Estimating Monetary Policy Reaction Functions Using Quantile Regressions

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Abstract

Monetary policy rule parameters are usually estimated at the mean of the interest rate distribution conditional on inflation and an output gap. This is an incomplete description of monetary policy reactions when the parameters are not uniform over the conditional distribution of the interest rate. I use quantile regressions to estimate parameters over the whole conditional distribution of the federal funds rate. Inverse quantile regressions are applied to deal with endogeneity. Real-time data of inflation forecasts and the output gap are used. I find significant and systematic variations of parameters over the conditional interest rate distribution. Testing for structural changes in regression quantiles shows that these parameter variations cannot be explained by preference shifts of the Fed. Asymmetric interest rate responses can rather be related to expansions and recessions and are consistent with a recession avoidance preference of the Fed during the Volcker-Greenspan era.

Keywords: monetary policy rules, IV quantile regression, real-time data, asymmetries, policy preferences

1. Introduction

Policy rules of the form proposed by Taylor (1993) to understand the interest rate setting of the Federal Open Market Committee (FOMC) in the late 1980s and early 1990s have been used as a tool to study historical monetary policy decisions. Although estimated versions describe monetary policy in the U.S. quite well, in reality the Federal Reserve does not follow a policy rule mechanically: "The monetary policy of the Federal Reserve has involved varying degrees of rule- and discretionary-based modes of operation over time," (Greenspan, 1997). This raises the question how the FOMC responds to inflation and the output gap during periods that cannot be described accurately by a linear policy rule. Except anecdotal descriptions of some episodes (e.g. Taylor, 1993; Poole, 2006) there appears to be a lack of studies that analyze deviations from policy rules systematically and quantitatively.

In addition to changes between discretionary and rule-based policy regimes, economic theory provides several reasons for deviating at least at times from a symmetric and linear policy rule framework. First, asymmetric central bank preferences can lead in an otherwise linear model to a nonlinear policy reaction function (Gerlach, 2000; Surico, 2007; Cukierman and Muscatelli, 2008). A nonlinear policy rule can be optimal when the central bank has a quadratic loss function, but the economy is nonlinear (Schaling, 1999; Dolado et al., 2005). Even in a linear economy with symmetric central bank preferences an asymmetric policy rule can be optimal if there is uncertainty about specific model parameters: Meyer et al. (2001) analyse uncertainty regarding the NAIRU and Tillmann (2010) studies optimal policy with uncertainty about the slope of the Phillips curve. Finally, when interest rates approach the zero lower bound, responses to inflation might increase to avoid the possibility of deflation (Orphanides and Wieland, 2000; Kato and Nishiyama, 2005; Tomohiro Sugo, 2005; Adam and Billi, 2006). Despite these concerns in the empirical literature estimation of linear policy rules prevails.

Among the few papers that consider the estimation of nonlinear policy rules, different assumptions regarding nonlinearities in monetary policy rule specifications lead to very different empirical results. For

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example Cukierman and Muscatelli (2008) find important nonlinearities that correspond to a recession avoidance preference of the Fed. Bunzel and Enders (2010) find in addition asymmetric reactions to inflation and Florio (2006) detects nonlinearities in the degree of interest rate smoothing. Rabanal (2004) shows that the Fed attaches a lot of weight on stabilizing output during contractions, while focussing more on controlling inflation and increasing interest inertia during expansions. In contrast, Dolado et al. (2005) find no evidence for a nonlinear policy rule in the U.S. and Surico (2007) finds asymmetric inflation and output responses only prior to 1979.

I take a more general approach to detect and analyze deviations from linear monetary policy rules. While standard linear policy rule estimates characterize the conditional mean of the interest rate, deviations from this linear rule correspond to interest rate responses above or below the conditional mean estimate. I use quantile regression to estimate the whole conditional distribution of the interest rate. In contrast to nonlinear monetary policy rules, there is no need to make particular assumptions regarding the functional form of asymmetries or nonlinearities. Asymmetric reactions of the interest rate to inflation, the output gap and the lagged interest rate are flexibly determined by the data. In contrast to nonlinear policy rule estimation, quantile regression does not yield a characterization of nonlinearities depending on the level of inflation or economic activity. Parameter estimates at different parts of the conditional distribution rather correspond to higher or lower than average interest rate reactions given inflation, the output gap and possibly the lagged interest rate. Thus, the estimated parameters for each quantile of the conditional interest rate distribution can directly be interpreted as deviations from a mean reaction or standard linear policy rule estimate.

