income growth. However, they display lower short and long term real interest rates. These preliminary statistics hint that a simple comparison of housing price inflation in IT vs non-IT countries is potentially affected by non-random selection of the "treated", which should bias the result. This again provides support to the program evaluation methodology we adopted here.

Finally, table 4 shows the results of the pooled probit estimations[20] in four cases corresponding to the two different timings of IT adoption and two different time periods

[19] See for instance Mishkin (2007, p. 411) for a list of prerequisites.

[20] As a robustness test, we estimated a panel probit with random effects to control for unobservable heterogeneity across countries. The magnitude and sign of all the coefficients has not changed.

for the control group of observations (i.e. 1980-2006 vs 1990-2006). For robustness, we also present in table 4 a model specification based on an alternative measure of financial development (the net households' savings to income ratio, SAR). Constant terms were included in the regressions but are not reported for clarity. The real short term interest rate (RIRS_1), the ratio of private credit to GDP (CREGDP_1), the fixed exchange rate dummy (FER) and mortgage structure dummy (MS) all show up to be significant and with the expected sign. The quality of the fit is reasonably good with a pseudo-R^2 between 0.31 and 0.44 depending on the model. Figure 4 displays the densities of the propensity score for IT and non-IT countries as derived for each of the estimated four models of table 4. Although the model has not been designed as a proper model of IT adoption, it is noteworthy that it does a relatively good job in discriminating the two types of countries. Indeed, we can see a marked difference in the densities of propensity score between targeters and non targeters in the upper right hand panel. It can also be seen that changes in the definition of IT adoption dates affects the densities to a lesser extent than changes in the control group. However, whatever the size of the control group or the timing of IT adoption, the densities relative to targeters and non-targeters still have a large common support[21], which warrants that we can implement a matching strategy based on a comparison of the propensity scores.

5 Result of matching

This section details the results of the matching procedure. Table 5 reports the estimated ATT of following an IT strategy on housing price inflation in real terms (RHOPG), while table 6 reports the estimated ATT on housing price inflation for an alternative specification of the probit. The first two rows of each table show the results when the control group covers the 1980-2006 period, contrasting the cases of soft and explicit IT, while the third and fourth rows show the results when the control group is restricted to data from 1990 on. The matching procedure can be implemented in several ways. All methods aims to construct an estimate of the expected unobserved counterfactual for each treated observation by taking a weighted average of the outcomes of the untreated observations.

[21] Defined as the intersection of the densities.

What differs among the various matching estimators is the specific form of the weights. The first two columns show the results for one-to-one-nearest neighbor and three-nearest-neighbor matching. Columns 2 to 6 correspond to alternative methods of matching as mentioned in section 3 and are presented here for robustness. Asymptotically, these estimators produce the same estimate, because in an infinite sample, they all compare only exact matches. Since we have a finite sample, they produce different estimates. We follow the previous literature and use the bootstrap method to obtain standard errors for the matching estimators (2000 bootstrap replications).

Overall, we find robust evidence of a positive and significant effect of running an IT strategy on housing price inflation. The average ATT on RHOPG across all matching methods and model variants is 2.1 percentage points when the control group covers the whole period. Note also that the observed positive ATT comes out to be larger when the control group is limited to post 1990 data, which tends to strengthen our hypothesis that IT does play a significant role.[22]

Finally, we have to check that the matching procedure correctly balances the distribution of the conditioning variables in both the control and treatment group. The initial balancing test was proposed in Rosenbaum and Rubin (1983). The standard test is a two-sample t-test that there are no significant differences left in the means of conditioning variables across both groups. Indeed, if the matching procedure was run in an appropriate way, no significant differences should remain. Table 7 shows the results of the balancing tests and displays the paired t statistics for the difference in the mean between IT and the matched sample of non IT. Under the two definitions of IT, the conditioning variables are well balanced. As suggested by Sianesi (2004) we re-estimate the propensity score on the matched sample and compare the pseudo-R^2 before and after matching. After matching, the pseudo-R^2 is lower because after matching there is no systematic differences in the distribution of covariates between both groups (see pseudo R^2 in the lower part of table 7). In addition, the joint significance of the regressors is then always rejected (see the p-values of the LR test). Hence, the matching procedure proves to wipe out most of the

[22] However, some caution is required here since results based on a smaller control group may be plagued with small sample biases.

initial selection bias.

