Does Monetary Policy React to Asset Prices? Some International Evidence[1]

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Abstract

This paper attempts to measure the reaction of monetary policy to the stock market. We apply the procedure of Rigobon and Sack (2003) to identify and estimate a VAR in the presence of heteroskedasticity. This procedure fully takes into account the endogeneity of interest rates and stock returns that is ignored in the traditional VAR literature. We find a positive and significant reaction in the US and the UK. However, since the end of the 1990s, in a period of large stock market fluctuations, this reaction declines in the US and disappears in the UK. In Japan and the EU, we do not find any reaction. We provide evidence that the lower response to stock prices in the last part of the sample in the US is compensated by a higher response to real estate prices.

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1 Introduction

While the main concern of central bankers, the inflation rate, is now low and stable in the main developed economies, financial instability has become one of the most discussed issues in the press and in the academic literature. Borio and Lowe (2002) document two boom-bust cycles in asset prices, one from the mid-1980s to early 1990s, the other from the end of the 1990s to 2003. These cycles appear to be growing in amplitude and length and are characterized by equity prices being more volatile than commercial and residential real estate prices. Large swings have been associated with strains in the financial sector and in the real economy. Important recessions have been experienced after the two cycles described above, in particular in Japan but also in many other countries (Borio, Kennedy and Prowse (1994)).

Developments in the financial markets have become increasingly important also for central banks. In the theoretical literature the most discussed policy issue is whether central banks should include asset prices in their reaction function. Bernanke and Gertler (2001) argue that price stability is the only objective of a central bank and asset prices have to be taken into account only as long as they signal changes in expected inflation. Simulations of various kinds of monetary policy rules (including or not including asset prices) in a new Keynesian model with nominal rigidities and financial accelerator show that the most stabilizing rule is one that responds strongly to inflation but does not react to asset price variations. The authors argue that the response to asset prices has destabilizing effects because it is almost impossible to know whether a change in asset prices is due to fundamental factors or not. These claims have not stood unchallenged. Cecchetti, Genberg, Lipsky and Wadhawani (2000), Bordo and Jeanne (2002), Akram and Eithreim (2008), Akram, Bårdsen and Eithreim (2006) among others provide examples where a more proactive policy has stabilizing effects on the economy. Iacoviello (2005), on the other hand, shows that reacting to real estate inflation causes little gain in terms of inflation and output volatility. The optimal coefficient in the reaction function is around 0.1 (for recent evidence on this issue in an estimated model see Finocchiaro and Queijo von Heideken (2007)).

A second strand of the literature takes a positive perspective and aims at evaluating empirically the impact of asset prices on interest rates in different countries over the last twenty years. Bernanke and Gertler (2000) extend the approach proposed by Clarida, Gali and Gertler (1998 and 2000) and estimate a forward looking extended policy rule where the interest rate also responds to stock returns. They find that the response is negative but not significantly different from zero for the United States and Japan. They take into account the endogeneity of stock returns instrumenting for the change in stock prices with lags of macroeconomic variables and stock returns. Refining the same methodology, Chadha, Sarno and Valente (2004) find different results. They carefully check the quality of the instruments and use an adjusted labor share as the appropriate, and theoretically grounded, proxy for the output gap. Over the period 1979-2000, they discover a positive and significant response in the US and the UK whereas they find no reaction in Japan.

Rigobon and Sack (RS) (2003) challenge the Bernanke-Gertler (2000) results arguing that the endogeneity issue is not considered properly. They advocate that it is hard to conceive any instrument which is highly correlated with changes in stock prices without affecting changes in the interest rate. Thus, in their opinion, this kind of regression uses weak instruments leading to biased estimates. RS (2003) aim at measuring the reaction of monetary policy to stock prices using a Vector Autoregression (VAR) model. Following Rigobon (2003), they fully take into account the endogeneity issue by using an appropriate identification technique based on heteroskedasticity present in daily data. Unlike Bernanke and Gertler (2000), they estimate a positive and significant reaction of monetary policy to the stock market in the US over the period 1985-1999. Bohl, Siklos and Werner (2007) use the same model for Germany and find a reaction that is not significant in the period 1985-1999.

In this paper we test power and weaknesses of the RS procedure by applying it to different countries and different sample periods. Moreover, since we consider the same countries as Chadha, Sarno and Valente (2004), our results can be useful to compare identification through heteroskedasticity and estimation of Taylor rules by Generalized Method of Moments (GMM) in a cross-country dimension. More specifically, the first objective of our paper is to measure the impact of stock prices on interest rates until 2006 in the US, checking whether there is a different reaction in different subperiods. Our second goal is to extend the analysis to other industrialized countries like the UK, Japan and the EU.

Our most important result concerns the US. We confirm the positive and significant response of interest rates found by RS (2003). However, our estimates indicate a lower reaction when we extend the sample. Following a 10% increase in the asset market index, the interest rate increases by 23 basis points over the period 1985-1995 and by only 6 basis points over the period 1996-2006. Both estimates are significant at the 95% level. While the first part of the sample is characterized by a relatively smooth growth of the stock market index, the second part exhibits two large boom-bust cycles. Hence, we find a lower reaction in a period of financial instability.

We provide a tentative interpretation for the lower response in the second part of the sample that is related to the wealth effect of asset prices on aggregate demand. RS (2003) argue that the estimated response is compatible with the wealth effect of stock prices on aggregate consumption. According to this view, the central bank reacts indirectly to stock prices because of their effects on aggregate demand. A lower reaction in the second part of the sample could reflect a lower relative importance of stock wealth, compared, for example, to real estate wealth. To test this conjecture we estimate the same model with REIT data which is a stock market index of companies active in the real estate sector. Consistent with our conjecture, we show that the response to our proxy for house prices is not significant in the first part of the sample whereas it becomes positive and significant in the second part of the sample. Quantitatively, the estimated response is very similar to the estimated response to stock prices. Hence, we conclude that the lower response to stock prices is compensated by a higher response to real estate prices. Interestingly, recent empirical evidence supports the importance of the wealth effect coming from the housing sector. Case, Quigley and Shiller (2005), Ludwig and Sløk (2004), Carroll, Otsuka and Slacalek (2006) among others find that the real estate wealth effect is increasing over time and higher than the stock market wealth effect.

Turning to the second goal of our paper, we show that the international evidence is relatively different from the evidence from the US. We do not find any reaction in the EU or Japan, either to stock prices or to the real estate proxy. In the UK, we only find a significant response to stock prices in the first part of the sample and no response to REIT data. According to our estimates, central banks in the EU, Japan and the UK pay less attention to asset prices. Consistent with empirical evidence provided in Altissimo et al. (2005) and with central bank speeches (Trichet (2002)), a possible explanation is that the wealth effect coming from asset prices is lower outside the US. Hence, the indirect reaction of monetary policy is lower.

Finally, this paper reconciles the result of Chadha, Sarno and Valente (2004) (GMM estimation of monetary policy reaction functions) with the results of RS (2003) (identification through heteroskedasticity). Although the two methodologies are very different, we find exactly the same results when we use the RS methodology on the sample period used by Chadha, Sarno and Valente (2004). This equivalence result strengthens the GMM approach, showing that the issue of endogeneity can be dealt with appropriately.

Nonetheless, identification through heteroskedasticity appears to be the only powerful tool to obtain reliable estimates in short samples. Using quarterly data, the approach based on GMM cannot disentangle the low or inexistent response of interest rates to stock prices in the recent years. The RS procedure can detect this new and interesting result because it exploits the enormous amount of information provided by daily data and, hence, can be used for much shorter samples.

This paper has the following structure. In section 2 we present the RS methodology. In section 3 we extend the evidence for the US and we discuss our interpretation. In section 4 we provide a cross-country analysis and in section 5 we compare our results with alternative methodologies. Concluding remarks are contained in section 6.