For example Cukierman and Muscatelli (2008) find a recession avoidance preference of the Fed. During recessions the interest rate deviates downwards from the values implied by a linear policy rule. The central bank, thus, reacts more to the negative output gap than on average, which leads to interest rate realizations in the lower tail of the conditional interest rate distribution. Another example is the Volcker disinflation. The Fed reacted much more to inflation than during other times to bring inflation down. The federal funds rate was set higher than on average by reacting more to inflation than conditional mean estimates would suggest. Hence, the federal funds rate was set at the upper part of the conditional interest rate distribution.

Chevapatrakul et al. (2009) (CKM henceforth) estimate interest rate reactions at various points of its conditional distribution. They interpret parameters on the lower part of the conditional distribution of the interest rate as interest rate reactions to inflation when interest rates are low. However, the *unconditional* interest rate distribution and the *conditional* interest rate distribution need not necessarily to coincide.[1] The lower and upper part of the conditional interest rate distribution can directly be interpreted as deviations from a mean inflation and output gap response. Rather than reactions at low interest rates, the lower part of the conditional distribution shows that the central bank has set the interest rate lower than on average in response to a given rate of inflation and a given output gap.

In addition to these differences in the interpretation of quantile regressions my paper is distinct from CKM's work in three important aspects: I use real-time data, a recent IV quantile method and I take into account a gradual adjustment of interest rates. First, using real-time data is crucial as the output gap has been perceived by the Federal Reserve to be negative in real-time for almost the whole period between 1970 and 1990. Furthermore, real-time inflation forecasts from the Fed are at times quite different from ex post realized inflation rates. Orphanides (2001) finds that the use of real-time data yields critically different results compared to estimations using ex post revised data. Second, using Hausman tests I find evidence that inflation forecasts and output gap nowcasts are endogenous with respect to the interest rate. Therefore, I use in addition to quantile regression (QR) an inverse quantile regression (IVQR) estimator proposed by Chernozhukov and Hansen (2005). IVQR yields, in contrast to the two-stage estimator used by CKM, consistent estimates even if changes in the endogenous variables affect the shape of the distribution of the dependent variables. In the presence of a zero lower bound of the interest rate this is clearly the case. The estimator of CKM leads to a bias in the estimated constant. IVQR yields unbiased and consistent estimates of *all* parameters. Third, interest rate smoothing has been documented in various studies (see e.g. Clarida

[1] For example, when the zero lower bound on nominal interest rates becomes binding, the central bank sets interest rates at the lowest part of the *unconditional* interest rate distribution. However, a binding zero lower bound means that the central bank would like to set interest rates even lower if this would be possible *given* current inflation and the output gap. Therefore, the interest rate is *not* set a the lowest part of the *conditional* interest rate distribution and possibly above its conditional mean.

et al., 1998, 2000) to be an important element of U.S. monetary policy and therefore needs to be included in a realistic monetary policy rule specification.[2]

I find clear evidence of a nonlinear relationship between the interest rate, inflation, the output gap and the lagged interest rate. Policy parameters fluctuate significantly over the conditional distribution of the federal funds rate. These deviations from the parameter estimates at the conditional mean of the interest rate are systematic. I find that the inflation coefficient increases over the conditional interest rate distribution. This confirms the result from CKM. For the output gap I find a decrease of the output gap coefficient over the conditional interest rate distribution. In the estimates by CKM this decrease is less pronounced, but they also find that the interest rate response to the output gap is only significant for the lower 50% of the conditional interest rate distribution. While CKM impose a zero interest rate smoothing parameter, I find highly significant monetary policy responses to the lagged interest rate. In addition, my estimation results exhibit a hump-shaped pattern of the interest rate smoothing parameter: it is higher at the median than at the tails of the conditional interest rate distribution. The estimated constant varies over the conditional interest rate distribution, too. I observe surprising differences in conditional mean and median estimates. This indicates that results from current monetary policy rule estimation practice might be affected by outliers and might therefore not be the best description of monetary policy even in a linear setting.