6 Conclusion

In this study we have used program evaluation techniques to assess the dimensions in which the choice of an inflation targeting strategy by the central bank has had an impact on housing price dynamics in 17 OECD countries. This exercise can very much be seen as an empirical test of the "paradox of credibility hypothesis" propounded at the beginning of this decade by Claudio Borio and other authors at the BIS. Our central findings support the idea that the adoption of IT, either in its soft or fully fledged version, has a significant impact on the growth rate of house prices. These results are robust to changes in the matching methodology and the size of the control group. That said, our results may suffer from several data limitations in particular regarding the quality and comparability of house price data. In addition, given that, for most countries, data on credit for house purchase is not available on a sufficiently long period, it was not possible to test simultaneously for an impact of IT on mortgage credit growth. This would have usefully completed the picture, since the latest housing price boom was clearly sustained by a concomitant credit boom.

Overall, the evidence presented in this paper provides an impetus for further research, both theoretical and empirical, on the relatively neglected issue of the consequences of inflation targeting strategies for financial stability.

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Appendix A: data

We use yearly data for 17 OECD countries covering a period that ranges from 1980 until 2006. Data are seasonally adjusted except for interest rates. The set of data series comprises:

- We used data on residential property prices provided by the Bank for International Settlements (BIS). The BIS collects the data from national sources. We used yearly nominal house price series. Series are indices at the end of the year[23].

- Real net household disposable income is from the OECD Economic Outlook database. Data were expressed in billions of national currency units. Growth is defined as year-on-year changes (NDIG).

- The short-term interest rate (IRS) is a 3-month money market rate taken from the OECD Economic Outlook database. The long-term interest rate (IRL) is the yield on long-term government bond on the secondary market with residual maturity of about 10-years. The interest rates used are yearly averages of daily figures taken from the OECD Economic Outlook database. Real rates are computed as ex-post real interest rates using annualized inflation rates (RIRS and RIRL).

- Data for credit to the private sector (CRE) is taken from the IMF IFS database (codes 32d which include gross credit from the financial system to individuals, enterprises and non financial public entities). Series are outstanding amounts at the end of the year. Many of the IMF credit series displayed large level shifts owing to changes in definitions or re-classifications. So, when series showed significant structural breaks as indicated by a TRAMO application, breaks have been corrected one by one. The level of the series was then adjusted by backdating the series starting from the sample end and based on the adjusted series. We detected level shifts and therefore we adjusted series for Belgium, Canada, Denmark, Ireland, New Zealand and Sweden. Then, we calculated, as in Borio and Lowe (2002), the ratio of nominal credit to nominal GDP (CREGDP).

[23] More details on the house-price series are available in Arthur (2005).

- We constructed a banking crisis dummy variable (BKCR) that takes the value 1 during the crisis. To identify banking crisis episodes, we rely on the updated database of Caprio and Klingebiel (2003) maintained by the World Bank .

- The FER variable is a dummy variable. We use the exchange rate classification proposed by Reinhart and Rogoff (2004). We consider the first two categories of the Reinhart and Rogoff's classification as fixed regimes (the dummy variable equals 1) and for the other categories, the dummy variable equals 0.

- The IMF mortgage market index is constructed using 5 institutional characteritics of the mortgage market (see Table 1 in IMF (2008)): mortgage equity withdrawal, the existence of early repayment fees, the loan-to-value ratio, the development of the covered bonds market and the mortgage-backed securities market.

