IDENTIFYING ASSET PRICE BOOMS AND BUSTS WITH QUANTILE REGRESSIONS

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Identifying asset price booms and busts with quantile regressions

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Abstract

This paper presents a methodology for detecting asset price booms and busts using non-parametric quantile regressions. The method consists in estimating the distribution of real stock prices as a function of fundamental determinants of stock returns, namely real economic activity and real interest rates. It is shown that changes in fundamentals affect not only the location but also the shape of the conditional distribution of stock prices. Asset price booms and busts are identified as realizations on the tails of that distribution. Then we use several indicators to analyse the behaviour of money and credit around the boom and bust episodes.

JEL classification: E43; E52.
Keywords: Quantile regression, quantile smoothing splines, asset prices.

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1   Introduction

When studying the relation between monetary policy and asset prices, it is often necessary to make a judgment as to what the fundamental price of the financial asset is. It is generally thought that it is undesirable that financial assets prices deviate too much from their fair values. In particular, the development of asset price bubbles which may later burst is a concern from the point of view of macro and financial stability.

While the question of how should monetary policy react to asset price misalignments remains an open one, and one which is beyond the scope of this paper, there is nevertheless a great deal of interest in detecting periods of asset price misalignment. Without indicators of asset price misalignments prescriptions on how to react to asset price booms and busts cannot go beyond the theoretical domain.

Despite the difficulties in detecting episodes of asset price misalignment, several proposals for such indicators have been put forward in the literature. Examples of these methods include looking at historical patterns of price-earnings ratio, dividend yields, discounted cash flows, etc (see Gürkaynak, 2005, for a review).

The purpose of this paper is to develop new indicators of stock price misalignment relying on quantile regressions.

In a recent study for 18 OECD countries, Detken and Smets (2004) define asset price booms as a period during which the aggregate real asset price index is continuously more than 10% above its trend. In turn, the trend is computed recursively using a one-sided Hodrick-Prescott filter. Implicit in this approach is the estimation of quantiles of the time-varying distribution of asset returns, whose ranks, however, remain unspecified. With formal quantile methods it is possible to estimate the whole conditional distribution of stock prices. Therefore, by monitoring its evolution over time, valuable information can be gained not only regarding possible booms or busts (that is "extreme" realizations) but also regarding the evolution of dispersion and asymmetry of the distribution of real stock prices.

The conditioning variables may be the calendar time, as in Detken and Smets, or other variables reflecting macroeconomic information. In the literature, several authors have found evidence that the distribution of stock returns varies according to the business cycle. For instance, Schwert (1989) and Hamilton and Lin (1996) find that the volatility of stock returns rises during recessions and decreases during booms. More recently, Péres-Quirós and Timmerman (2001) show that there are significant business cycle asymmetries in the behaviour of US stock returns. These authors look at the conditional density of stock returns modelled as a two-state Markov process, where the conditional distribution of stock returns in each regime is a function of the short-term interest rate, the default period and the dividend yield. Thus, methods of detecting asset price booms that ignore the effect of the business cycle may provide erroneous indications.

A final advantage of the quantile regression approach is that it allows significant flexibility in modelling the conditional distribution of returns over time. Quantile regressions allow for period by period changes in the conditional distribution of returns to depend on a set of conditioning variables and not only on a limited number of states, as in Péres-Quirós and Timmerman (2001). Thus, such indicators are useful for detecting possible episodes of asset price misalignment as well as for providing information on the evolution of asset price uncertainty over time. In addition to helping with inferring instances of unsustainable asset

price valuation, the quantile approach presented here can also be used to determine Value at Risk (VaR) or, more precisely, conditional VaR. Examples of quantile applications with this aim include Engle and Manganelli (1999) and Chernozhukov and Umantsev (2001). The underlying idea of the approach is that VaR should be measured conditionally. For instance, in times of economic slowdown it is more likely that firms make losses than in good times. Correspondingly, VaR, defined as the highest loss made for a given level of probability, is likely to decline in recessions and rise in expansions. Similarly, VaR measures for aggregate stock price indices should fluctuate with the business cycle, as allowed by the technique proposed in this paper but not by other methods.

In sum, it appears desirable to develop measures of asset price over/undervaluation that take the overall macroeconomic environment into account. Quantile regressions are a useful instrument in this respect as they provide estimates that help to characterise the distribution of the returns conditional on a set of "fundamental" variables.

This paper identifies misalignments as instances where the real asset price index is in the tails (say, right and left 10% tails) of its distribution conditional on the macroeconomic determinants of asset prices (basically trend GDP and trend real interest rate). Given the information on the "fundamentals" , the conditional distribution of asset prices is estimated by nonparametric quantile regression based on the quantile smoothing splines proposed by Koenker, Ng and Portnoy (1994) (see also He and Ng, 1999) for univariate smoothing problems and extended to bivariate settings by Koenker and Mizera (2003).

The paper is organized as follows. Section 2 develops the basic intuition for considering the impact of the macroeconomic environment on the distribution of stock prices. In section 3 we present the statistical methods used in the paper. Section 4 presents the empirical results of estimating different conditional distributions of asset prices for the Euro area (EMU Price Index). In section 5 the estimated distributions are used to date booms and busts, and this dating is compared with monetary and credit indicators. Section 6 concludes.

2   Macroeconomic fundamentals and the conditional distribution of stock prices

One important advantage of the use of the quantile regression approach for detecting periods of asset price misalignment is that it allows the modelling of the distribution of stock returns as a function of a set of economic fundamentals. There are many reasons to argue that the distribution of stock returns may be affected by changes in the economic environment. For instance, an improvement in economic prospects should lead to a rise in the potential for appreciation of the stock market and reduce the probability of lower returns. As a result, one should expect that stock returns would "normally" be higher in good economic periods than in periods of weak economic activity. This consideration is important when assessing whether the level of stock returns can be considered as justified by fundamentals or may be abnormally high or low. In fact, when referring to asset price booms and busts, one must have formed an estimate of what constitutes an exceptionally high or low return. As argued in this paper, past stock market performance is not the most appropriate benchmark for such assessment, as in the case of the univariate approaches such as those of Detken and Smets (2004). Instead, it appears more appropriate to condition the distribution of returns

on measures characterising the macroeconomic environment.

For the purpose of identifying periods of asset price booms or busts it appears preferable to work with levels rather than returns. In fact, the concept of asset price misalignment is usually understood as a deviation between the level of the asset price and its fundamental value. In order to derive a model of fundamental stock price valuation, one can resort to a standard model of asset pricing. For instance, in a study focusing on the euro area, Cassola and Morana (2002) resort to the Gordon (1962) growth model to link the level of real stock prices and the level of real GDP in the euro area. Following a similar approach, one can start from a standard asset pricing model where the level of real stock prices (P_t) is specified as:

$$P_t = E_t \sum_{t=0}^{\infty} \beta^j \frac{u'(D_{t+j})}{u'(D_t)} D_{t+j} \tag{1}$$

where D represents dividends, β is a subjective discount factor and u' represents marginal utility. In the special case of a log utility function, the following result holds:

$$P_t = \frac{\beta}{1-\beta} D_t \tag{2}$$

Proceeding as in Cassola and Morana (2002), one may assume that there is a proportional relation between real dividends and real output of the form:

$$D_t = k Y_t^{\phi} \exp(\varepsilon_t) \tag{3}$$

where ε_t is a stationary disturbance, k is a proportionality constant and $\phi > 0$. Given this, the following relation can be specified between the logarithm of real stock prices and the logarithm of real output (where lower case letters denote logarithms):

$$p_t = \ln(\frac{\beta}{1-\beta}) + k + \phi y_t + \varepsilon_t \tag{4}$$

Finally, setting the discount factor β equal to $\frac{1}{1+r}$ where r is the discount rate, then, one obtains:

$$p_t = -\ln r + k + \phi y_t + \varepsilon_t \tag{5}$$

Thus, real stock prices are positively related to the level of real GDP growth and negatively related to the level of the subjective discount rate (r). Given this result, a simple model of real stock prices can be specified where the level of real stock prices is a function of real GDP and an alternative real rate of return.