For a comparison with the results by CKM, I repeat the estimation with revised data. The patterns of the coefficients over the conditional interest rate distribution is similar to the results with real-time data, however, with revised data parameter variations over the range of quantiles are overestimated compared to results based on the information that has been actually available to policy makers at the time of policy decisions.

The results are robust to variations in the sample. They indicate that the FOMC has sought to stabilize inflation more and output less when setting the interest rate higher than implied by the conditional mean of standard policy rule estimates and vice versa. The hump of the interest rate smoothing coefficient over the range of quantiles reflects periods without any changes in the federal funds rate and thus a large degree of smoothing at the conditional median. Interest rate hikes and decreases are usually done in a sequence of consecutive steps leading to a somewhat lower smoothing coefficient when the fed funds rate is set higher or lower than at the conditional mean. A fraction of deviations from an estimated linear policy rule are possibly not caused by policy shocks, but by asymmetric policy reactions.

I run tests for structural changes in regression quantiles that have been developed by Qu (2008) and Oka and Qu (2011) to check whether the detected parameter variations reflect shifting preferences of policy makers. In a specification with interest smoothing the parameter estimates are stable over almost the whole conditional distribution of the federal funds rate. The variations of parameter estimates over the conditional interest rate distribution can therefore not be explained by changes in monetary policy preferences.[3]

An alternative explanation of parameter variations might be asymmetric policy preferences. By mapping parameter variations into the time domain I can check whether asymmetric policy reactions are correlated with the inflation rate and expansions or recessions. I find mixed results for the correlation between deviations from a linear policy rule and the inflation rate. Regarding expansions and recessions, the estimation results clearly indicate that the Fed deviated anticyclically from a linear policy rule during the Volcker-Greenspan era. Particularly, deviations of the output gap response from the average output gap response are correlated with the business cycle. The Fed reacted more to the output gap during recessions than during expansions. This leads to lower interest rates than implied by a linear policy rule during recessions. A recession avoidance preference of the FOMC found for example by Rabanal (2004) and Cukierman and Muscatelli (2008) is thus confirmed.

[2] Other authors have argued that a large and significant interest rate smoothing coefficient is the results of a misspecified monetary policy rule (see e.g. Rudebusch, 2002). However, tests by English et al. (2003), Castelnuovo (2003) and Gerlach-Kristen (2004) show doubts that these concerns are justified. I estimate two specifications of monetary policy rules, one with and one without interest rate smoothing, to get results comparable to the different views in the existing literature.

[3] In contrast, for a version without interest rate smoothing, the tests indicate three structural breaks in the conditional interest rate distribution. As I do not find structural breaks in the version *with* interest rate smoothing, I take this as an indication, that a linear policy rule *without* interest rate smoothing is misspecified. The estimated policy parameters are unstable and parameter variations over the conditional distribution may in this case simply reflect this misspecification.

The remainder of this paper is organized as follows: Section 2 presents the real-time dataset. Section 3 presents estimation results for standard methods. Afterwards, section 4 gives an overview on quantile regression methods. In section 5 the quantile regression results are presented and discussed. In section 6 I test for structural change in regression quantiles to detect possible preference shifts. Section 7 links parameter variations to the business cycle. Finally, section 8 concludes.

2. Data

I use real-time data from 1969Q4 through 2005Q4 that were available at the Federal Reserve at the time of policy decisions.[4] For expected inflation I compute year-on-year inflation forecasts four quarters ahead of the policy decisions using four successive quarter-on-quarter forecasts of the GDP/GNP deflator computed by Federal Reserve staff for the Greenbook.[5] Data sources for output gap nowcasts as used by the Federal Reserve are described in Orphanides (2004) in detail. From 1969 until 1976 output gap estimates were computed by the Council of Economic Advisors. Afterwards the Federal Reserve staff started to compute an own output gap series. The output gap estimates by the Fed were not officially published in the Greenbook, but were used to prepare projections of other variables included in the Greenbook. Finally, the interest rate is measured as the annual effective yield of the federal funds rate.