- In our own index, we considered the following variables: the presence of mortgage equity withdrawal, the loan-to-value ratio, securitization, the share of owner-occupied homes, the type of interest rate adjustment (fixed or variable). Sources are available in IMF (2008), in Calza et al. and in Assenmacher-Wesche and Gerlach (2008). For securitization, values of 0, 0.5, and 1 are assigned to each country depending on whether this feature is nonexistent, limited, or widespread, respectively. For loan-to-value ratio and share of owner-occupied homes, each country is assigned a value between 0 and 1, equal to the ratio to the maximum value across all countries. Then, our index is computed as a simple average of these four features. It ranges from 0 to 1 with higher values indicating easier access to household mortgage finance. The group of 17 countries is split in two groups where each country is classified as having either a "high developed" (the dummy variable MS equals 1) or a "low developed" (the dummy variable MS equals 0) mortgage market (see table 2)

Appendix B: A bird's-eye view of matching methods

The matching method is quite intuitive but rests on a number of assumptions:

- The Conditional Independence Assumption (CIA).means that given a set of observable covariates X which are not affected by treatment, potential outcomes are independent of treatment assignment. Rosenbaum and Rubin (1983) show that if potential outcomes are independent of treatment conditional on covariates X, they are also independent of treatment conditional on a balancing score p(X). In our case, this condition is verified as shown by the balancing tests.

- Another assumption is the so-called SUTVA assumption (Stable Unit Treatment Value Assumption) which states that the impact of the treatment on one country does not depend on the other treated units. This assumption is resaonable in our case.

- The common support requirement (aka the overlap condition) ensures that units with the same conditioning variables values have a positive probability of being both treated and non-treated. This ensures the existence of both comparable treated units for each control unit and comparable control units for each treated unit.

There are a number of possible ways of identifying the matched group:

- The nearest-neighbour method involves matching each treated unit with a control unit with the closest propensity score. It may be that a control unit provides the closest match for a number of treated units. In this case, a control unit may be matched to more than one treated unit. Dehejia and Wahba (1998) find that allowing for control units to be used more than once as comparators improves the performance of the match (matching with replacement). In our case, we allow replacement to increase the quality of matching.

- More than one nearest neighbour (oversampling) involves a trade-off between variance and bias. It reduces the variance because of using more information to construct the counterfactual but increases bias due to poorer matches. In our case, we decided to allow for three neighbours for each treated unit with a uniform weight.

- Radius matching (Dehejia and Wahba, 2002): the idea is to use all of the control unit within a radius. This approach enables to use only as many comparison units as are available within the radius and therefore allows for usage of extra (fewer) units when good matches are (not) available. Hence, it enables to reduce the variance, but avoids the risk of bad matches.

- Kernel and local linear matching: these matching estimators construct a match for each treated unit using a weighted average over several units in the control group. The 'kernel' is a function that weights the contribution of each control unit, usually so that more importance is attached to those comparators providing a better match. Formally, it can be expressed as follows:

$$ATT_k = \frac{1}{n_1} \sum_{i \in I_1} \left(Y_{1i} - \frac{\sum_{j \in I_0} Y_{0i} G\left(\frac{P_j - P_i}{\alpha_n}\right)}{\sum_{j \in I_0} G\left(\frac{P_j - P_i}{\alpha_n}\right)} \right) \tag{6}$$

  where I_1 denotes the set of treated, I_0 the set of controls, n_1 the number of units in the common support region and P_j is the estimated propensity scores of unit i. G(.) is the kernel function and α_n the bandwidth parameter. In our case, we decided to choose the Epanechnikov kernel defined as $G(u) = \frac{3}{4}\left(1- \mid u \mid ^2\right)$ and a bandwidth parameter of 0.8.

Small sample bias:

- Small sample size presents some specific problems for propensity score matching (Heckman, Ichimura, and Todd, 1997). First, with a small sample, gaps appear in the common support, so that treatment effects can only be retrieved for a limited number of the treated units, resulting in a bias. Second, small samples increase the variance of estimated effects, making identification of significant effects more difficult. To circumvent this, some matching methods are more robust to the small sample size problem. Frölich (2004) investigates finite-sample performance of matching estimators. He concludes that kernel and ridge matching are the most robust to small sample problems.