2 The Rigobon and Sack's procedure[1]

VAR models are the most frequently used tool to measure the interactions between macroeconomic variables. As we are interested in interest rates and stock prices, the structure of the simplest VAR is the following:

$$A\begin{bmatrix} i_t \\ s_t \end{bmatrix} = C\left(L\right)\begin{bmatrix} i_{t-1} \\ s_{t-1} \end{bmatrix} + B\begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix}$$

where i_t is the three-month Treasury bill interest rate, s_t are stock returns, A is a 2×2 matrix that describes contemporaneous relations among the variables, $c(L)$ is a finite order lag polynomial, ε_t and η_t are structural disturbances. B is a 2×2 matrix in which non zero off-diagonal elements allow some shocks to affect both endogenous variables.

We use the three-month Treasury bill rate rather than the federal funds rate. While the federal funds rate is changed every six weeks or so, the three month Treasury bill rate adjusts daily, reflecting expectations of future variations in the federal funds rate, and is closely monitored by the central bank. RS (2003) and Bohl, Siklos and Werner (2007) carefully motivate this choice. In this paper we follow the literature to facilitate results comparability.

The usual assumptions to achieve identification in this kind of model are to impose a triangular form to matrix A (Cholesky decomposition) and a diagonal structure to matrix B. In this way the model is exactly identified. But a triangular matrix A implies that one of the two variables does not react contemporaneously to the other. This assumption, which is reasonable in other contexts, is clearly inappropriate in this case. In our application, each shock to one of the variables has an immediate effect on the other in the financial markets.

RS do not impose a triangular structure on matrix A and build an identification procedure relying on the heteroskedasticity that is present in the data and that usually is not considered in VAR studies. In figure 1, we represent the thirty-day rolling volatility of daily changes in the stock market index and daily changes in

[1] **This section draws heavily on Rigobon and Sack (2003).**

the interest rate in the US. There are rich patterns that highlight the importance of modelling heteroskedasticity. We observe that shifts in volatility affect the correlation between interest rates and stock returns. In figure 1, we see that this correlation is negative most of the time but becomes positive when stock market volatility is high. The RS procedure exploits these shifts in covariance to identify the model without imposing inappropriate exclusion restrictions (as in the traditional approach). It is crucial to use daily data to exploit fully the heteroskedasticity present in the data. In fact, heteroskedasticity diminishes a lot in lower frequency data.

Realizations of interest rates and stock returns can be seen as the intersection between two schedules. The first is the reaction function of asset prices to changes in the interest rate (supposed to be downward sloping because an increase in the interest rate lowers the discounted value of future dividends, i.e. the value of the asset). The second is the reaction of the interest rate to the evolution of the stock market. The objective of the procedure is to estimate the slope of this second schedule. Because of heteroskedasticity, endogeneity and unobservability of a common shock z_t, introduced below, OLS estimates are biased. Thus, we look for a variable (an instrument) that shifts the stock market curve without affecting the monetary policy response. An increase in the variance of the stock market shock changes the covariance between stock returns and the interest rate and this change plays the role of an instrument.

RS estimate the following VAR:

$$i_t = \beta s_t + \theta x_t + \gamma z_t + \varepsilon_t$$

$$s_t = \alpha i_t + \phi x_t + z_t + \eta_t$$

where i_t is the three-month interest rate (Tbill), s_t is the daily return on the S&P 500 index, x_t includes 5 lags of the two endogenous variables and some macroeconomic shocks (measured as monthly releases of some macro indicators and subtracting the value expected by market participants, see RS (2003)), and z_t

represents some unobserved shocks affecting both i_t and s_t. The common shock takes into account any macroeconomic shock not included in x_t or shifts in risk preferences of the agents.[2] ε_t is a monetary policy shock, η_t is a stock market shock.

The structure of the model is quite rich, but our objective is very simple. We want to estimate the coefficient β that measures the response of the interest rate to the stock market return.

The assumption on the correlation structure of the shocks is the following: the shocks ε_t and η_t and the unobserved shock z_t are supposed to be orthogonal and at this stage all three can be heteroskedastic. Note that ortoghonality of ε_t and η_t does not imply that disturbances are uncorrelated: In fact, the presence of z_t induces correlation.

We can rewrite the structural form of the VAR in the following way:

$$\begin{bmatrix} 1 & -\beta \\ -\alpha & 1 \end{bmatrix} \begin{bmatrix} i_t \\ s_t \end{bmatrix} = \begin{bmatrix} \theta \\ \phi \end{bmatrix} x_t + \begin{bmatrix} \gamma z_t + \varepsilon_t \\ z_t + \eta_t \end{bmatrix}$$

This system cannot be estimated directly, because of the endogeneity problem discussed above and because z_t is an unobservable variable, but we can write it in reduced form:

$$\begin{bmatrix} i_t \\ s_t \end{bmatrix} = \begin{bmatrix} \frac{1}{1-\alpha\beta} & \frac{\beta}{1-\alpha\beta} \\ \frac{\alpha}{1-\alpha\beta} & \frac{1}{1-\alpha\beta} \end{bmatrix} \begin{bmatrix} \theta \\ \phi \end{bmatrix} x_t + \begin{bmatrix} \frac{1}{1-\alpha\beta} & \frac{\beta}{1-\alpha\beta} \\ \frac{\alpha}{1-\alpha\beta} & \frac{1}{1-\alpha\beta} \end{bmatrix} \begin{bmatrix} \gamma z_t + \varepsilon_t \\ z_t + \eta_t \end{bmatrix}$$

or:

$$\begin{bmatrix} i_t \\ s_t \end{bmatrix} = \Phi x_t + \begin{bmatrix} \upsilon_t^i \\ \upsilon_t^s \end{bmatrix} \tag{1}$$

where:

[2] The impact of z_t on s_t is normalized to one.

$$\begin{aligned}
\upsilon_t^i &= \frac{1}{1-\alpha\beta}\left(\left(\gamma+\beta\right)z_t+\beta\eta_t+\varepsilon_t\right) \\
\upsilon_t^s &= \frac{1}{1-\alpha\beta}\left(\left(1+\alpha\gamma\right)z_t+\eta_t+\alpha\varepsilon_t\right) \\
\Phi &= \begin{bmatrix} \frac{1}{1-\alpha\beta} & \frac{\beta}{1-\alpha\beta} \\ \frac{\alpha}{1-\alpha\beta} & \frac{1}{1-\alpha\beta} \end{bmatrix} \begin{bmatrix} \theta \\ \phi \end{bmatrix}
\end{aligned}$$

In the VAR literature, it is common practice to recover the estimates of structural form parameters from reduced form residuals. Given the structure of correlations specified above, the covariance matrix of reduced form residuals is the following:

$$\Omega = \begin{bmatrix} \Omega_{1,1} & \Omega_{1,2} \\ \Omega_{2,1} & \Omega_{2,2} \end{bmatrix} = \begin{bmatrix} var\left(i_t\right) & cov\left(i_t,s_t\right) \\ cov\left(i_t,s_t\right) & var\left(s_t\right) \end{bmatrix} =$$

$$= \frac{1}{\left(1-\alpha\beta\right)^2}\begin{bmatrix} \left(\beta+\gamma\right)^2\sigma_z^2+\beta^2\sigma_\eta^2+\sigma_\varepsilon^2 & \left(1+\alpha\gamma\right)\left(\beta+\gamma\right)\sigma_z^2+\beta\sigma_\eta^2+\alpha\sigma_\varepsilon^2 \\ \left(1+\alpha\gamma\right)\left(\beta+\gamma\right)\sigma_z^2+\beta\sigma_\eta^2+\alpha\sigma_\varepsilon^2 & \left(1+\alpha\gamma\right)^2\sigma_z^2+\sigma_\eta^2+\alpha^2\sigma_\varepsilon^2 \end{bmatrix}$$

By estimating the model in reduced form, we obtain a consistent estimate for the covariance matrix of reduced form residuals. Unfortunately, the covariance matrix provides only three moments $\Omega_{11,}\Omega_{12,}\Omega_{22}$, which are not enough to achieve identification. The maximum number of parameters that can be identified is three, but in matrix Ω we have six unknowns: $\alpha,\beta,\gamma,\sigma_z^2,\sigma_\eta^2,\sigma_\varepsilon^2$. Hence, we do not have enough restrictions to recover the structural form parameters.