An important aspect of the analysis is that the different data series correspond exactly to the information available at the dates of the specific FOMC meetings. I use observations of as many FOMC meetings as possible to describe U.S. monetary policy with high accurracy. Therefore, the frequency of the observations is not equally spaced. From 1988 to 2005 data for all eight FOMC meetings per year is available. Prior to 1988 observations for some FOMC meetings are missing. The total number of observations is 208. In addition, I create a roughly quarterly distributed dataset with a maximum of four equally spaced observations per year for robustness checks. For comparison with the results by CKM, I create a third dataset with revised data. Table 1 shows how many observations are available per year for the three datasets.

Table 1: Frequency of Observations in the Three Datasets

	observations per year		
period	full dataset	quarterly dataset	revised data
1969-1971	1	1	4
1972-1973	2	1	4
1974	3	3	4
1975-1986	4	4	4
1987	6	4	4
1988-2005	8	4	4

The revised year-on-year inflation rate four quarters after a FOMC meeting is used as the revised inflation forecast (cf. Clarida et al., 1998). The revised output gap is constructed by HP-filtering revised log real GDP data. The output gap series used by CKM is similarly constructed using the HP-filter, however, they use monthly industrial production instead of quarterly GDP. A plot of real-time and revised data is shown in figure 1.

There are no revisions to the effective federal funds rate. For inflation forecasts and output gap nowcasts one can see large differences between real-time and revised data. The Fed perceived the output gap to be negative in real-time for large parts of the sample. The revised output gap looks quite different. By construction it fluctuates around zero. While the level of the two output gap series is different, the dynamics show some similarities. The two output gaps have a correlation of 0.53. The unreliability of real-time

[4] Greenbook data remains confidential for some years, so I cannot use data after 2005.

[5] To be sure, these forecasts need not to coinicide with the forecasts of the FOMC members. Orphanides and Wieland (2008) use the forecasts of the FOMC members from the semiannual Humphrey-Hawkins Reports to estimate monetary policy rules. I stick to the staff's forecast as the higher frequency of the data is useful to get precise estimates using quantile regression methods. Orphanides (2001) notes that the Greenbook forecasts are an useful approximation for the forecasts of the FOMC.

output gap estimates and possible large revisions of output gap series have been analysed in detail in Orphanides and van Norden (2002). The interest rate reactions to the very low real-time output gap estimates between 1970 and 1980 might have been one factor that has led to too low interest rates and high inflation in the 1970s (Orphanides, 2004). The large differences between the two data series show that it is important to use exactly the same information set that has been available to policy makers at the time of interest rate decisions to arrive at reliable policy parameter estimates.

The revision problem is somewhat smaller for inflation. Revised inflation rates are relatively close to real-time inflation forecasts. The two inflation series have a correlation of 0.87. However, there are several episodes where the two series deviate from each other. For example, in the early part of the sample inflation forecasts underestimated actual inflation rates. Another example is the episode from 2003 to 2006, where inflation forecasts were again lower than actual inflation rates. This underestimation has had important consequences for monetary policy. Taylor (2007) argues that the Fed has set the federal funds rate too low during that period according to an outcome-based Taylor rule and helped to cause a bubble in house prices. Bernanke (2010) responded that Fed policy was in line with a forecast-based policy rule. This discussion shows that using revised data would lead for this episode to an estimated inflation response parameter that is lower than the actual response to real-time inflation forecasts.