Table 1: Inflation targeters and dates of IT adoption

Countries	Starting year of IT strategy	
	soft (IT 1)	explicit (IT 2)
Australia	1994	1994
Canada	1991	1994
Finland	1993	1993
New Zealand	1990	1991
Norway	2001	2001
Spain	1994	1995
Sweden	1993	1995
Switzerland	2000	2000
United Kingdom	1992	1992

Source: Vega and Winkelried (2005).

Table 2: Structural features of national mortgage markets

	Mortgage equity withdrawal	Loan-to-value ratio (in %)	Interest rate adjustment	Securitisation	Share of owner occupied homes (%)	IMF index	Dummy MS1
Australia	yes	80	V	yes	70	0.69	1
Belgium	no	83	F	no	72	0.34	0
Canada	yes	75	F	yes	66	0.57	1
Denmark	yes	80	F	no	59	0.82	0
Finland	yes	75	V	no	64	0.49	1
France	no	75	F	no	56	0.23	0
Germany	no	70	F	no	42	0.28	0
Ireland	limited	70	V	yes	78	0.39	1
Italy	no	50	F	no	80	0.26	0
Netherlands	yes	90	V	yes	53	0.71	1
New Zealand	yes	-	F	-	-	-	0
Norway	yes	70	V	no	77	0.59	1
Spain	limited	70	V	yes	85	0.4	1
Sweden	yes	80	F	no	61	0.66	0
Switzerland	no	-	V	no	36	-	0
UK	yes	75	V	yes	70	0.58	1
US	yes	80	F	yes	69	0.98	1

F = fixed and V = variable.

Sources: IMF (2008); Calza, Monacelli and Stracca (2008); Gerlach and Assenmacher-Wesche (2008).

Table 3: Descriptive statistics

	IT1=0, 1980-2006			IT1=1, 1980-2006		
Variables	Obs	Mean	Std.Dev.	Obs	Mean	Std.Dev.
RHOPG	343	2.13	7.71	99	3.99	5.87
RIRS	343	4.15	3.18	99	3.25	1.83
RIRL	343	4.56	2.66	99	4.24	1.75
NDIG	323	2.27	2.40	99	2.68	2.41
CREGDP	343	0.70	0.43	99	1.01	0.35
MS1	343	0.51	0.50	99	0.62	0.49
SAR	343	11.50	9.74	99	5.85	5.21
BKCR	343	0.10	0.30	99	0.05	0.22

Table 4: Probit regressions

Variables/regression	IT1	IT2	IT1 (post 1990)	IT2 (post 1990)	IT1 with SAR	IT2 with SAR
RIRS(-1)	-0.15	-0.23	-0.16	-0.24	-0.205	-0.28
	(0.06)**	(0.05)***	(0.07)**	(0.07)**	(0.05)***	(0.05)***
RIRL(-1)	0.30	0.37	0.46	0.51	0.24	0.308
	(0.06)**	(0.07)***	(0.10)***	(0.11)***	(0.06)***	(0.06)***
NDIG(-1)	-0.01	0.04	0.03	0.10	-0.06	-0.008
	(0.03)	(0.03)	(0.04)	(0.04)**	(0.03)*	(0.03)
FER	-1.94	-2.08	-2.15	-2.30	-1.66	-1.78
	(0.23)***	(0.25)***	(0.23)***	(0.24)***	(0.20)***	(0.22)***
MS1	0.40	0.34	0.48	0.40	0.07	0.04
	(0.18)**	(0.19)*	(0.19)**	(0.20)**	(0.16)	(0.16)
CREGDP(-1)	1.75	1.76	1.57	1.53	-	-
	(0.23)***	(0.24)***	(0.29)***	(0.36)***	-	-
SAR(-1)	-	-	-	-	-0.05	-0.05
	-	-	-	-	(0.01)***	(0.01)***
Obs.	425	425	289	289	425	425
Countries	17	17	17	17	17	17
Pseudo-R^2	0.38	0.40	0.43	0.44	0.31	0.34

Note: robust standard errors in parenthesis based on Huber-White sandwich estimator for variance

Constant terms are included but not showed for the sake of concision

*, **and *** indicate the significance level of 10%, 5% and 1% respectively

Table 5: Estimates of the ATT on housing price inflation: baseline (financial development proxied by the credit to GDP ratio).