Still, heteroskedasticity can help in our task if we can identify different regimes for the covariance matrix of the reduced form residuals. The additional regimes provide new restrictions and may enable us to identify the parameters of the structural form. Unfortunately, for each new regime indexed by the subscript i, we add three new equations but also three new unknowns $\sigma_{i,z}^2,\sigma_{i,\eta}^2,\sigma_{i,\varepsilon}^2$. Nevertheless, if we assume that the monetary policy shock ε is homoskedastic (thus σ_ε^2 is constant across regimes), we add three equations and only two unknowns for each regime. With three regimes we have nine equations and ten unknowns $\left(\alpha,\beta,\gamma,\sigma_{\varepsilon}^{2},\sigma_{1,z}^{2},\sigma_{1,\eta}^{2},\sigma_{2,z}^{2},\sigma_{2,\eta}^{2},\sigma_{3,z}^{2},\sigma_{3,\eta}^{2}\right)$ but this is enough to achieve partial identification, and in particular we can estimate the parameter β.

The assumption that σ_{ε}^{2} is constant is not very restrictive because it does not imply that i_t is homoskedastic. In fact, the variance of the interest rate is also composed of $\sigma_{i,z}^{2}$ and $\sigma_{i,\eta}^{2}$ which change through time. The other essential assumption to achieve identification is that the parameters α,β and γ are constant across regimes. This is common practice in the VAR literature, also when heteroskedasticity is not considered.

For each regime, we have the following covariance matrix:

$$\Omega_i=\frac{1}{\left(1-\alpha\beta\right)^2}\begin{bmatrix}\left(\beta+\gamma\right)^2\sigma_{i,z}^{2}+\beta^2\sigma_{i,\eta}^{2}+\sigma_{\varepsilon}^{2} & \left(1+\alpha\gamma\right)\left(\beta+\gamma\right)\sigma_{i,z}^{2}+\beta\sigma_{i,\eta}^{2}+\alpha\sigma_{\varepsilon}^{2}\\ \left(1+\alpha\gamma\right)\left(\beta+\gamma\right)\sigma_{i,z}^{2}+\beta\sigma_{i,\eta}^{2}+\alpha\sigma_{\varepsilon}^{2} & \left(1+\alpha\gamma\right)^2\sigma_{i,z}^{2}+\sigma_{i,\eta}^{2}+\alpha^2\sigma_{\varepsilon}^{2}\end{bmatrix}$$

In appendix B, we show that with three regimes one solution of the following quadratic equation is a consistent estimator for β:

$$a\beta^2-b\beta+c=0$$

where:[3]

$$\begin{aligned}a &= \Delta\Omega_{31,22}\Delta\Omega_{21,12}-\Delta\Omega_{21,22}\Delta\Omega_{31,12}\\ b &= \Delta\Omega_{31,22}\Delta\Omega_{21,11}-\Delta\Omega_{21,22}\Delta\Omega_{31,11}\\ c &= \Delta\Omega_{31,12}\Delta\Omega_{21,11}-\Delta\Omega_{21,12}\Delta\Omega_{31,11}\end{aligned}$$

With four regimes. we have overidentifying restrictions that allow us to estimate β by GMM.

A nice feature of this model is that many assumptions are testable. In fact, if the model is correctly specified we should find the same results for β under any

[3] $\Delta\Omega_{31,22}$ is the (2,2) element of matrix $\Delta\Omega_{31}$. $\Delta\Omega_{31}=\Omega_3-\Omega_1$.

three regimes, since the parameter β is supposed to be constant in the sample period. If not, the parameters are unstable across regimes, the assumption of homoskedasticity for the monetary policy shock is not correct or there are non linearities that are not captured in the Rigobon and Sack's formulation.

Thus far, we have proved that with at least three regimes we are able to consistently estimate the parameter β. To determine the regimes, we estimate the VAR (1) in reduced form and take the residuals. The heteroskedasticity of the shocks allows us to identify four regimes: regime 1 where both shocks have low volatility, regime 2 where the interest rate shock has low volatility and the stock market shock has high volatility, regime 3 where both shocks have high volatility, regime 4 where the interest rate shock has high volatility and the stock market shock has low volatility. We split the observations into the four regimes according to the following criterion: one observation is considered to have high variance if the thirty-day rolling variance of the residual is more than one standard deviation over the average of the series (lim=1 in our notation).[4] RS admit that this approach is arbitrary, but at least two arguments can justify this choice:

1) As shown in Rigobon (2003), the estimates are consistent even if the regimes are badly specified. The estimates are not consistent only if the misspecification is so large that the system fails the following order condition:[5]

$$\Omega_{11,i}\Omega_{12,j} - \Omega_{11,j}\Omega_{12,i} \neq 0$$

for regimes i and j with $i \neq j$.

This condition has an intuitive explanation. It fails when two covariance matrices are proportional, i.e. relative variances are constant across regimes. In this case, some moment conditions are not independent and heteroskedasticity cannot be helpful (for a proof of this result and more details see Rigobon (2003)).[6]

[4] It can happen that, using this criterion, very few observations enter the high volatility regimes. In these cases, we will lower the window to 0.75 of a standard deviation or to one-half of a standard deviation (lim=0.75 or lim=0.5).

[5] In this case, the parameters are not even identified because this condition is the equivalent of the rank condition that is tested in the identification literature once the order condition (number of equations equal to number of unknowns to achieve just-identification) is satisfied.

[6] Rigobon (2003) proves that the estimates are consistent also when the windows of the het-

2) The same criterion is largely used in the literature to identify periods of excessive volatility in asset markets (Bordo and Jeanne (2002)).

The last step is to compute the distributions of the estimated coefficients. The distributions are calculated by bootstrap. Residuals are supposed to be normal with mean zero and variance Ω_i for each regime. We simulate 1000 draws for each Ω_i. For each covariance matrix, we estimate β using different subsets of regimes. In the end, we obtain 1000 estimates and we are able to compute the distributions.

3 The US: 1985-2006

In this section, we reproduce the results of RS for the US and we extend their analysis until 2006. We then suggest some possible interpretations and we discuss some issues in the specification of the model.

3.1 Results

In our first experiment, we replicate the results of RS (2003). The sample period is January 1985-December 1999 and the data are daily.[7]

RS (2003) include in the variable x_t some observable macroeconomic shocks measured as the difference between the released value and the expected value of five monthly macroeconomic indicators: the consumer price index (CPI), the National Association of Purchasing Managers survey (NAPM), non-farm payrolls (NEPAY), the core producer index (PPI) and retail sales (RETL). The role of these shocks in the model is negligible and in fact we are even able to reproduce the results for the US without them.[8] In our specification, the variable x_t only consists of 5 lags of the two endogenous variables.

eroskedasticity are wrongly specified (but the number of regimes is correct) and when there are more regimes in the data than the ones assumed in the model. Of course, if the regimes are badly specified the differences across regimes are lower and the power of the model is reduced.

[7] All the data are taken from Datastream.

[8] We investigate this issue more deeply in section 4.3.

The results (shown in table 1) are consistent with the assumptions of the model. The estimates of the coefficient β are almost identical across regimes and quite precise.

Table 1: Estimates for the US, 1985-1999

	Regimes all	Regimes 1,2,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4
Mean of distribution	0.0183	0.0180	0.0185	0.0177	0.0191
Std. dev. of distribution	0.0457	0.0093	0.0055	0.0055	0.0058
Median of distribution	0.0185	0.0186	0.0185	0.0178	0.0192
Mass below zero	0.7%	2.3%	0.1%	0.2%	0.2%

Our results are very similar to the ones found by RS (2003), which we present in table 2. We observe minor differences in the estimates but larger differences in the standard deviations under regimes 1,3,4, 2,3,4 and 1,2,3,4. We can conclude that the inclusion of monthly macroeconomic shocks plays very little role in the RS results. Using different subsets of regimes, we obtain an estimate of 0.017-0.018 with a standard error of 0.005 (except in one case where the standard error is bigger because of seven outliers with large negative values). On average, our specification achieves more stable and precise results.