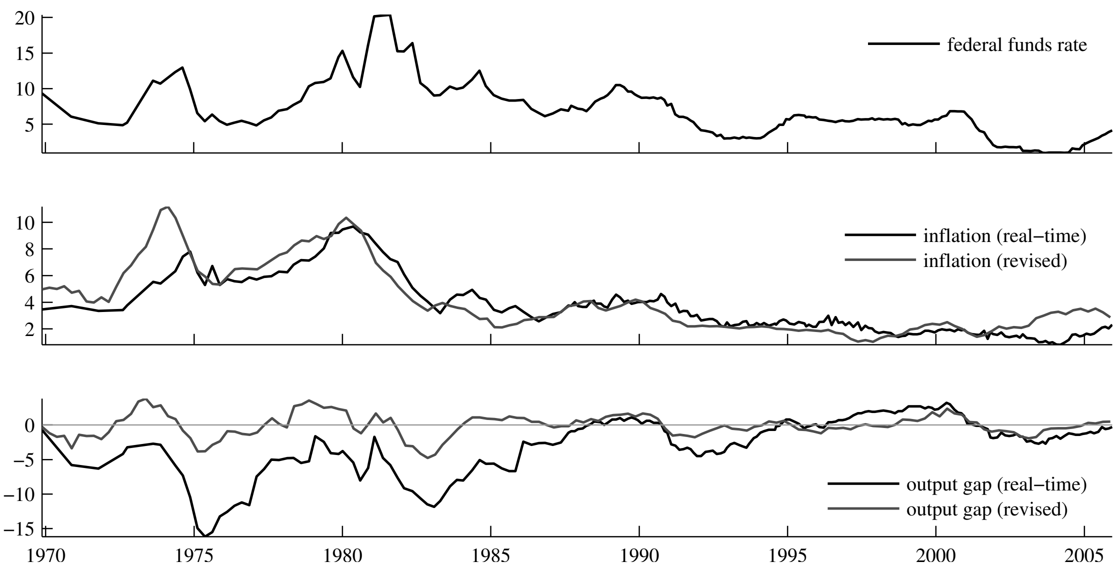

Figure 1: Federal Funds Rate, Inflation Forecasts and Output Gap Nowcasts. Notes: Inflation forecasts reflect percentage year-over-year changes in the GDP/GNP deflator. Output gap nowcasts measure deviations of real output from potential output in percent. The interest rate is the annual effective yield of federal funds rate.

While the FOMC sets a target for the federal funds rate, I use the effective federal funds rate instead. The target rate is set in discrete steps of 25 or 50 basis points most of the time. Thus, one cannot use standard econometric methods, but would need to use probit or logit approaches. In the context of quantile regression this is difficult and would inhibit a comparison with the existing literature on estimated monetary policy rules.[6]

3. Least Squares Regressions

I estimate a monetary policy rule of the form:

$$i_t = \rho i_{t-1} + (1-\rho)(i^* + \beta(\pi_{t+4|t} - \pi^*) + \gamma y_t) + \varepsilon_t, \tag{1}$$

[6]While the effective federal funds rate is available for the whole sample, fed funds rate targeting has been replaced by reserve targeting from October 1979 to October 1982. The effective fed funds rate is close to the target rate for the sample in this paper. The usage of the effective fed funds rate instead of the target rate should therefore have very little effect on the estimation results.

where i_t is the nominal short term interest rate, i^* is the targeted nominal rate, $\pi_{t+4|t}$ is a four-quarter-ahead inflation forecast, π^* is the inflation target, y_t is the output gap and ε_t is a policy shock. ρ, β and γ are policy parameters. Thus, the federal funds rate responds systematically to deviations of the inflation forecast from a target and to the output gap. The interest rate is adjusted gradually to its target. Orphanides (2001) shows that forward-looking policy rules provide a better description of U.S. monetary policy than backward-looking rules in the sense that they do not violate the Taylor principle when being estimated with real-time data.
The nominal interest rate target can be decomposed into the targeted real interest rate and the inflation target: $i^* = r^* + \pi^*$. To use linear estimation techniques equation (1) is rewritten:

$$i_t = \alpha_0 + \alpha_i i_{t-1} + \alpha_\pi \pi_{t+4|t} + \alpha_y y_t + \varepsilon_t, \tag{2}$$

where $\alpha_0 = (1-\rho)(r^* + (1-\beta)\pi^*)$, $\alpha_i = \rho$, $\alpha_\pi = (1-\rho)\beta$ and $\alpha_y = (1-\rho)\gamma$. Parameters can be estimated at the conditional expected value of the federal funds rate with standard methods like ordinary least squares (OLS) or two-stage least squares (TSLS) to handle endogeneity problems:

$$E(i_t | i_{t-1}, \pi_{t+4|t}, y_t) = \alpha_0 + \alpha_i i_{t-1} + \alpha_\pi \pi_{t+4|t} + \alpha_y y_t. \tag{3}$$