In order to illustrate how quantile regressions can be helpful in detecting periods of abnormal returns, chart 1 shows the effect of a rise in the level of real GDP on the conditional distribution of the real stock prices represented by a box and whiskers chart. All other things constant, a rise in real GDP is expected to lead to an upward movement in the conditional distribution of real stock prices. As shown in the chart, this implies that if a particular real stock price level would fall in the region of "too low" or "too high" stock prices in the previous period, it may now be considered as normal, given the more benign macroeconomic conditions. For instance, in period 0 and given a level of potential real GDP (y_0), the real
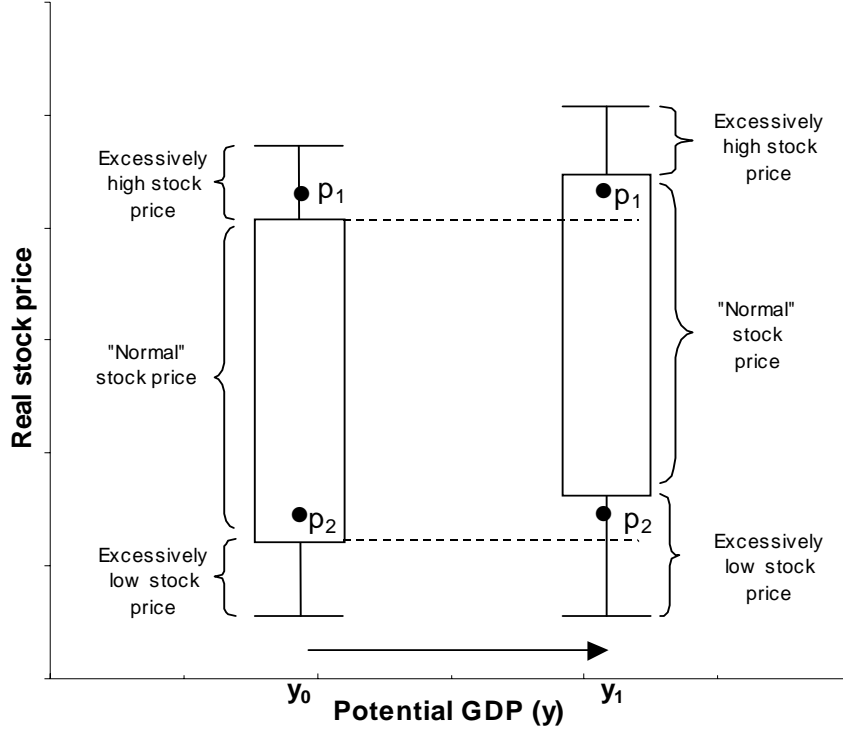
Figure 1: Effect of an increase in potential real GDP on the conditional distribution of real stock prices

stock price p_1 can be considered as being excessively high. However, with a higher level of real GDP growth (y_1) in period 1, the same real stock price can be considered as being within normal levels given the improvement in fundamentals.

3 Quantile smoothing

The basic idea of nonparametric quantile regression via quantile smoothing splines is best introduced in a univariate case. Let p_t be the logarithm of real stock prices and X_t a random variable representing, say, the trend GDP. The $\tau - th$ conditional quantile of p_t given $X = x$ is a function of x, $g_\tau(x)$, such that:

$$P(p_t \leq g_\tau(x)|X_t = x) = \tau. \tag{6}$$

Koenker et al. (1994) introduced the quantile smoothing spline estimator of $g_\tau(x)$ obtained as a solution to

$$\min_g \text{``fidelity''} + \lambda \text{``roughness''} \tag{7}$$

where, λ is a tuning parameter controlling the smoothness of the fitted function and

$$"fidelity" = \sum_{i=1}^{n} \rho_{\tau}(y_i - g(t_i)) \tag{8}$$

with, ρ_{τ} is the check function defined as:

$$\rho_{\tau}(u) = \begin{cases} \tau u & \text{for } u \geq 0 \\ (\tau - 1)u & \text{for } u < 0 \end{cases} \tag{9}$$

The roughness term may have two alternative forms. Either the total variation of the first derivative of g which, for smooth enough functions, can be written as

$$"roughness" = V(g') = \int |g''(x)| dx \tag{10}$$

or the sup-norm of its second derivative

$$"roughness" = \max_{t} g''(t). \tag{11}$$

It can be shown that the former yields estimates that are linear splines while the latter produces quadratic splines.

The quantile smoothing splines approach is easily seen to be analogous to the widely used Hodrick-Prescott (HP) filter. Unlike the HP case, however, the "conditioning variable" for quantile smoothers is not necessarily a time index. The basic intuition is that the quantile functions should be faithful to the general patterns followed by the quantiles of the conditional distribution of stock prices but, in addition, should be smooth. One way of interpreting the results is that these smooth functions provide indications regarding the fundamental characteristics of the conditional distribution of the real stock price index. As in the case of the applications of the HP filter to, say, the estimation of potential output, the basic assumption is that the fundamental valuation of real stock prices should change only in a smooth fashion and short-run oscillations in the conditional distribution are probably linked to noise or conjunctural movements.

The estimation strategies of the nonparametric quantile model differ according to the dimensionality of the conditioning variables X_t. For univariate X_t (e.g, a time index or the trend output) the quantile model was estimated using the COBS (Constrained B-splines Smoothing) algorithm (He and Ng, 1999; Ng, 2005). The implementation of this algorithm in the statistical package R[1] enables the choice of the type of roughness penalty, the automatic search for λ using SIC, and the imposition of qualitative constraints on $g_{\tau}(x)$. Our estimated models use the sup-norm roughness ($g_{\tau}(x)$ being a quadratic spline) and make $g_{\tau}(x)$ an increasing function of the trend output.

Unfortunately COBS does not apply when there is more than one conditioning variable. Thus, it would not cover the interesting case of analysing the distribution of the stock prices conditional both on the trend output and the real interest rate. The reason is rather technical and stems from the difficulty in finding satisfactory measures of the roughness of

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[1]R: A language and environment for statistical computing, R Development Core Team, R Foundation for Statistical Computing,Vienna, Austria, 2004, 3-900051-07-0,url=http://www.R-project.org.

surfaces. For the bivariate case, Koenker and Mizera (2003) proposed a method of estimating the nonparametric quantile smoother defined by (7) known as penalized quantile triograms. Basically, the $g_\tau(x)$ is restricted to be piecewise-linear on a set of triangulations of the data (set of planar triangles, with disjoint interiors, covering the convex-hull of the data points). This method is also implemented in R although the code is yet less well developed than COBS as it, for instance, does not enable the automatic choice of the smoothing parameter besides, of course, restricting the estimates to be linear splines.

4 Empirical application

4.1 Data

The data on stock prices used corresponds to the EMU Price Index taken from Datastream and expressed in euros. As for the fundamental variables, the real GDP series (as well as the nominal GDP data used for the calculation of the GDP deflator) is constructed by aggregating logs of seasonally adjusted national accounts data (ESA95 whenever available). Potential real GDP has been obtained by applying the HP filter to quarterly real GDP data and setting the parameter λ equal to 1600. The short-term interest rate corresponds to a weighted average of euro-11 (euro-12 from January 2001) short-term interest rates. The weights correspond to 2001 GDP weights at Purchasing Power Parity exchange rates. Up to the end of 1999, national interest rate series are obtained from the Bank for International Settlements. After 1999, the short-term interest rate corresponds to the three-month EURIBOR (from Reuters). All data is monthly (quarterly data on real GDP and GDP deflator have been converted to monthly frequency by cubic spline interpolation) and the sample covers the period from May 1980 to December 2003.