The reader can notice that the quality of estimates involving both regimes 3 and 4 in the RS specification is significantly worse than the others. In regimes 3 and 4, the residuals in the interest rate equation exhibit high volatility. Apparently, regimes with high stock market volatility are more useful for identifying the parameters. This fact is confirmed in all the following tables. We provide extensive sensitivity analysis in appendixes A and C.

Table 2: Results of Rigobon and Sack (2003), the US 1985-1999

	Regimes All	Regimes 1,2,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4
Mean of distribution	0.0210	0.0214	0.0210	0.0273	0.1402
Std. dev. of distribution	0.0052	0.0058	0.0052	0.314	3.8122
Median of distribution	0.0208	0.0217	0.0208	0.0169	0.0191
Mass below zero	0.0%	0.0%	0.0%	1.4%	1.4%

The major result of the RS paper is that by employing an appropriate identification procedure, the reaction of monetary policy to stock prices movements is positive and significant. A point estimate of 0.018 means that a 10% rise in the S&P 500 index increases the three-month interest rate by 18 basis points. RS argue that this result is very plausible and corresponds to the impact of stock prices on aggregate demand, mainly through the wealth effect on consumption.

The RS sample ends in December 1999. Since more data are available, we extend the analysis until April 2006. The results shown in table 3 are considerably different from the evidence provided above:

Table 3: Estimates for the US, 1985-2006

	Regimes All	Regimes 1,2,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4
Mean of distribution	0.0066	0.0057	0.0072	0.0177	0.0189
Std. dev. of distribution	0.0025	0.0029	0.0023	0.0051	0.0054
Mass below zero	0.7%	2.5%	0.1%	0%	0%

Even though all five estimates are still positive and significant, according to three of them, the monetary policy reaction is consistently lower (around 6 basis points following a 10% increase of the stock market index).[9]

Hence, we find a considerable instability in the estimates over the period 1985-2006. Our conjecture is that the assumption of constant parameters over the

[9] The differences in the estimates are statistically different from zero at a 95% level in three cases out of four (see table C3 in appendix C).

sample is violated. A second possible reason is the violation of the homoskedasticity assumption on σ_ε. To test our conjecture, we split our large sample of twenty years of daily data in December 1995. Thus, the two sub-samples have approximately the same size. We believe that our choice is sensible because stock market indexes exhibit a smooth growth over the first part of the sample and a series of boom and bust cycles in the second part.[10]

Results in tables 4 and 5 confirm a considerable difference in the estimates over the two sub-samples. The response is lower in the second part of the sample.

Table 4: Estimates for the US, 1985-1995 lim=0.5

	Regimes All	Regimes 1,2,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4
Mean of distribution	0.0230	0.0237	0.0020	0.0199	0.0204
Std. dev. of distribution	0.0057	0.0060	0.0723	0.0045	0.0046
Mass below zero	0.1%	0%	58%	0%	0%

Table 5: Estimates for the US, 1996-2006 lim=1

	Regimes All	Regimes 1,2,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4
Mean of distribution	0.0063	0.0062	0.0063	0.0113	0.0087
Std. dev. of distribution	0.0020	0.0021	0.0020	0.0990	0.0303
Mass below zero	0%	0.1%	0%	36.7%	36.5%

The results for the period 1985-1995 confirm a positive and significant reaction. Given the estimates for the period 1985-1999, this is not surprising. The results are extremely stable and precise across regimes with the considerable exception of the estimate under regimes 1,2,4. A possible explanation is that we found very

[10] Of course, several econometric techniques could be used to identify precisely the date of a possible structural break. However, we think that splitting the sample at the end of 1995 is a simple device to separate two periods that look meaningfully different, at least from an economic point of view.

few observations in regime 2 in this sample period.[11] RS locate residuals in the high volatility regime if the observation is at least one standard deviation over the average of the series (lim=1 in our notation). Our result above is referred to as one-half of a standard deviation (lim=0.5) because otherwise we would find even fewer observations in regime 2. This analysis shows that the results for the period 1985-1999 are driven by the structure of heteroskedasticity that is especially favorable over this period. In particular, many observations belonging to regime 2 are located in the period 1996-1999. Hence, a limitation of the procedure that otherwise works well is that in some cases it is difficult to have enough observations in all the four regimes to perform the estimation.

For the period 1996-2006 (table 5) we do not find any specific reaction to the huge swings in the stock market index. Instead, we observe a sizeable decline in the response of the interest rate.

In the period 1996-2006, there are three distinct phases corresponding to the huge stock market boom (January 1996-September 2000), the following bust (September 2000-March 2003) and the subsequent recovery (March 2003-April 2006). We believe that it is interesting to discover whether the interest rate response is the same in the boom and in the bust phases of the cycle. In table 6, we show the statistics for the estimate based on all four regimes in the three subperiods described above:

Table 6: Estimates for the US

	Regimes all 1996-2000	Regimes all 2000-2003	Regimes all 2003-2006
Mean of distribution	0.0078	0.0076	0.0067
Std. dev. of distribution	0.0040	0.0031	0.0069
Median of distribution	0.0076	0.0075	0.0060
Mass below zero	1.8%	0.4%	14.7%

The reaction does not change across the three subperiods. According to our estimates, the response of the three-month interest rate is the same in the boom

[11] See table C4 in appendix C.

and in the bust phase of the stock market cycle. The response is still positive and significant (at least up to 2003), but it is low when compared to the period 1985-1995.

3.2 Interpretations

According to our estimates, at the end of the 1990s something changed in the relationship between stock prices and the three-month interest rate. Since this interest rate reflects near term expectations of future monetary policy, something also changed in the relationship between monetary policy and stock prices.

Even though recent large stock market swings had no significant impact on CPI inflation (moreover, Stock and Watson (2003) show that asset prices have low and unstable forecasting power for CPI inflation), there is increasing empirical evidence pointing to a significant impact of asset price swings on aggregate demand through a wealth effect on consumption, a Tobin's Q and financial accelerator effects on investment (see Maki and Palumbo (2001) among many others). Hence, if a lower forecasting power for inflation would justify a lower response to asset prices, a larger stock market wealth effect would call for a higher response.

Our interpretation is that the lower reaction can reflect the growing impact of other forms of wealth on aggregate demand, in particular housing wealth. We conjecture that a lower impact of stock prices on aggregate demand can be compensated by a higher response to real estate prices. This reasoning would imply that the monetary policy authority has devoted more attention to developments in the housing market rather than the stock market. The recent boom in the real estate market can reconcile a decrease in the marginal propensity to consume out of financial wealth and an increase in the marginal propensity to consume out of real wealth (real estate). To test this conjecture, we can use our model and measure the reaction to house prices. Obviously, daily data on house prices are not available. Nevertheless, a proxy exists which in our opinion can provide meaningful results: the REIT index. It includes specific publicly traded securities of real estate trusts and real estate operating companies. Data are daily and thus are a reliable indicator of the high frequency evolution in the real estate market.

We estimate the model since the beginning of the 1990s, because the REIT series starts at that time. We report the estimates for the periods 1990-1996 and 1996-2006, as we did for stock prices:

Table 7: Estimates for the US, REIT Data, 1990-1995 lim=1

	Regimes All	Regimes 1,2,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4
Mean of distribution	0.0009	0.0004	0.0011	0.0266	0.0250
Std. dev. of distribution	0.0057	0.0063	0.0055	0.0190	0.0164
Mass below zero	44.1%	46.3%	41.4%	5.1%	4.8%

Table 8: Estimates for the US, REIT Data, 1996-2006 lim=1

	Regimes All	Regimes 1,2,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4
Mean of distribution	0.0046	0.0043	0.0050	0.0173	0.0168
Std. dev. of distribution	0.0030	0.0031	0.0029	0.0165	0.0163
Mass below zero	8.7%	4.9%	6.4%	12.8%	21.3%

We remark that the estimate is not significant in the first part of the sample, whereas it becomes significant at the 90 % level in the second part of the sample. Thus, while the reaction to stock prices has declined over time, the reaction to house prices has followed the opposite pattern. Pushing the argument further, this result is consistent with an increase in the wealth effect of non-financial assets and with an increase in the importance of house prices in the monetary policy strategy.