3.1. Specification Tests

Clarida et al. (2000) find using revised data differences in policy rule parameters prior to Paul Volcker's appointment as Fed chairman and afterwards. Especially, the response to expected inflation is much stronger for the Volcker-Greenspan era than prior to 1979. Orphanides (2004) finds using a real-time dataset similar to the one used in this study a more activist policy response to the output gap prior to 1979 than afterwards, but no change in the inflation response. I estimate equation (3) and examine restrictions on the constancy of parameters to decide on an appropriate specification. Based on these prior studies a possible breakpoint is in August 1979 when Paul Volcker became Federal Reserve chairman. I use the Chow test to check for possible breaks in the different policy parameters. Inflation forecasts and output gap nowcasts might be endogenous and therefore all specification tests are repeated using TSLS.[7]

Table 2: p-Values of Subsample Stability Tests

	OLS			TSLS		
Parameters	baseline	quarterly	revised	baseline	quarterly	revised
All	**0.04**	0.07	0.06	**0.04**	0.06	0.14
α_0	0.17	0.18	**0.02**	0.11	0.12	**0.02**
α_π	0.12	0.15	**0.01**	0.10	0.11	**0.01**
α_y	**0.01**	**0.01**	0.87	**0.01**	**0.01**	0.38
α_i	0.08	0.12	**0.00**	0.14	0.17	**0.01**
α_π (α_0 varies)	0.46	0.57	0.14	0.62	0.86	**0.03**
α_y (α_0 varies)	**0.02**	**0.02**	0.78	**0.03**	**0.02**	0.41
α_i (α_0 varies)	0.25	0.38	**0.05**	0.25	0.36	0.08
α_0 (α_π varies)	0.79	0.91	0.70	0.89	0.67	**0.01**
α_y (α_π varies)	**0.04**	**0.03**	0.78	**0.05**	**0.03**	0.37
α_i (α_π varies)	0.42	0.53	0.22	0.44	0.88	0.59
α_0 (α_y varies)	0.45	0.46	**0.02**	0.59	0.57	**0.02**
α_π (α_y varies)	0.63	0.59	**0.01**	0.46	0.60	**0.01**
α_i (α_y varies)	0.89	0.96	**0.00**	0.51	0.69	**0.01**
α_0 (α_i varies)	0.61	0.78	0.61	0.92	0.65	0.52
α_π (α_i varies)	0.82	0.93	0.97	0.47	0.34	0.23
α_y (α_i varies)	0.06	**0.04**	0.85	0.06	**0.04**	0.34

Notes: The entries show p-values of parameter stability tests across the subsamples 1969Q4-1979Q2 and 1979Q3-2005Q4. Row 1 examines the null hypothesis of joint constancy of all parameters. Rows 2-5 test the null hypothesis that the specific parameter shown is constant, under the assumption that remaining parameters are constant. Rows 6-17 test the null hypothesis that the specific parameter shown is constant when the parameter in brackets is allowed to vary and remaining parameters are constant.

[7] For the results using TSLS I use lags up to four quarters of the federal funds rate, inflation and the output gap as instruments as in Clarida et al. (2000) and Orphanides (2001). These lagged variables are predetermined and are thus appropriate instruments for the inflation forecast and the output gap nowcast.

Table 2 shows p-values of structural break tests for the subsamples 1969Q4-1979Q2 and 1979Q3-2005Q4. Results are shown for all available FOMC meetings (baseline), quarterly and revised data. I will focus on the real-time dataset first. Row 1 shows that the null hypothesis of no structural break in all parameters is rejected in several cases. In the following I will check whether the break is specific to one of the policy parameters. Rows 2-5 show that the hypothesis of no structural breaks in the output gap parameter is rejected, while there is no clear evidence for a structural break in the other parameters. In rows 6-17 I allow one parameter to vary and test for an additional break in one other parameter. Allowing for a change of the output gap parameter in 1979Q3, the null hypothesis of no structural break in all the other parameters cannot be rejected. When I allow the constant, the inflation parameter or the interest rate smoothing coefficient to vary, the null hypothesis of no structural break in the output gap parameter is still rejected (bold numbers in rows 7, 10 and 17). Based on these results with real-time data I proceed in the remainder of the paper to estimate policy rules over the period 1969Q4-2005Q4, allowing for a structural change of α_y in 1979Q3. I do not model a break in α_π as the structural break test results show no evidence for this.