	Matching methods						Number of	
	Nearest neighbor matching	Three nearest neighbor	Radius matching r=0.01	Radius matching r=0.05	Local linear regression	kernel matching	controls units	treated units
IT1 whole sample	2.174	3.162	2.845	2.721	3.141	2.566	198	99
	(1.584)	(1.582)**	(1.337)**	(1.315)**	(1.377)**	(1.45)**		
IT2 whole sample	2.665	2.607	2.113	2.761	2.508	2.808	186	92
	(1.151)**	(1.130)**	(1.186)*	(0.915)***	(1.029)**	(1.379)***		
IT1 post-1990 sample	5.729	5.559	5.075	5.521	4.905	5.577	121	99
	(1.844)***	(1.856)***	(1.690)***	(1.544)***	(1.794)***	(1.169)***		
IT2 post-1990 sample	4.668	4.072	4.493	5.294	5.298	5.303	94	92
	(1.359)***	(1.422)***	(1.719)***	(0.886)***	(1.389)***	(1.610)***		

Bootstrapped standard errors for ATT are reported in parenthesis (2000 replications)

*, **, and *** indicate the significance level of 10%, 5%, and 1% respectively.

Table 6: Estimates of the ATT on real housing price growth: variant (financial development proxied by households' savings to income ratio).

	Matching methods						Number of	
	Nearest neighbor matching	Three nearest neighbor	Radius matching r=0.01	Radius matching r=0.05	Local linear regression	kernel matching	controls units	treated units
IT1 whole sample	1.222	1.466	0.970	1.705	1.411	1.653	253	98
	(1.073)	(1.254)	(0.953)	(0.953)*	(0.957)	(0.923)*		
IT2 whole sample	1.689	1.462	1.341	1.950	1.633	1.946	225	91
	(1.254)	(1.065)	(1.020)	(0.900)**	(0.977)*	(0.901)**		
IT1 post-1990 sample	4.254	3.765	4.024	3.671	3.936	4.493	122	98
	(1.476)***	(1.421)***	(1.622)**	(1.228)***	(1.343)***	(1.116)***		
IT2 post-1990 sample	3.426	3.790	3.493	1.089	3.859	4.015	116	91
	(1.261)***	(1.220)***	(1.160)***	(1.171)***	(1.158)***	(1.128)***		

Bootstrapped standard errors for ATT are reported in parenthesis (2000 replications)

*, **, and *** indicate the significance level of 10%, 5%, and 1% respectively.

Table 7: Balancing tests (Three Nearest Neighbor Matching)

	IT1A model 1		IT2A model1		IT1A 1990-2006		IT2A 1990-2006	
Variables	Difference	Paired t Statistics	Difference	Paired t Statistics	Difference	Paired t Statistics	Difference	Paired t Statistics
RIRS	0.333	-0.92	0.134	-0.41	0.2823	-0.82	-0.083	0.26
RIRL	0.321	-0.99	0.379	-1.25	0.3439	-1.27	0.191	-0.71
NDIG	0.061	-0.19	-0.04	0.12	-0.341	1.06	-0.51	1.53
CREGDP	0.011	-0.19	-0.036	0.58	-0.067	1.04	-0.034	0.52
FER	0.013	-0.32	0.014	-0.35	0.013	-0.32	0.018	-0.44
MS1	-0.11	1.62	-0.065	0.90	-0.026	0.39	-0.03	0.55
Pseudo-R^2 before matching	0.256		0.259		0.309		0.238	
Pseudo-R^2 after matching	0.035		0.022		0.015		0.026	
$Pr > \chi^2$	0.424		0.478		0.658		0.348	

Note: $Pr > \chi^2$- denotes the p-value of the likelihood ratio test after matching.

Figure 1: Real house prices: growth rate (% rate of change). Source: BIS. Shaded area indicates inflation targeting regime.