These results confirm our conjecture that the lower response to stock prices is accompanied by a higher response to real estate prices. According to the financial literature (Paiella (2004) and Altissimo et *al*. (2005) among others), different assets are not necessarily fungible. Certain assets are more appropriate to use for current expenditure, others for long-term savings or for bequest. Wealth effects can thus differ across assets and can be influenced by shifts in household preferences and portfolios. Our results can thus reflect a more relevant macroeconomic impact of real estate prices and a lower relative impact of stock prices.

The evidence provided above is consistent with extensive recent literature on the housing wealth effect. Case, Quigley and Shiller (2005) find that the housing wealth effect is positive and significant with an elasticity ranging from 0.11 to 0.17. This effect is statistically significantly higher than the financial wealth effect, which is not statistically different from zero in their estimates. Interestingly, from their tables we discover that not only does housing wealth have a more important effect than stock market wealth, but this effect is also increasing over time. They argue convincingly that fiscal reforms and deregulation in the mortgage markets have favored home equity loans. Carroll, Slacalek and Otsuka (2006) also find that the housing wealth effect is substantially larger than the stock market wealth effect. They estimate the long-run marginal propensities to consume out of housing wealth to be 0.09 for housing and out of stock market wealth to be 0.04. Ludwig and Sløk (2004) also find that the housing wealth effect is significantly increasing over time in the OECD countries, whereas it is unclear whether the housing wealth effect is larger than the stock market wealth effect.

Speeches from members of the Federal Reserve Board (Greenspan (2001) among others) confirm that house prices have gained attention in the formulation of the monetary policy strategy. Greenspan (2001) states clearly that the marginal propensity to consume out of housing wealth might be higher than the marginal propensity to consume out of stock market wealth. Hence, our results can reflect an evolution in the monetary policy strategy over the last ten years.

Interestingly, and unlike the case for asset prices, we discover different behavior in the very last part of the sample:

Table 9: Estimates for the US, REIT Data

	Regimes all 1996-2000	Regimes all 2000-2003	Regimes all 2003-2006
Mean of distribution	0.0116	0.0096	-0.0008
Std. dev. of distribution	0.0058	0.0061	0.0053
Mass below zero	2.2%	4.2%	59.6%

Surprisingly, when the increase in real estate prices accelerates (2003-2006), we detect a sudden stop in the interest rate response.

3.3 The role of macroeconomic shocks

One possible criticism to the specification of our model is that it is excessively simple. A simple bivariate VAR can miss important information coming from other macroeconomic variables affecting at the same time the interest rate and the stock market index.

We defend our choice on the basis of three arguments:

1) RS (2003) include some measures of macroeconomic shocks in their baseline specification. We have shown above that the presence of these shocks does not affect the results, since we are able to closely reproduce the RS results.

2) We think that the inclusion of monthly macroeconomic shocks in a model with daily data is questionable. We propose a specification including as shocks daily variations in the trade weighted exchange rate and in the oil price index. These shocks have limited effects on the estimates, as can be seen in tables A1 to A5 in appendix A.

3) The presence of the unobservable common shock z_t, in our opinion, takes into account to a large extent all the possible shocks driving interest rates and stock prices. Identification through heteroskedasticity heavily relies on the common shocks and, in fact, when the common shock is excluded, the results worsen significantly. As an example, we report the estimates for the two sub-samples excluding the common shock:[12]

[12] Without common shocks only two regimes are enough to identify β.

Table 10: Estimates for the US, 1985-1995 lim=1, no Common Shock

	Regimes 1,2	Regimes 1,3	Regimes 1,4	Regimes all
Mean of distribution	0.3051	0.0259	0.0052	0.0178
Std. dev. of distribution	3.4414	0.0065	0.0027	0.0083
Mass below zero	5.4%	0%	2.6%	3.1%

Table 11: Estimates for the US, 1996-2006, no Common Shock

	Regimes 1,2	Regimes 1,3	Regimes 1,4	Regimes all
Mean of distribution	0.0083	-0.0008	0.0003	0.0045
Std. dev. of distribution	0.0026	0.0024	0.0017	0.0017
Mass below zero	0%	61.6%	42%	0.3%

Comparing these results with tables 4 and 5, we see that the common shock is essential and it is likely to capture dynamics induced by omitted macroeconomic shocks.

Of course, although the presence of the common shock is relevant, we are careful in the interpretation of our coefficient β. It can reflect any direct or indirect reaction to stock prices, but it can also be influenced by other factors we do not successfully control for.

4 Results for the UK, the EU and Japan

In this section we estimate our model with data for the UK, the EU and Japan.

4.1 The UK

We split the sample in January 1996, as we did for the US. In this way we can compare the behavior of the Bank of England to the Federal Reserve in the two subperiods. The FTSE index, like the S&P, behaves relatively smoothly in the first sample and is subject to a big boom-bust cycle in the second sample.

The results for the period 1985-1995 are presented in table 12:

Table 12: Estimates for the UK 1985-1995 lim=0.75

	Regimes All	Regimes 1,2,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4
Mean of distribution	0.0157	0.0162	0.0154	0.0026	0.0017
Std. dev. of distribution	0.0071	0.0075	0.0069	0.0204	0.0174
Mass below zero	1.4%	1.6%	1.5%	46.2%	46.8%

The estimate of β is around 0.015, meaning that an increase of 10% in the stock market index causes an increase in the three-month interest rate of 15 basis points. The estimated coefficient appears to be of the same order of magnitude as the one estimated for the US. Changes in the window to select the regimes affect critically the two estimates based on regimes 3 and 4 together. Nonetheless, the estimate that exploits all the four regimes is relatively stable as can be seen in table A3 in appendix A.

In the second part of our sample (January 1996-April 2006), the estimates of β are negative and not significantly different from zero (table 13).

Table 13: Estimates for the UK 1996-2006 lim. 1

	Regimes All	Regimes 1,2,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4
Mean of distribution	-0.0001	-0.0001	-0.0000	-0.0044	-0.0034
Std. dev. of distribution	0.0009	0.0008	0.0008	0.0237	0.00268
Mass below zero	56.1%	56.2%	54.8%	58.4%	56.7%

The results are very sharp. In the second part of the sample, the interest rate did not react at all to stock prices. Hence, according to our estimates, while the Federal Reserve maintained a positive and significant reaction in the second period, the Bank of England ignored stock prices.

In the case of the UK, we also analyze house prices, like in the US case. However, we do not identify any reaction to house prices, as shown in table A6 in appendix A.

4.2 The EU

We now present the results for the EU. The sample period is January 1999-April 2006:

Table 14: Estimates for the EU 1999-2006 lim.1

	Regimes all	Regimes 1,2,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4
Mean of distribution	-0.0003	0.0005	0.0005	0.0062	0.0063
Std. dev. of distribution	0.0193	0.0006	0.0006	0.0070	0.0086
Mass below zero	18.9%	19.5%	18.4%	17.6%	18%

The ECB reaction turns out to be not significant. The estimates are robust to changes in the criteria to select the regimes and to the introduction of macroeconomic shocks (see table A5 in appendix A).

The size of the sample is smaller than for the other countries, due to the introduction of the euro in 1999, but is sufficient to derive some evidence on European monetary policy. In 2002, Governor Trichet said explicitly that "*it is not opportune to introduce asset prices in the central bank's reaction function*" and our result confirms this attitude.[13] A topic of discussion is whether we should find some sign of indirect reaction. Governor Trichet recognizes that recent changes in asset prices have influenced private spending more than past swings because of the more widespread stock ownership in a number of industrialized countries. He states, however, that this impact is still low compared to the US. And in fact our results do not show any sign of indirect reaction in the last seven years.

Also in the EU we do not find any reaction to house prices (see table A6 in appendix A).