Interestingly, the structural break results with revised data are contrary to the real-time data results. With revised data one cannot reject the null hypothesis of no structural break in the ouput gap parameter. Revised data points to a structural break in the inflation response and the degree of interest rate smoothing. The usage of revised data can thus lead to quite different conclusions than the usage of the data that has been actually available to policy makers in real-time. With revised data the output gap in the pre-Volcker period is much higher than with real-time data. With real-time data one usually gets a high estimated response to the output gap for the pre-Volcker period. To get policy coeffients that are inaccordance with the relatively low interest rates before 1980 in the absence of a high reaction to negative output gap estimates, one needs lower estimates of the inflation response possibly coupled with a lower degree of interest rate smoothing (the structural inflation response $\beta = \alpha_\pi/(1-\alpha_i)$ decreases with a decrease of the interest rate smoothing coefficient). Using least squares estimates one usually finds a high inflation response coupled with a high degree of interest rate smoothing after 1980. Thus, the artificial low inflation response and the artificial low degree of interest rate smoothing prior to 1980 could lead to structural breaks in α_π and α_i. For example Clarida et al. (2000) find using revised data a lower inflation response and a lower interest rate smoothing coefficient before 1979 than afterwards. They attribute the high inflation period of the 1970s to this low inflation response coefficient.

Policy rule estimates using revised data of inflation and the output gap have relied on instrumental variable methods (see, e.g., Clarida et al., 1998). The central bank raises the nominal interest rate in response to an expected rise in inflation or an increase in the output gap and at the same time the rising interest rate has a dampening effect on inflation and the output gap. This is the standard simultaneity problem. In contrast, the literature using real-time data has not used instrumental variable methods as inflation forecasts and output gap nowcasts are prepared before the FOMC meetings and are not revised afterwards. However, forecasts might be based on fairly accurate expectations about the policy actions of the FOMC and still a simultaneity problem with the interest rate can arise. I compute Hausman tests to detect possible endogeneity problems. The test results in table 3 indicate that, except for the pre-Volcker subsample, endogeneity of inflation expectations and the output gap cannot be rejected at high significance levels for both real-time datasets. Therefore, I will focus in this paper on quantile regression results for instrumental variable estimators. The test results based on revised data are again different from the real-time data results, but also indicate an endogeneity problem for several specifications.

Table 3: p-Values of Tests for Exogeneity

	$\alpha_i = 0$			$\alpha_i \neq 0$		
	baseline	quarterly	revised	baseline	quarterly	revised
1969Q4 - 2005Q4	**0.00**	**0.00**	**0.01**	**0.00**	**0.00**	0.76
1969Q4 - 1979Q2	0.54	0.54	**0.00**	0.26	0.26	**0.02**
1979Q3 - 2005Q4	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.04**
1983Q3 - 2005Q4	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.10
α_y varies	**0.00**	**0.00**	**0.05**	**0.00**	**0.00**	0.18

Notes: The entries show p-values of Hausman tests of the null hypothesis of no endogeneity. Specifications with and without interest rate smoothing are estimated. Rows 1-4 show results for different subsamples. Row 5 shows p-values for the whole sample when the output gap reaction α_y is allowed to change in 1979Q3.