4.2 Conditioning on a time index

The first variable that can be used for conditioning real stock prices is a time index. We use the COBS approach which can be seen as an analogue to the HP filter, as it aims at estimating smooth functions of the quantiles of real stock returns around a time index. In the estimation of the smoothed measures, the restriction is imposed that the smooth function is nondecreasing with time. The motivation for this approach is not statistical but is instead based on economic theory. As shown in section 2, in the long-run the fundamental level of real stock prices should be positively related to the level of real GDP. This implies that, in economies with positive long-run economic growth, the fundamental level of real stock prices should also exhibit an upward trend which in our model is incorporated by imposing the nondecreasing option used in this section. This option turned out to be useful given that relaxing it would lead to the smoothed series following excessively the patterns of the real stock price index. Finally, we let the program select automatically the roughness penalty λ.

The result is shown in chart 2. Each conditional decile interval (from 10-20% up to 80-90%) is shown with a different shade of grey which grows lighter with the distance from the median. The median is the darkest grey line at the centre of the distribution. As can be seen in the chart, there is clear evidence that the conditional distribution of real stock prices has changed over time. One can see that the conditional distribution was narrower up to
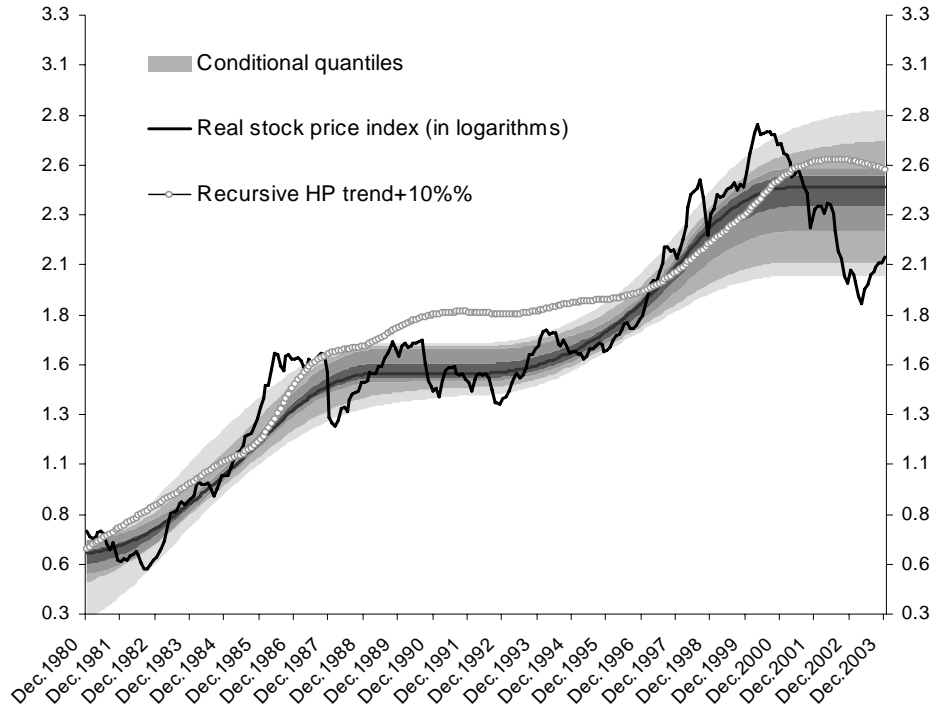
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Figure 2: Real stock prices (in logarithms) and quantiles obtained with constrained smoothing around a time index

the end of 1997 but became much wider towards the end of the sample. According to the results, at the end of the sample, large swings in real stock prices can still be interpreted as being "normal" occurrences.

Also shown in the chart is the result of a methodology similar to the one of Detken and Smets (2004). It consists in applying a recursive Hodrick-Prescott filter to the series of real stock prices, setting the lambda coefficient to a high value and then multiplying the resulting series by a factor of 1.1. The resulting variable is chosen as the threshold for identifying asset price booms (i.e. periods when the real stock price index is continuously more than 10% above its trend). Assessing the HP filter measure in the light of the results from the quantile approach, one can see that in some instances the HP trend measure appears to be too strict in terms of what defines an asset price boom as it moves well above the 90% quantile, thereby attributing a very low probability to a boom occurring. In other periods, the HP trend measure approaches (and in some occasions even falls below) the median of the distribution, thereby representing too low a threshold for defining periods of exceptionally high real stock prices.

4.3 Conditioning on trend output

Now the conditioning vector X includes the level of real potential GDP as the explanatory variable.[2] This corresponds closely to the Gordon model outlined in section 2. It should be noted that standard cointegration tests[3] fail to reject the null hypothesis that in the euro area the level of the real stock price index is cointegrated with the level of real GDP. This result is in line with the previous findings of Cassola and Morana (2002) for the euro area.

Chart 3 shows the real stock price together with the conditional decile ranges (from 10-20% to 80-90%). The quantiles are derived using COBS and imposing the theoretically justified restriction that real stock prices should be nondecreasing with potential real GDP. This restriction is implied by equation 3 in section 2 and basically means that the fundamental level of real stock prices should rise over time in expanding economies.

The results are not too different from the ones obtained with the time index. In general, the distribution of real stock returns conditioning on trend output seems to be wider than in the case of the time trend. This implies that larger fluctuations in real stock prices around the median are seen as more likely than in the case of the time trend. In particular, since 1990 the extreme quantile ranges become quite thin. As in the case of the time trend, there is a substantial increase in the dispersion of real stock prices over the last few years of the sample.

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[2] The value of potential real GDP is lagged by two months as it is assumed that there are informational delays.

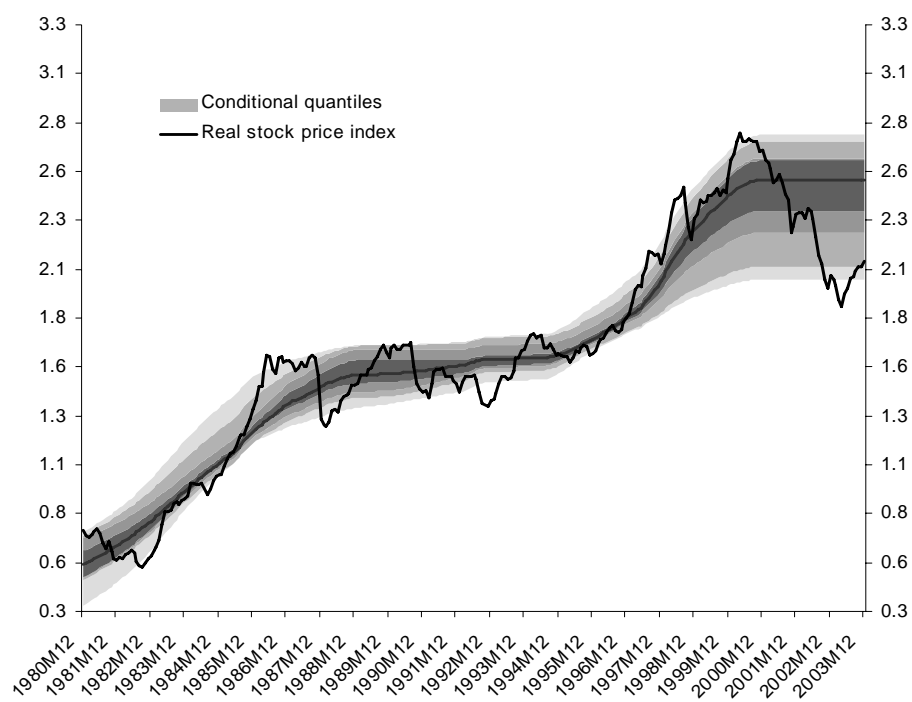[3] These results are available from the authors upon request.