[13] Speech available at http://www.banque-france.fr/gb/instit/telechar/discours/sp230402.pdf

All these results are consistent with the recent evidence provided in Paiella (2004) and Altissimo et *al.* (2005) showing that the wealth effect, coming either from stock prices or from housing, seems to be extremely low in Europe.

4.3 Japan

The case of Japan is difficult to analyze because the monetary policy strategy has changed several times in the last twenty years. During the 1980s monetary policy was strongly oriented to the stabilization of the exchange rate. During the 1990s the Bank of Japan was forced to change its strategy many times to fight against the zero interest rate bound. Therefore, the assumptions of constant coefficients and homoskedastic monetary policy shocks seem too strong. And in fact, although we have run many regressions over several sample periods, changing the specification of the model and the frequency of the data, and using many interest rates, we have always found unstable results. It is the case for the whole period (1985-2006), for the bubble period (1985-1990) and also for the liquidity trap period (1996-2005). Considering that after 1996 the Bank of Japan could not lower the interest rate because this was already close to zero, we show estimates for the period 1991-1996 in table 15. We find evidence of no reaction:

Table 15: Estimates for Japan 1991-1996 lim.1

	Regimes all	Regimes 1,2,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4
Mean of distribution	0.0005	0.0002	0.0007	-0.0060	-0.0085
Std. dev. of distribution	0.0012	0.0012	0.0013	0.0616	0.0085
Mass below zero	35.5%	42.4%	29.3%	66.2%	86.7%

The case of Japan shows that the RS procedure cannot always provide meaningful estimates. Most likely, several shifts in the monetary policy stance violate the assumption of homoskedastic monetary policy shocks.

5 GMM or identification through heteroskedasticity?

According to RS (2003), identification through heteroskedasticity improves the existing literature because it can deal appropriately with the endogeneity problem between interest rates and stock prices. RS show that extended Taylor rules estimated by GMM deliver responses that are not statistically significant (as in Bernanke and Gertler (2000)) and they argue that this is due to weak instruments. However, Chadha, Sarno and Valente (2004), using the same methodology, find a significant response of the interest rate to stock price movements.

Estimating our model in sample periods as close as possible to Chadha, Sarno and Valente (2004), we find very similar results, as can be seen in table 16:[14]

Table 16: Comparison to Chadha et al. (2004)

	Chadha et al. (2004)	Furlanetto (2008)
	1979-2000	1985-2000
US	0.015	0.018
	(0.005)	(0.005)
UK	0.007	0.008
	(0.003)	(0.003)
Japan	0.0002	0.0005
	(0.0005)	(0.0012)

The two sets of estimates are almost indistinguishable. Thus, our work seems to reconcile the two approaches. A careful choice of the instruments and a theoretically grounded measure of the output gap (as in Chadha, Sarno and Valente (2004)) can correct for the endogeneity bias emphasized by RS (2003).

Nevertheless, the fact that extended Taylor rules are able to provide significant estimates does not mean that identification through heteroskedasticity becomes less useful. On the contrary, our results show that the RS procedure is

[14]Standard errors are in parenthesis. Our sample period is 1985-2000 for the UK and the US and 1991-1996 for Japan.

extremely powerful. Using identification through heteroskedasticity, we can estimate the model in very short samples (only few years) and obtain meaningful results, whereas the Taylor rule approach needs much larger samples (twenty years or so). The use of daily data enables the RS approach to discover interesting subsample dynamics, as shown in the preceding sections. Using Taylor rules we could not detect with precision the decline in reaction observed in the last ten years and we could not estimate the model for such small samples as the boom and bust cycles at the end of the 1990s.

Using a combination of short-run and long-run restrictions in a VAR, Bjørnland and Leitemo (2008) find a large interest rate response on the impact of a stock market shock. According to their estimates, a 10% increase in stock prices would lead to an increase in the interest rate of 40 basis point over the period 1983-2002. This value is double than ours. Interestingly, changing the sample period, Bjørnland and Leitemo (2008) also find a decline in the response over time.

A recent study which also exploits heteroskedasticity is D'Agostino, Sala and Surico (2005). They find nonlinearities in the Federal Reserve response to asset prices over the period 1985-2003. Estimating a Threshold VAR (TVAR) on monthly data with two regimes (high and low financial volatility), they find a non-significant reaction in periods of low financial volatility and a positive and significant reaction in periods of high financial volatility with the point estimate at 0.037. In their sample average stock returns are -0.9% in the high volatility regime and 1.8 in the low volatility regime Consequently, they empathize that the Federal Reserve reaction is asymmetric and significant only in the downturn phase of stock market cycles. At first glance, their results are different from ours. We do not find this non-linear reaction for stock prices (see as an example table 6 for a recent boom-bust cycle) whereas we identify a similar effect for house prices (see table 9).

6 Conclusion

In this paper, we attempt to measure the reaction of monetary policy to asset prices in the four major world economies. The main results can be summarized as follows:

1) We find a positive and significant reaction in the US and the UK (but only up to the late 1990s). Our result is of the same order of magnitude as the findings in RS (2003) and Chadha, Sarno and Valente (2004).

2) We find that the reaction of the Federal Reserve is much lower in the period 1996-2006, although the reaction is still positive and significant. In the same period, the Bank of England, the European Central Bank and the Bank of Japan do not react at all to asset prices.

3) We explain the reduced response by the Federal Reserve in the second part of the sample as a result of more attention being paid to house prices than to stock prices. We showed that the reaction to house prices has increased over time whereas the response to stock prices has decreased over time. A more important role for house prices is consistent with speeches by Greenspan (2001) and empirical evidence provided by Case, Quigley and Shiller (2005) among many others.

4) This paper reconciles results in the Taylor rule literature and in the identification through heteroskedasticity literature. However, we show that only the RS approach can discover short-term dynamics that are essential in the interpretation of the results.

An interesting extension of this paper would be the estimation of the interest rate response to the stock market in a model with time-varying parameters. We plan to work on this project in the future.

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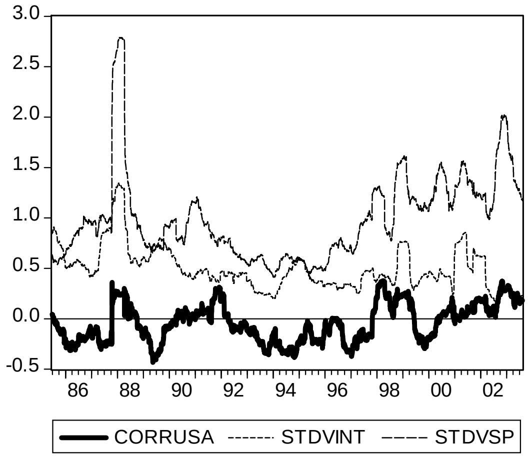

Figure 1: Thirty-day rolling standard deviation of daily changes in the interest rate (STDEVINT), of daily changes in the stock market index (STDEVSP) and rolling correlation of daily changes of the interest rate and the stock market index (CORRUSA).