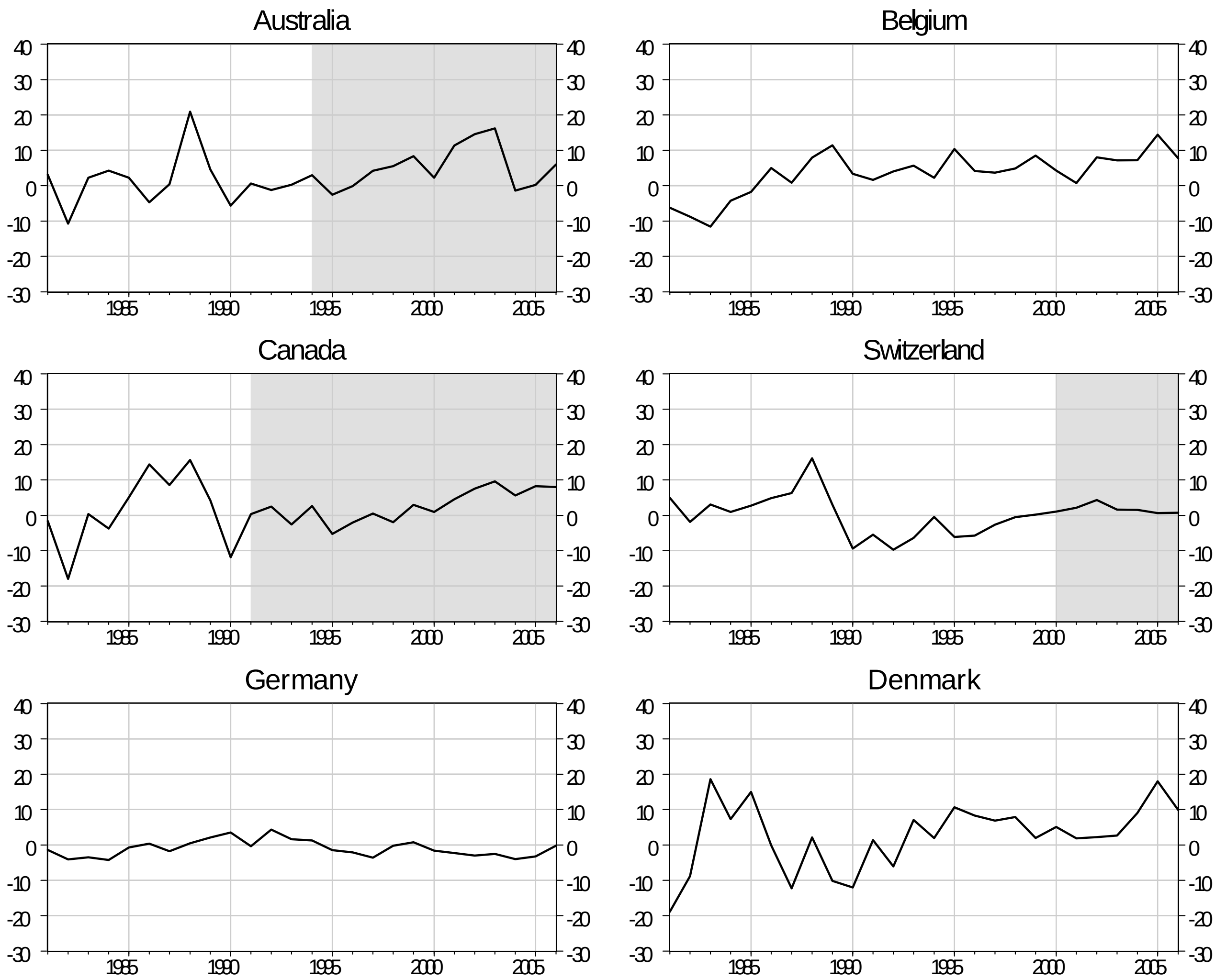

Figure 2: Real house prices: growth rate (% rate of change). Source: BIS. Shaded area indicates inflation targeting regime.