Figure 3: Real stock prices (in logarithms) and conditional quantile intervals obtained with constrained smoothing around potential real GDP (HP filtered)

4.4 Conditioning on trend output and real interest rates

Now X includes, in addition to trend real GDP, the ex-post real short-term interest rate (i.e. the short-term interest rate minus annualised monthly inflation). The reason for including the real ex-post interest rate is that during the period covered by this study real ex-post interest rates in the euro area have shown a downward trend. Therefore, the assumption that the discount factor is constant required by the Gordon model no longer applies. As in the case of trend real GDP, the real short-term interest rate is also smoothed by the Hodrick-Prescott filter. On the basis of informational delays assumptions, trend real GDP enters lagged by two months while the trend real rate enters lagged by one month.

The estimation method is the one of Koenker and Mizera (2003) based on penalised triograms. The smoothing parameter λ is set equal to 3.5 and no constraint is imposed on the relation between the variables.

The results of the estimation of the model are shown in figures 4 and 5. The charts show the level curves of the quantiles for ranks 10, 20, 70 and 90%. As can be shown in the figures, increases in real GDP and decreases in real interest rates tend to decrease the conditional quantiles of real stock prices (i.e. make it more likely that stock prices may rise to a higher level than before). In addition, the effect of interest rates seems to be smaller in the lowest quantiles and to increase in the highest quantiles. This is evidenced by the fact that the contour lines become almost vertical at the 10% quantile and are increasingly leaning to the right at the highest quantiles.
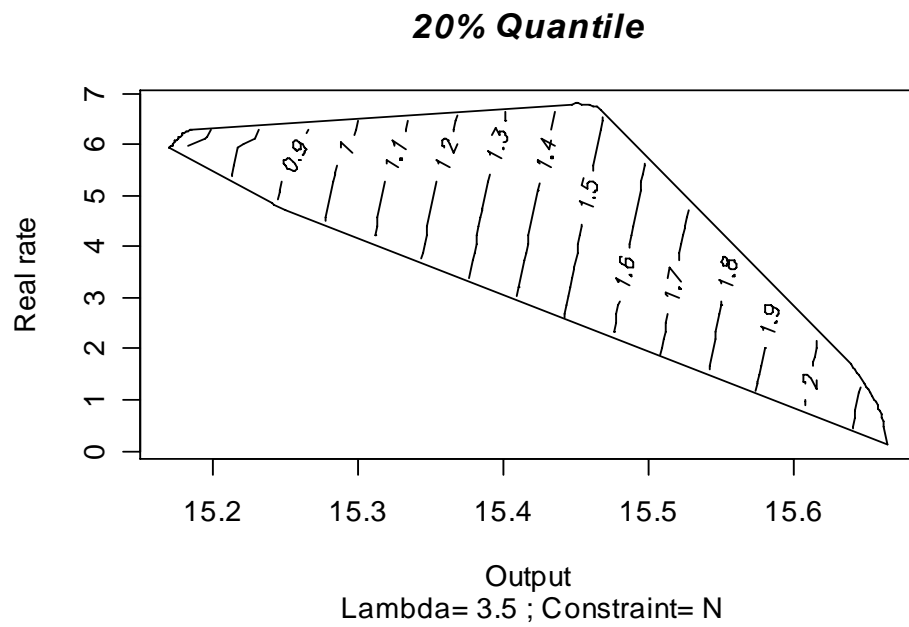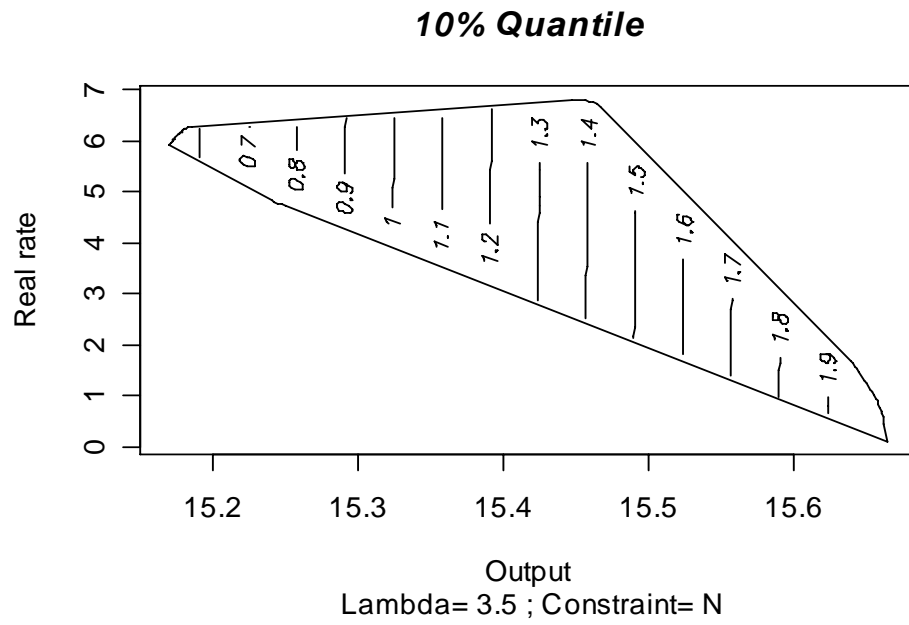
10% Quantile

Output
Lambda= 3.5 ; Constraint= N

20% Quantile

Output
Lambda= 3.5 ; Constraint= N

Figure 4: Lower quantiles of the real stock price distribution as a function of real output and the real short-term interest rate