Appendix A

Table A1: Estimates for the US, 1985-1995

	Regimes all lim=1	Regimes all macro shocks
Mean of distribution	0.0159	0.0224
Std. dev. of distribution	0.0303	0.0058
Mass below zero	13.5%	0.1%

Table A2: Estimates for the US, 1996-2006

	Regimes all lim=0.5	Regimes all lim=1.5	Regimes all macro shocks
Mean of distribution	0.0063	0.0062	0.0064
Std. dev. of distribution	0.0026	0.0027	0.0020
Mass below zero	0.6%	0.7%	0%

Table A3: Estimates for the UK, 1985-1995

	Regimes all lim=0.5	Regimes all lim=1	Regimes all macro shocks
Mean of distribution	0.0086	0.0106	0.0135
Std. dev. of distribution	0.0071	0.0072	0.0451
Mass below zero	10.7%	6.8%	0.5%

Table A4: Estimates for the UK, 1996-2006

	Regimes all lim=0.5	Regimes all lim=1.5	Regimes all macro shocks
Mean of distribution	-0.0008	-0.0007	-0.0001
Std. dev. of distribution	0.0008	0.0016	0.0008
Mass below zero	86%	66.7%	55.5%

Table A5: Estimates for the EU, 1999-2006

	Regimes all lim=0.5	Regimes all lim=1.5	Regimes all macro shocks
Mean of distribution	0.0006	-0.0031	0.0023
Std. dev. of distribution	0.0006	0.0005	0.0402
Mass below zero	12.7%	18.6%	25.4%

Table A6: Reaction to Real Estate Index (REIT) using all regimes

	UK (1996-2006)	EU (1999-2006)
Mean of distribution	-0.0006	-0.0014
Std. dev. of distribution	0.0010	0.0020
Mass below zero	71.6%	75.7%

Appendix B

In this appendix, we show how to estimate β using three regimes. First, we subtract the first covariance matrix from the other two:

$$\Delta\Omega_{21} = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} (\beta+\gamma)^2\Delta\sigma^2_{21,z} + \beta^2\Delta\sigma^2_{21,\eta} & (1+\alpha\gamma)(\beta+\gamma)\Delta\sigma^2_{21,z} + \beta\Delta\sigma^2_{21,\eta} \\ (1+\alpha\gamma)(\beta+\gamma)\Delta\sigma^2_{21,z} + \beta\Delta\sigma^2_{21,\eta} & (1+\alpha\gamma)^2\Delta\sigma^2_{21,z} + \Delta\sigma^2_{21,\eta} \end{bmatrix}$$

$$\Delta\Omega_{31} = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} (\beta+\gamma)^2\Delta\sigma^2_{31,z} + \beta^2\Delta\sigma^2_{31,\eta} & (1+\alpha\gamma)(\beta+\gamma)\Delta\sigma^2_{31,z} + \beta\Delta\sigma^2_{31,\eta} \\ (1+\alpha\gamma)(\beta+\gamma)\Delta\sigma^2_{31,z} + \beta\Delta\sigma^2_{31,\eta} & (1+\alpha\gamma)^2\Delta\sigma^2_{31,z} + \Delta\sigma^2_{31,\eta} \end{bmatrix}$$

Let $\theta = \frac{1+\alpha\gamma}{\beta+\gamma}$. From the two estimated covariance matrices above we can write the six following equations where $\Delta\Omega_{21,11}$ is the (1,1) element of the matrix $\Delta\Omega_{21}$:

$$(\beta+\gamma)^2\Delta\sigma^2_{21,z} + \beta^2\Delta\sigma^2_{21,\eta} = (1-\alpha\beta)^2\Delta\Omega_{21,11}$$

$$\theta(\beta+\gamma)^2\Delta\sigma^2_{21,z} + \beta\Delta\sigma^2_{21,\eta} = (1-\alpha\beta)^2\Delta\Omega_{21,12}$$

$$\theta^2(\beta+\gamma)^2\Delta\sigma^2_{21,z} + \Delta\sigma^2_{21,\eta} = (1-\alpha\beta)^2\Delta\Omega_{21,22}$$

$$(\beta+\gamma)^2\Delta\sigma^2_{31,z} + \beta^2\Delta\sigma^2_{31,\eta} = (1-\alpha\beta)^2\Delta\Omega_{31,11}$$

$$\theta(\beta+\gamma)^2\Delta\sigma^2_{31,z} + \beta\Delta\sigma^2_{31,\eta} = (1-\alpha\beta)^2\Delta\Omega_{31,12}$$

$$\theta^2(\beta+\gamma)^2\Delta\sigma^2_{31,z} + \Delta\sigma^2_{31,\eta} = (1-\alpha\beta)^2\Delta\Omega_{31,22}$$

From the six equations above we obtain:

$$\theta = \frac{\Delta\Omega_{21,12} - \beta\Delta\Omega_{21,22}}{\Delta\Omega_{21,11} - \beta\Delta\Omega_{21,12}} \tag{2}$$

$$\theta = \frac{\Delta\Omega_{31,12} - \beta\Delta\Omega_{31,22}}{\Delta\Omega_{31,11} - \beta\Delta\Omega_{31,12}} \tag{3}$$

which is a system of two equations in two unknowns (β, θ). Solving this system, we find an estimate for β, the parameter of interest, and an estimate for θ combining α, β and γ (this is the reason why we achieve only partial identification). RS (2003) choose the root using the following criterion. If the two roots have different signs, they select the positive one. If they have the same sign, they choose the smaller in absolute value. From a theoretical point of view, we expect β to be small and positive but we do not have a prior for $\frac{1}{\theta} = \frac{\beta+\gamma}{1+\alpha\gamma}$. As a guide, we can choose the GMM estimate that is 0.018 for β and -0,9090 for θ for the US. Thus, it is reasonable that if we find only one positive root this has to be β and that if the two roots have the same sign β is the smaller one, otherwise our model would be completely misspecified.

We used the RS selection criterion for Japan, the UK and the EU but we found very different estimates in each subset of regimes with big standard errors. The model seemed to be completely misspecified. We modified the regimes and estimated the model for different samples, but the problem was always present. It turned out that the procedure for the selection of the roots was not efficient and thus we modified it to pick up correctly β and not $\frac{1}{\theta}$. We chose the root that was lower in absolute value and thus in case of different signs we did not force β to be positive as RS (2003). This slight modification did not change the results in the RS sample but matters a lot for the other countries and the other samples. In that way, we are able to select the correct root most of the time.

Substituting (2) in (3) , we have the following quadratic equation in β:

$$a\beta^2 - b\beta + c = 0$$

where:

$$\begin{aligned} a &= \Delta\Omega_{31,22}\Delta\Omega_{21,12} - \Delta\Omega_{21,22}\Delta\Omega_{31,12} \\ b &= \Delta\Omega_{31,22}\Delta\Omega_{21,11} - \Delta\Omega_{21,22}\Delta\Omega_{31,11} \\ c &= \Delta\Omega_{31,12}\Delta\Omega_{21,11} - \Delta\Omega_{21,12}\Delta\Omega_{31,11} \end{aligned}$$

The quadratic equation always has a real solution and after some tedious algebra we can rewrite it in the following way

$$(1+\alpha\gamma)\, d\beta^2 - (2\beta + \alpha\gamma\beta + \gamma)\, d\beta + \beta\,(\gamma+\beta)\, d$$

where:

$$d = \sigma^2_{z3}\sigma^2_{\eta2} - \sigma^2_{z3}\sigma^2_{\eta1} - \sigma^2_{z1}\sigma^2_{\eta2} - \sigma^2_{z2}\sigma^2_{\eta3} + \sigma^2_{z1}\sigma^2_{\eta3} + \sigma^2_{z2}\sigma^2_{\eta1}$$

Provided that d is different from zero, the equation has two solutions:

$$\beta_1 = \beta$$

$$\beta_2 = \frac{1}{\theta} = \frac{\beta+\gamma}{1+\alpha\gamma}$$

Hence, we are able to estimate consistently β as long as we choose the right solution of the quadratic form and we have at least three regimes for the covariance matrix.

With four regimes, the model is overidentified and the parameters can be estimated by GMM using the three moment conditions:

$$\theta = \frac{\Delta\Omega_{21,12} - \beta\Delta\Omega_{21,22}}{\Delta\Omega_{21,11} - \beta\Delta\Omega_{21,12}}$$

$$\theta = \frac{\Delta\Omega_{31,12} - \beta\Delta\Omega_{31,22}}{\Delta\Omega_{31,11} - \beta\Delta\Omega_{31,12}}$$

$$\theta = \frac{\Delta\Omega_{41,12} - \beta\Delta\Omega_{41,22}}{\Delta\Omega_{41,11} - \beta\Delta\Omega_{41,12}}$$

Appendix C

The US: 1985-1999

In table C1, we observe that the covariance, which on average is slightly negative, becomes positive when the stock market shock exhibits high variance. These shifts in the covariance matrix enable us to identify the model using the estimated covariance matrices to recover the parameters of the structural form. In table C1, we show the estimates of the four covariance matrices Ω_i for $i = 1$ to 4.