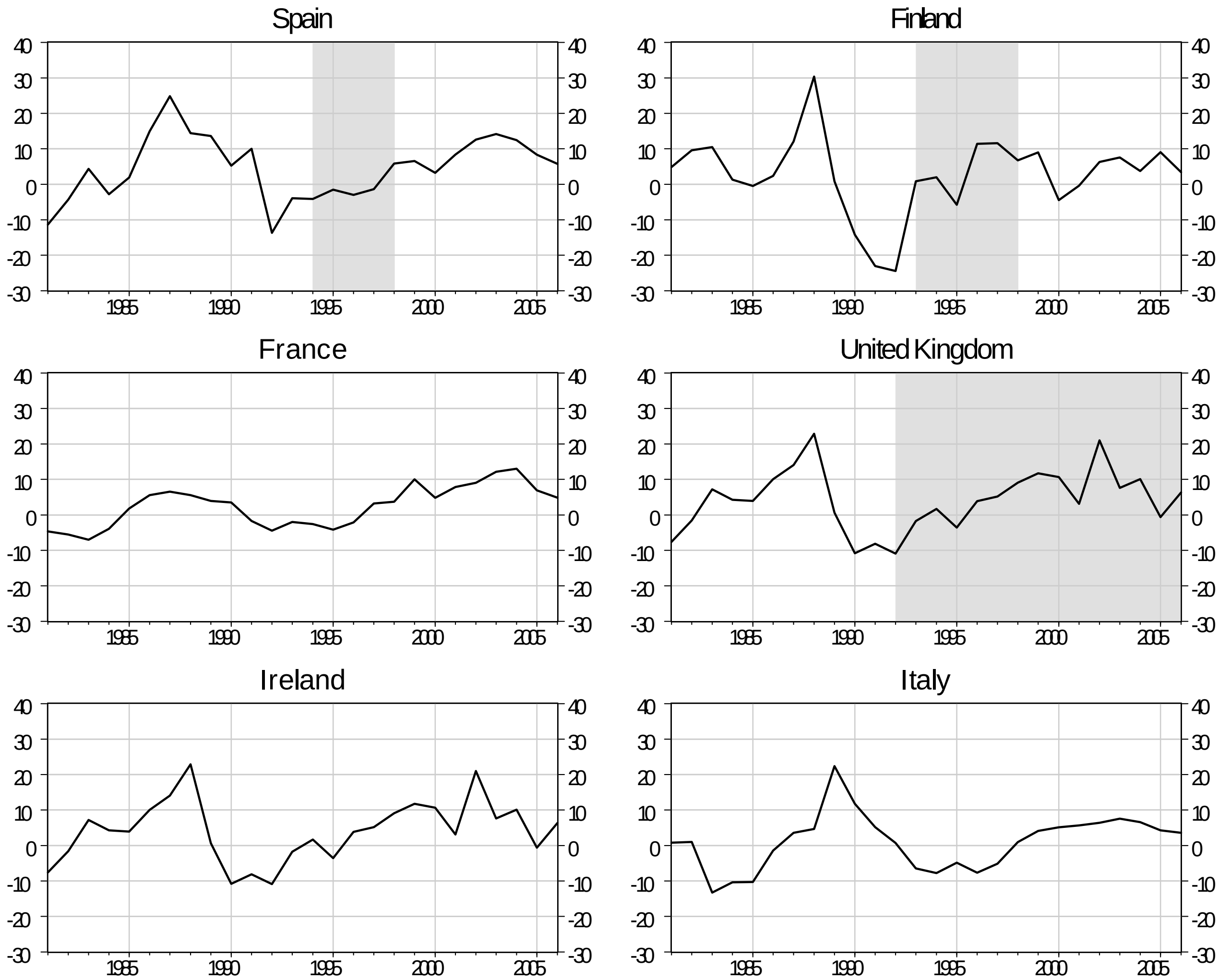

Figure 3: Real house prices: growth rate (% rate of change). Source: BIS. Shaded area indicates inflation targeting regime.