70% Quantile
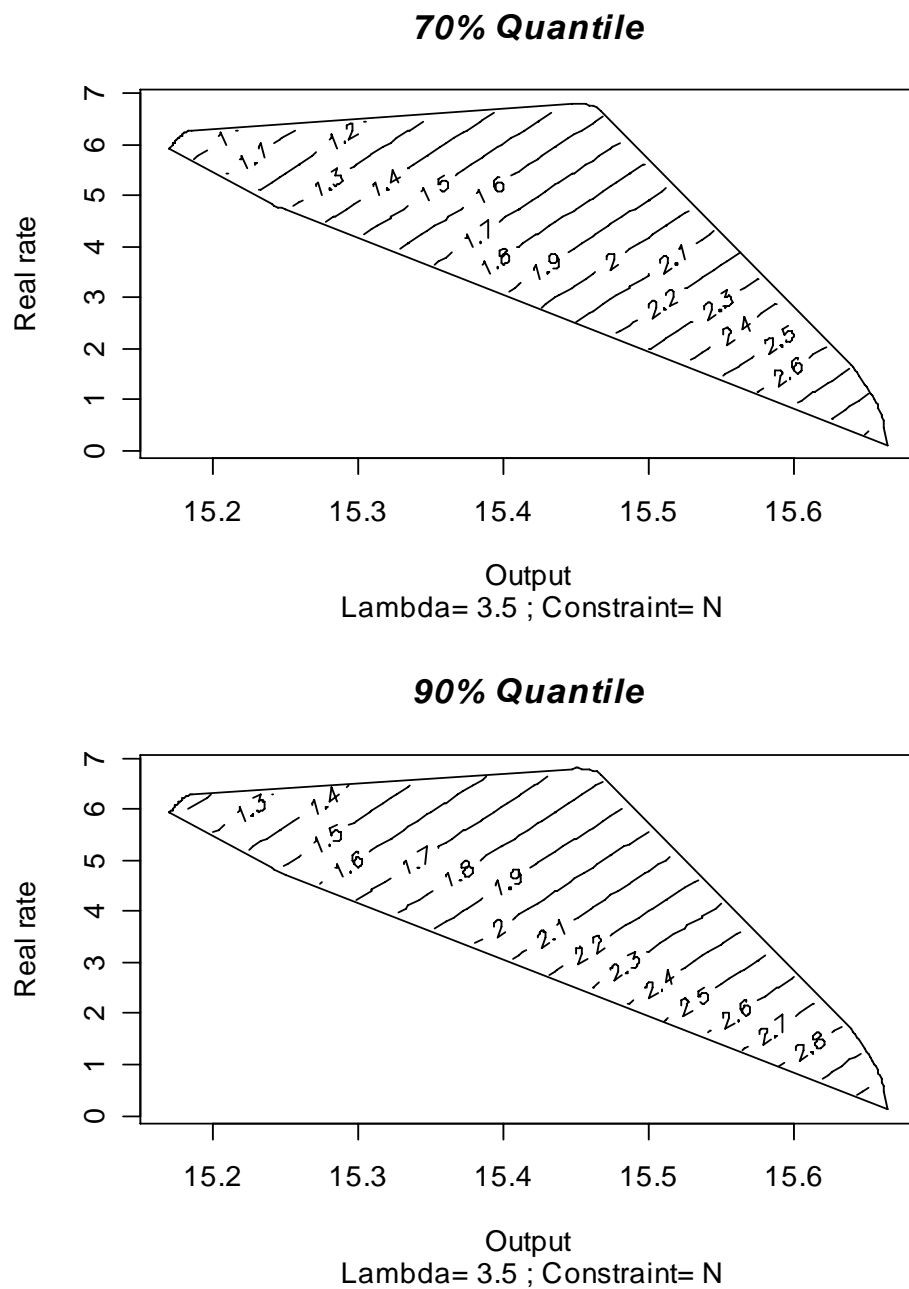

Output
Lambda= 3.5 ; Constraint= N

90% Quantile

Output
Lambda= 3.5 ; Constraint= N

Figure 5: Upper quantiles of the real stock price distribution as a function of real output and the real short-term interest rate
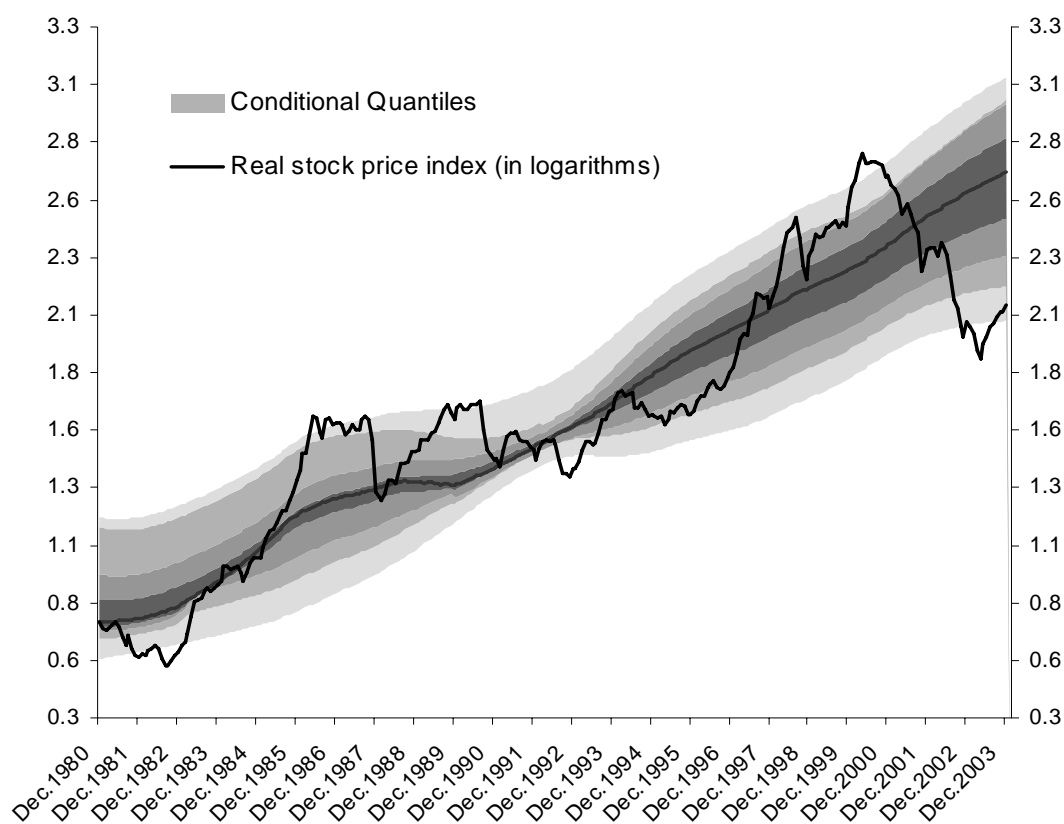
Figure 6: Real stock prices and conditional distribution obtained with bivariate smoothing

In order to better grasp how the conditional distribution of stock returns has evolved over time, chart 6 shows the real stock price index together with the conditional quantiles. The chart clearly shows that there are significant changes over time in the conditional distribution of real stock prices as a result of changes in trend real GDP and the real interest rate. For instance, the conditional distribution narrows significantly during the period from the beginning of 1991 to 1993, a period characterised by weak, at times negative, economic growth and by high real interest rates. Since then, the conditional distribution of real stock prices has continued to move upwards (reflecting both the rising trend in real GDP and lower real interest rates) and has also widened. Thus, recently, the range over which real stock prices should be considered as being "fundamentally-justified" is much larger than in the past. A major difference relative to the previous estimates concerns the period before 1991, for which the conditional distribution is now much wider than before.

Charts 7 and 8 show the periods of asset price booms and busts detected by the method. We took the 10% and the 90% quantiles as delimiting the range of "fundamentally-justified" real stock price levels. While there is some degree of arbitrariness in this choice of quantiles, the option to rely on relatively extreme levels of the distribution provides more confidence

in detecting periods of misalignments of stock returns given fundamentals.