Table C1: Variance-Covariance Matrix of Reduced Form Shocks

	Variance of Policy Shocks	Variance of Stk Mkt shocks	Covariance	Frequency of Obs.
Regime 1	0.2220	70.8844	-0.3434	91.2%
Regime 2	0.4550	363.7233	4.8330	1.8%
Regime 3	2.1157	991.9111	14.3440	2.3%
Regime 4	0.9828	72.9241	-1.0091	4.7%

The four estimates obtained using three regimes can be compared to a GMM estimate that uses all four regimes. With four regimes, the model is overidentified. We test that the four estimates using three regimes are statistically equal to the GMM estimate by computing the difference between the estimates for each draw of the bootstrap. We obtain 1000 observations that represent the distribution of the difference in the estimates. This distribution should have zero mean and obviously zero should be inside the 95% confidence interval for the mean. Using the language of RS, we call this test ”test of overidentifying restrictions”. Over the period 1985-1999, the test is passed in each case, as is shown in table C2:

Table C2: Test of Overidentifying Restrictions, the US 1985-1999

	Confidence interval	Median
$\hat{\beta}_{GMM} - \hat{\beta}_{123}$	[-0.0064, 0.0074]	-0.0000
$\hat{\beta}_{GMM} - \hat{\beta}_{124}$	[-0.0020, 0.0022]	-0.0000
$\hat{\beta}_{GMM} - \hat{\beta}_{134}$	[-0.0179, 0.0165]	-0.0005
$\hat{\beta}_{GMM} - \hat{\beta}_{234}$	[-0.0169, 0.0180]	0.0008

We present below the same tables for the other estimates.

The US: 1985-2006

Table C3: Test of Overidentifying Restrictions, the US 1985-2006

	Confidence interval	Median
$\hat{\beta}_{GMM} - \hat{\beta}_{123}$	[-0.0000, 0.0026]	0.0007
$\hat{\beta}_{GMM} - \hat{\beta}_{124}$	[-0.0016, 0.0000]	-0.0006
$\hat{\beta}_{GMM} - \hat{\beta}_{134}$	[0.0000, 0.0232]	0.0107
$\hat{\beta}_{GMM} - \hat{\beta}_{234}$	[0.0000, 0.0247]	0.0118

The US: 1985-1995

Table C4: Variance-Covariance Matrix of Reduced Form Shocks

	Variance of Policy Shocks	Variance of Stk mkt shocks	Covariance	Frequency of Obs.
Regime 1	0.2388	61.24	-0.33	86.7%
Regime 2	0.0653	44.45	0.36	0.7%
Regime 3	1.6679	959.74	14.53	3.2%
Regime 4	0.8582	58.55	-2.01	9.5%

Table C5: Test of Overidentifying Restrictions, the US 1985-1995

	Confidence interval	Median
$\hat{\beta}_{GMM} - \hat{\beta}_{123}$	[-0.0031, 0.0003]	-0.0003
$\hat{\beta}_{GMM} - \hat{\beta}_{124}$	[-0.0975, 0.1034]	0.0272
$\hat{\beta}_{GMM} - \hat{\beta}_{134}$	[-0.0093, 0.0021]	-0.003
$\hat{\beta}_{GMM} - \hat{\beta}_{234}$	[-0.0084, 0.0028]	-0.0025

The US: 1996-2006

Table C6: Variance-Covariance Matrix of Reduced Form Shocks

	Variance of Policy Shocks	Variance of Stk mkt shocks	Covariance	Frequency of Obs.
Regime 1	0.1033	93.23	0.11	84.2%
Regime 2	0.2023	398.65	2.10	9%
Regime 3	0.9209	189.30	1.52	3.2%
Regime 4	1.0289	139.93	0.72	3.6%

Table C7: Test of Overidentifying Restrictions, the US 1996-2006

	Confidence interval	Median
$\hat{\beta}_{GMM} - \hat{\beta}_{123}$	[-0.0006, 0.0008]	0.0000
$\hat{\beta}_{GMM} - \hat{\beta}_{124}$	[-0.0007, 0.0006]	-0.0000
$\hat{\beta}_{GMM} - \hat{\beta}_{134}$	[-0.0859, 0.0909]	0.0057
$\hat{\beta}_{GMM} - \hat{\beta}_{234}$	[-0.0650, 0.0595]	0.0034

The UK: 1985-1995

Table C8: Variance-Covariance Matrix of Reduced Form Shocks

	Variance of Policy Shocks	Variance of Stk mkt shocks	Covariance	Frequency of Obs.
Regime 1	0.8331	62.71	-0.73	87.8%
Regime 2	2.3197	1375.31	18.76	1.3%
Regime 3	3.3478	236.08	-1.73	2.4%
Regime 4	5.7884	52.71	-3.72	8.5%

Table C9: Test of Overidentifying Restrictions, the UK 1985-1995

	Confidence interval	Median
$\hat{\beta}_{GMM} - \hat{\beta}_{123}$	[-0.0025, 0.0012]	-0.0003
$\hat{\beta}_{GMM} - \hat{\beta}_{124}$	[-0.0010, 0.0022]	0.0003
$\hat{\beta}_{GMM} - \hat{\beta}_{134}$	[-0.0545, 0.0307]	-0.013
$\hat{\beta}_{GMM} - \hat{\beta}_{234}$	[-0.0505, 0.0246]	-0.014

The UK: 1996-2006

Table C10: Variance-Covariance Matrix of Reduced Form Shocks

	Variance of Policy Shocks	Variance of Stk mkt shocks	Covariance	Frequency of Obs.
Regime 1	0.0779	86.09	-0.00	80.7%
Regime 2	0.0447	494.29	-0.09	7.1%
Regime 3	0.7679	201.86	0.57	2.7%
Regime 4	0.6388	110.8	0.63	9.5%

Table C11: Test of Overidentifying Restrictions, the UK 1996-2006

	Confidence interval	Median
$\hat{\beta}_{GMM} - \hat{\beta}_{123}$	[-0.0002, 0.0002]	0.0000
$\hat{\beta}_{GMM} - \hat{\beta}_{124}$	[-0.0002, 0.0002]	-0.0000
$\hat{\beta}_{GMM} - \hat{\beta}_{134}$	[-0.0539, 0.04]	-0.0032
$\hat{\beta}_{GMM} - \hat{\beta}_{234}$	[-0.0608, 0.0538]	-0.0029

The EU: 1999-2006

Table C12: Variance-Covariance Matrix of Reduced Form Shocks

	Variance of Policy Shocks	Variance of Stk mkt shocks	Covariance	Frequency of Obs.
Regime 1	0.0194	122.21	0.0695	83.3%
Regime 2	0.0212	597.88	0.3278	8.4%
Regime 3	0.4094	457.61	1.9612	1.7%
Regime 4	0.2576	77.41	-0.3623	6.5%

Table C13: Test of Overidentifying Restrictions, the EU 1999-2006

	Confidence interval	Median
$\hat{\beta}_{GMM} - \hat{\beta}_{123}$	[-0.0000, 0.0000]	0.0000
$\hat{\beta}_{GMM} - \hat{\beta}_{124}$	[-0.0000, 0.0000]	-0.0000
$\hat{\beta}_{GMM} - \hat{\beta}_{134}$	[-0.0069, 0.0198]	0.0053
$\hat{\beta}_{GMM} - \hat{\beta}_{234}$	[-0.0080, 0.0238]	0.0064

Japan 1991-1996

Table C14: Test of Overidentifying Restrictions, Japan 1991-1996

	Confidence interval	Median
$\hat{\beta}_{GMM} - \hat{\beta}_{123}$	[-0.0002, 0.0008]	0.0002
$\hat{\beta}_{GMM} - \hat{\beta}_{124}$	[-0.0008, 0.0002]	-0.0002
$\hat{\beta}_{GMM} - \hat{\beta}_{134}$	[-0.1174, 0.1315]	-0.0153
$\hat{\beta}_{GMM} - \hat{\beta}_{234}$	[-0.0281, 0.0073]	-0.0087