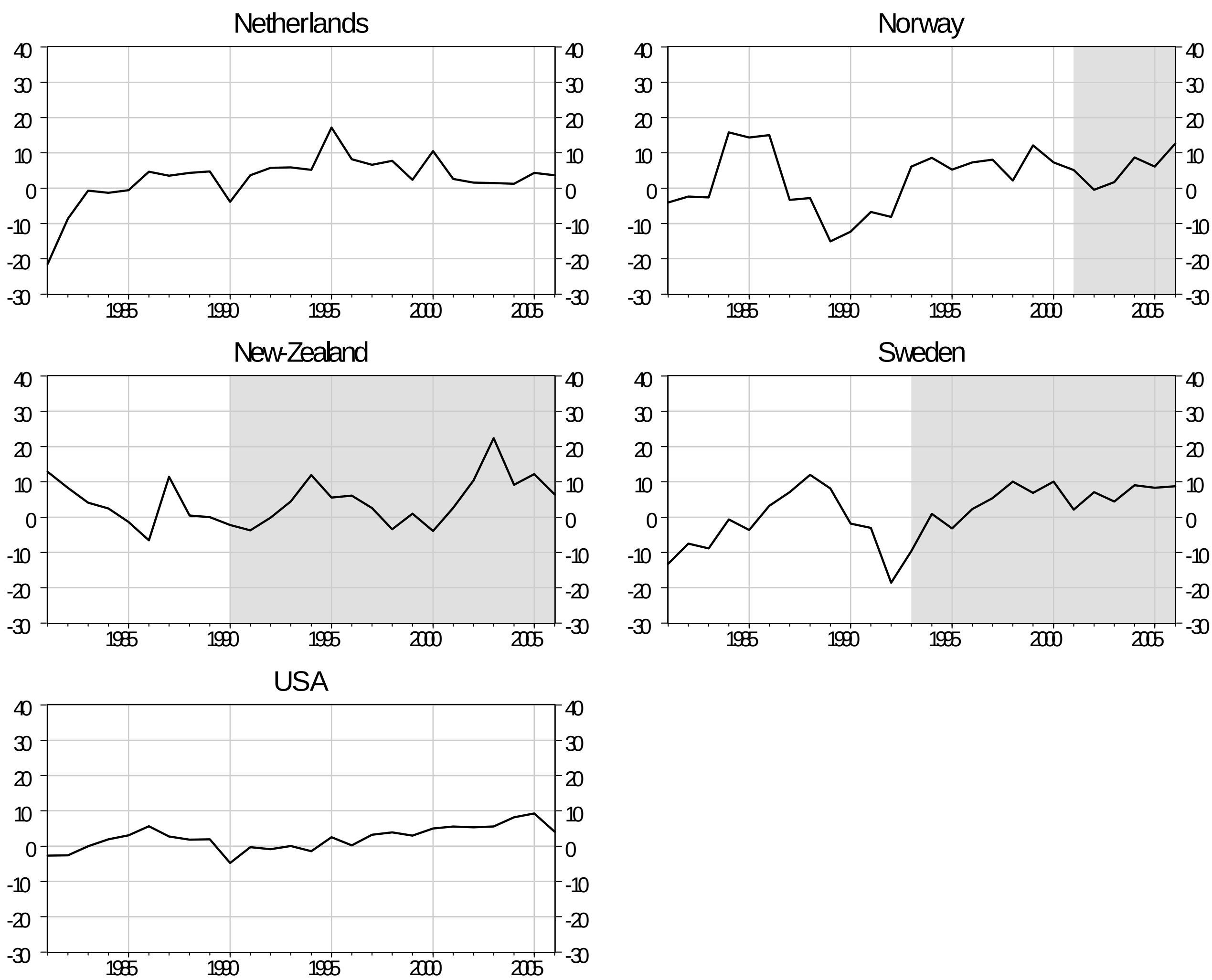

Figure 4: Densities of estimated propensity scores. First row: controls over 1980-2006, second row: controls over 1990-2006. First column: IT1, second column: IT2.