Some interesting features are noteworthy. First, as seen in the charts, periods of asset price booms/busts seem to be clustered. Second, periods of strong increases in real stock prices do not necessarily correspond to periods of asset price booms. For instance, during the years between 1984 and mid-1986, real stock prices rose significantly but most of the time the rise was fundamentally justified. The decline in real stock prices in 1987 is not seen as being a bust. In fact, during the year before the crash, real stock prices were often above the levels justified by the fundamentals or within the 80-90% quantile range (see chart 6). Therefore, the crash can be seen as a correction that brought real stock prices down into line with the "normal" levels. The method identifies the period of 1989-1990 as one of a stock market boom, even though real stock prices were broadly stable. Again, the large drop in real stock prices following this period (which the method does not consider to be a bust) suggests that indeed there was a correction of a fundamental misalignment then. Finally, the method considers that a boom has occurred in 2000, but only after of a long upward movement of real stock prices. Similarly, the bust period in 2003 seems to occur only after a long period of stock market decline, reflecting the wider conditional distribution of real stock prices at the end of the sample referred to above. In fact the period from 1997 to 2000 is widely thought of as corresponding to an asset price boom (see for instance Bordo and Wheelock, 2004). Thus, one may think that the excesses detected in that period were afterwards corrected by a stronger decline in real stock prices than justified by fundamentals.
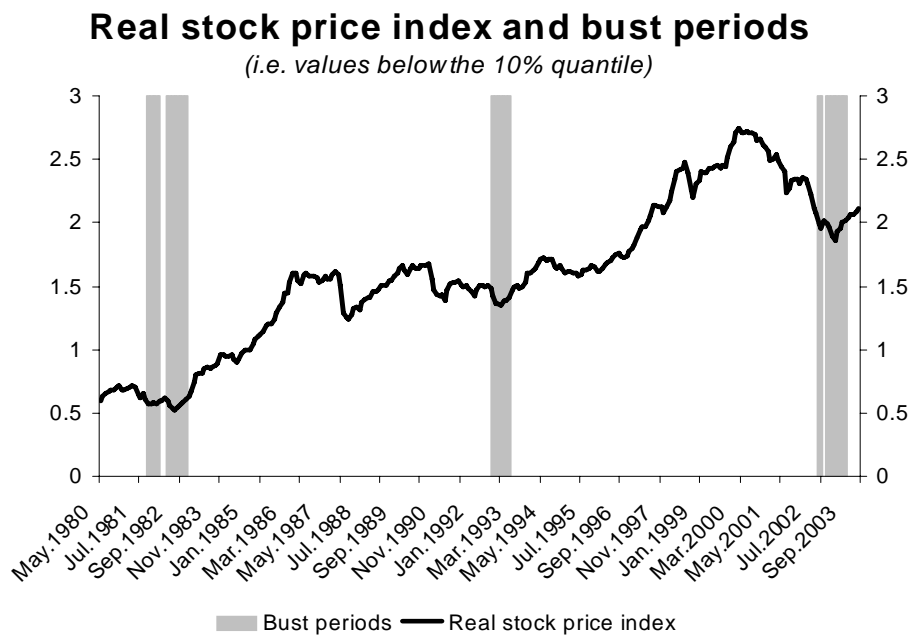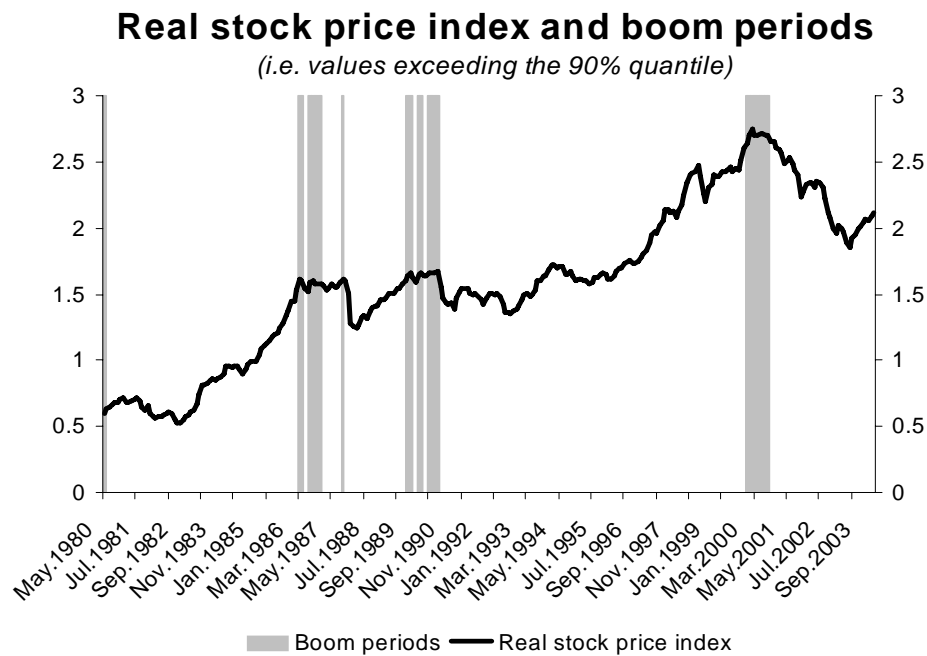
Real stock price index and bust periods
(i.e. values below the 10% quantile)

Figure 7: Real stock price index and bust periods

Real stock price index and boom periods
(i.e. values exceeding the 90% quantile)

Figure 8: Real stock price index and boom periods

Quantile	Intercept		y_{t-2}		rrs_{t-1}	
	Value	Conf. interval	Value	Conf. interval	Value	Conf. interval
0.1	-43.308	[-54.70; -7.88]	2.895	[0.63; 3.62]	-0.011	[-0.25; 0.03]
0.2	-42.802	[-54.81; -0.48]	2.878	[0.22; 3.65]	-0.036	[-0.38; 0.03]
0.3	-42.637	[-52.85; -4.63]	2.872	[0.50; 3.54]	-0.043	[-0.25; -0.004]
0.4	-41.490	[-55.82; -15.52]	2.802	[1.17; 3.72]	-0.048	[-0.23; 0.004]
0.5	-41.503	[-54.13; -5.83]	2.814	[0.51; 3.63]	-0.070	[-0.38; -0.00002]
0.6	-43.414	[-61.03; -10.15]	2.946	[0.81; 4.04]	-0.078	[-0.25; 0.04]
0.7	-42.676	[-60.84; -14.55]	2.903	[1.08; 4.17]	-0.077	[-0.24; -0.003]
0.8	-43.392	[-61.01; -13.79]	2.953	[1.04; 4.12]	-0.068	[-0.25; -0.005]
0.9	-43.075	[-59.24;-15.93]	2.942	[1.18; 3.98]	-0.076	[-0.26; -0.04]

Table 1: Estimates of real stock price quantiles conditional on real GDP growth and the real short-term interest rate

4.5 Parametric quantile regressions

Estimating quantile regressions of real stock prices on real potential GDP and the real interest rate constitutes a useful complement of the non-parametric analysis of the previous sections. Such estimations allow assessing to what extent the fundamentals are statistically significant in influencing trend real output and the trend real interest rate.[4]

The results are shown in Table 1, where y is the level of in real GDP and rrs the ex-post short-term real interest rate. The table shows the point estimates for each decile and the 95% confidence intervals obtained with block bootstrap. Starting from a model containing contemporaneous terms and three lags of each variable and dropping insignificant terms one obtains a model where the real return quantiles are a function of real GDP lagged two months and of the real interest rate lagged one month. As before, the fact that only lagged variables enter the regressions could be justified on the basis of informational delays.

The effect of changes in real GDP on real stock prices seems to be positive and relatively constant along the quantiles. A higher level of real output leads to a right shift of the conditional distribution of real stock prices, reducing the likelihood of low returns.

As for the real interest rate, the effect of an increase in real interest rates is stronger for the upper quantiles of the distribution of real stock prices. In fact, the effect of changes in real rates on the lowest quantiles is statistically insignificant. One possible interpretation for these results is that increases in real interest rates tend to curb the potential for increases in stock prices but do not influence very much the potential for losses. To a large extent, these results confirm the evidence found with the multivariate smoothing techniques in section 4.4.

5 Money, credit and asset price booms and busts

In this section, we compare the results obtained in dating periods of asset price misalignment with money and credit indicators. The aim is to assess how money or credit developments might have played a role in these episodes. We date the boom and bust periods using the method based on penalised triograms. We condition on the level of real potential GDP and

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[4]Notice that the results from nonparametric methods in figures 4 and 5 imply that the linear model may not be seriously misspecified.
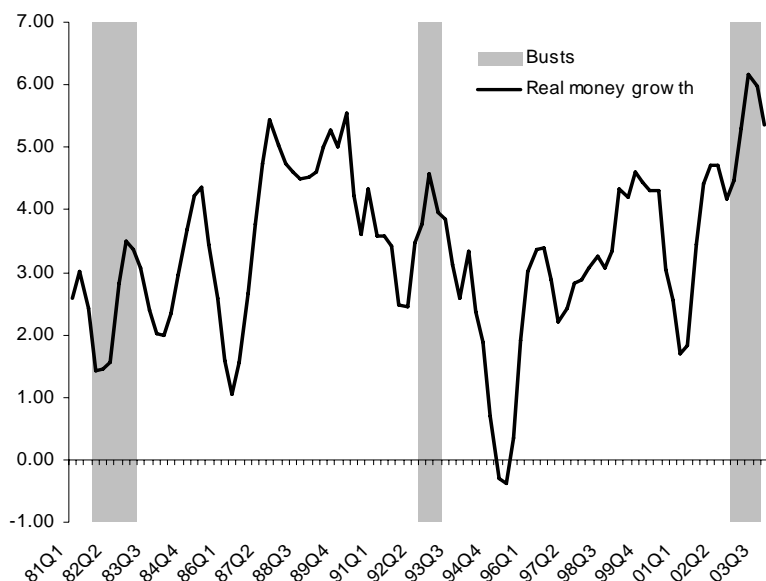
Figure 9: Stock market busts and real money annual growth (computed as differences in logarithms)

the real short-term interest rate and use the 10 to 90% range as the one defining the range of fundamentally justified real stock prices. We convert the dummy variables defining the booms and busts from monthly to quarterly according to the following rule: a quarter is considered to be a boom (or a bust) period if there is a boom (or a bust) in at least one of its months.

Starting with money indicators, we compare the asset price booms and busts with monetary growth and with the overhangs from two money demand models estimated up to 2001Q3, namely the Calza, Gerdesmeier, Levy (CGL, 2001) model and the Bruggeman, Donati and Warne model (BDW, 2003).

As seen in chart 9, real money (i.e. M3 deflated by the GDP deflator) growth tends to rise following asset price busts. This suggests that asset price busts seem to result in higher monetary growth which could reflect safe haven flows from equity into money holdings. In the case of the asset price booms (see 10), the results are not so clear as in some cases real M3 growth rises and in other it declines. Thus, it appears more difficult to establish a link between high real M3 growth and asset price booms. Of course, as in the case of the asset price misalignment indicators, looking only at the series of real money growth appears to be insufficient as it provides too little conditioning of the nominal money growth series. Such conditioning can be more conveniently provided by using monetary overhangs that take into account that money is held also for transaction purposes and as a store of value.
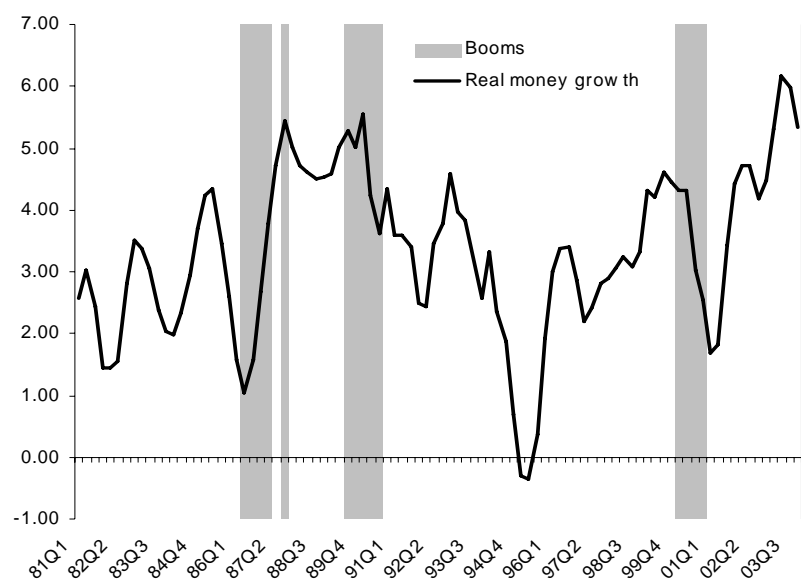
Figure 10: Stock market booms and real money annual growth (computed as differences in logarithms)
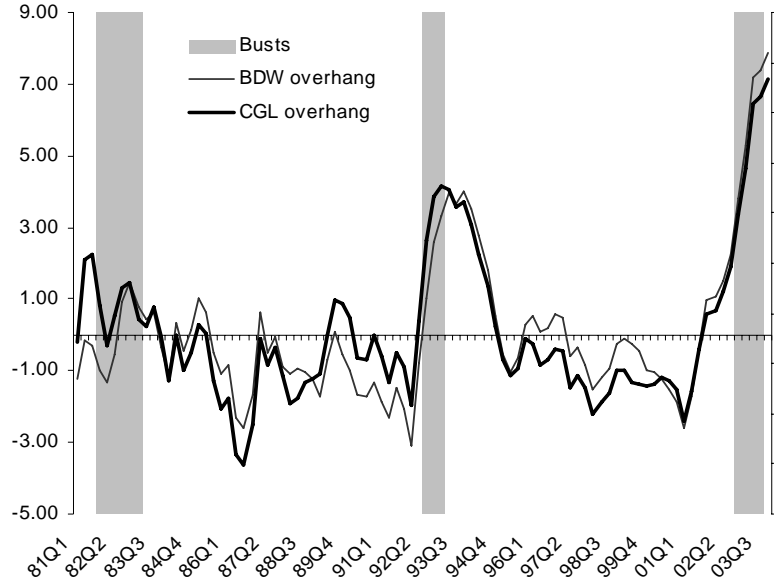
Figure 11: Asset price busts and monetary overhangs

Starting with the bust periods (see chart 11), periods identified as a stock market bust have often been accompanied by sizeable positive monetary overhangs (namely the periods from 1992Q3 to 1993Q1 and from 2002Q4 to 2003Q3). In the other bust period, from 1981Q4 to 1983Q1, the CGL overhang is also positive but the BDW overhang is only positive in part of the episode. These findings seem to confirm the view that in periods of weak stock market prices there are portfolio flows away from equity and into the less risky monetary assets thereby resulting in a rise in liquidity as measured by the overhangs.

As regards the boom periods (see chart 12), it is interesting to note that most of the time booming stock markets have been accompanied by low or negative overhangs. Thus, booming stock prices (in a conditional sense) appear to lure investors away from money holdings and into the stock market.
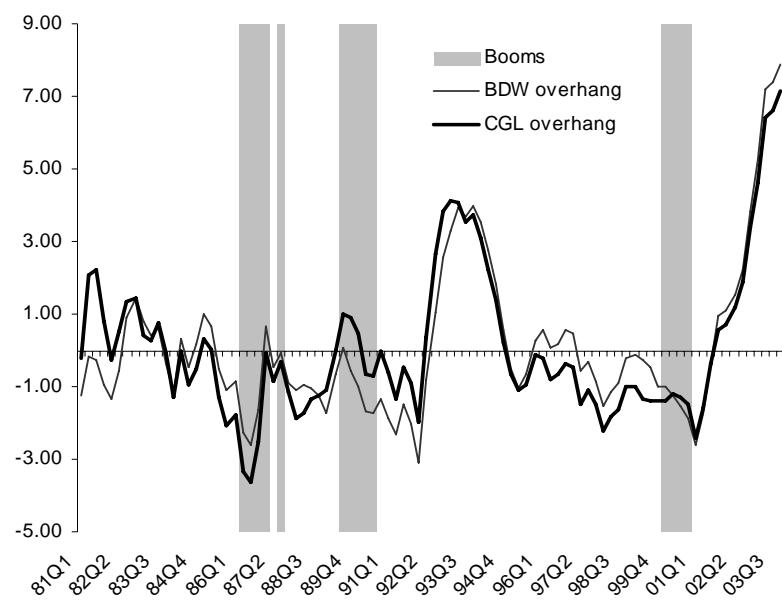
20

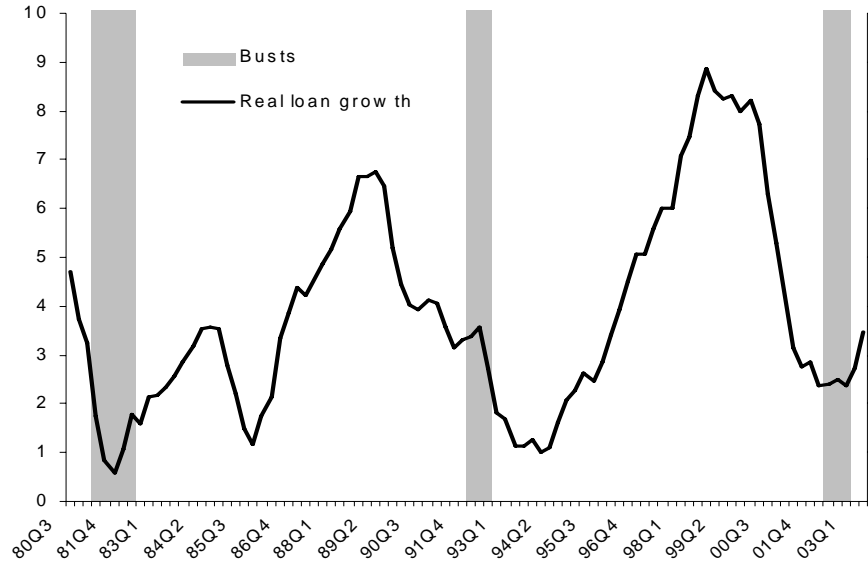Figure 12: Asset price booms and monetary overhangs

Figure 13: Asset price busts and real loan growth

As for credit, we use two measures for assessing its role around periods of asset price booms and busts. The first one is simply the annual growth rate of real loans to the private sector (deflated with the GDP deflator). The second measure can be seen as an indicator of credit conditions. It is based on the results of the threshold VAR of Calza and Sousa (2005). The method of Calza and Sousa (2005) is particularly suited for detecting periods of credit constraints which may play a role on asset price busts.

Charts 13 and 14 compare asset price booms and busts with real loan growth to the euro area private sector. As can be seen in the charts, periods of asset price busts correspond either to periods when real loan growth is low or declining. Asset price booms tend to occur either when real loan growth is increasing sharply or after long periods of rising real loan growth as was the case of the periods 1989Q3 to 1990Q3 and from 2000Q1 to 2000Q4.
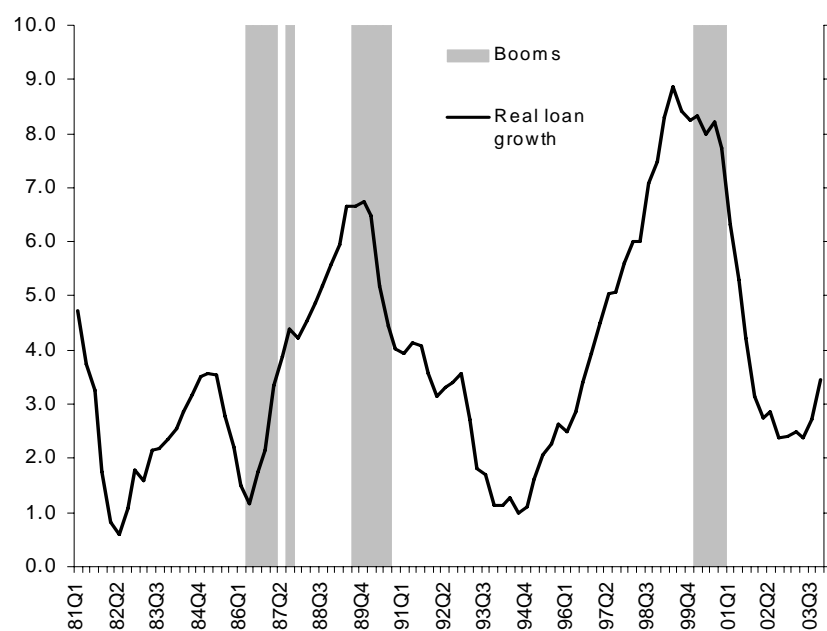
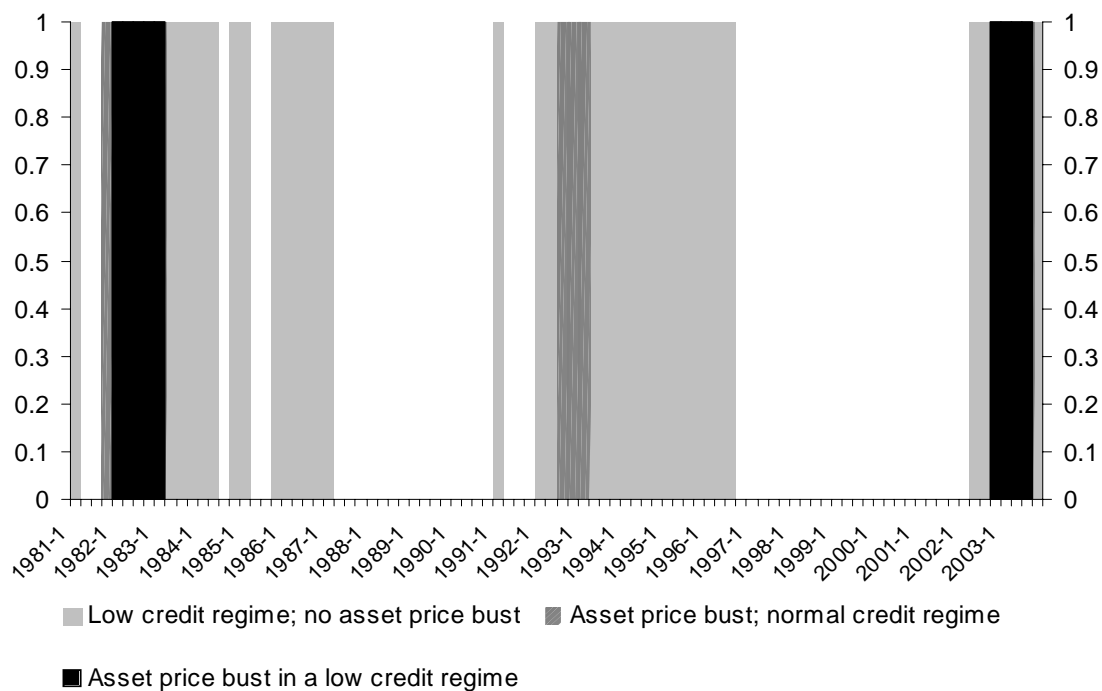Figure 14: Asset price booms and real loan growth

Figure 15: Asset price busts and Calza/Sousa (2005) credit regimes

As regards the threshold VAR information, chart 15 shows that asset price busts seem to occur around periods where the economy is in the low credit regime. In fact, in two of the three periods of asset price busts the economy was most of the time in the low credit regime. During the third real stock price bust, namely the one during the period from 1992Q3 to 1993Q1, the economy was in a normal credit regime. However, both before and after the bust the economy was in a low credit regime.

6 Conclusions

This paper shows that quantile regressions can be useful for identifying episodes of asset price misalignment. Modeling the whole conditional distribution of real stock prices provides a rich set of information, allowing probabilistic statements to be made regarding the level of real stock prices. In an empirical application to the euro area it is found that the conditional distribution of real stock prices tends to change over time and with the macroeconomic fundamentals. This implies that simpler measures of fundamental asset prices based solely on the real stock price series may lead to erroneous indications. Namely, simple dating methods do not guarantee that the identified booms or busts fall within the tails of the conditional distribution of real stock prices, as they should.

After identifying some periods where, based on historical patterns, asset prices could be considered as being excessively high or low, we analyse several money and credit indicators and investigate how they evolve during such asset price misalignment periods. The results suggest that the link between real money growth and asset price booms is generally weak. By contrast, asset price booms seem to occur at times of strongly rising credit growth or at times when loan growth is close to its peak following prolonged periods of accelerating real credit. Thus, monitoring real credit appears to be more useful for detecting asset price booms than monitoring real money growth. Finally, periods of asset price busts seem to lead to higher liquidity in terms of money holdings, which could reflect safe haven flows away from capital markets. As asset price busts tend to occur in periods of tight credit conditions, the results suggest that when there are asset price busts M3-based measures of excess liquidity may portray a too benign picture of the liquidity conditions in the euro area.

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