3.2. Least Squares Estimation Results

Table 4 shows the estimated policy reaction parameters at the conditional mean of the federal funds rate. Results typically found in the real-time policy rule literature are confirmed: the Taylor principle is fulfilled over the whole sample. The reaction to the output gap is high for the first part of the sample while it is close to zero and insignificant in the second part. The high inflation of the 1970's might have been caused by the high reaction to the output gap that was perceived to be highly negative in real-time. Interest rate smoothing parameters are high and significant.[8]

Table 4: Estimated Policy Reaction Parameters

	$\alpha_i = 0$		$\alpha_i \neq 0$	
	OLS	TSLS	OLS	TSLS
α_0	1.05	0.54	-0.06	-0.04
	(0.68)	(0.79)	(0.26)	(0.27)
α_π	1.75	1.93	0.43	0.39
	(0.26)	(0.31)	(0.12)	(0.16)
α_y: 1969Q4-1979Q2	0.46	0.52	0.15	0.12
	(0.14)	(0.17)	(0.05)	(0.06)
α_y: 1979Q3-2005Q4	0.04	0.08	0.06	0.04
	(0.14)	(0.14)	(0.04)	(0.04)
α_i	-	-	0.82	0.83
			(0.04)	(0.05)

Notes: The entries show estimated parameters together with bootstrapped standard errors in brackets. The estimated equation is $i_t = \alpha_0 + \alpha_i i_{t-1} + \alpha_\pi \pi_{t+4|t} + (\alpha_{y,1} + D\alpha_{y,2})y_t + \varepsilon_t$, D is a dummy variable that equals zero until 1979Q2 and one afterwards. The output gap coefficients are computed as follows: $\alpha_y = \alpha_{y,1}$ until 1979Q2 and $\alpha_y = \alpha_{y,1} + D\alpha_{y,2}$ afterwards.

The estimation results impose the untested restriction that the parameters are the same across the quantiles of the conditional distribution of the federal funds rate. The restriction of parameter constancy across quantiles is testable by estimating equation (2) at different quantiles and checking for significant differences in policy reaction parameters at different parts of the conditional distribution of the interest rate.

4. Quantile Regression

Quantiles are values that divide a distribution such that a given proportion of observations is located below the quantile. The τ^{th} conditional quantile is the value $q_\tau(i_t|i_{t-1}, \pi_{t+4|t}, y_t)$ such that the probability that the conditional interest rate will be less than $q_\tau(i_t|i_{t-1}, \pi_{t+4|t}, y_t)$ is τ and the probability that it will be more than $q_\tau(i_t|i_{t-1}, \pi_{t+4|t}, y_t)$ is $1-\tau$:

$$\int_{-\infty}^{q_\tau(i_t|i_{t-1},\pi_{t+4|t},y_t)} f_{i_t|i_{t-1},\pi_{t+4|t},y_t}(x|i_{t-1}, \pi_{t+4|t}, y_t)dx = \tau, \quad \tau \in (0,1) \tag{4}$$

[8] I also computed results without a change in the output gap coefficient and for the subsamples 1969Q4-1979Q2, 1979Q3-2005Q4, 1983Q3-2005Q4 and for quarterly and revised data. The results are similar to what has been reported previously in the literature for real-time and revised data and the different samples. The results are available upon request.

where $f(.|.)$ is a conditional density function. The policy rule at quantile τ can accordingly be written as:

$$q_\tau(i_t|i_{t-1},\pi_{t+4|t},y_t) = \alpha_0(\tau)+\alpha_i(\tau)i_{t-1}+\alpha_\pi(\tau)\pi_{t+4|t}+\alpha_y(\tau)y_t. \tag{5}$$

Estimating policy parameters at different quantiles instead of the mean can be done with quantile regressions as introduced by Koenker and Bassett (1978). Estimating this equation for all $\tau \in (0,1)$ yields a set of parameters for each value of τ and characterizes the entire conditional distribution of the federal funds rate. While preserving the linear policy rule framework, quantile regression imposes no functional form constraints on parameter values over the conditional distribution of the interest rate.

As in the case of least squares, parameters estimated using quantile regression are biased when regressors are correlated with the error term. A two-stage least absolute deviations estimator has been developed by Amemiya (1982) and Powell (1983) and has been extended to quantile regression by Chen and Portnoy (1996). The first stage equals the standard two-stage least squares procedure of regressing the endogenous variables on the exogenous variables and additional instruments. The second stage estimates obtained by quantile regression yield the parameters $\tilde{\alpha}_i(\tau)$, $\tilde{\alpha}_0(\tau)$, $\tilde{\alpha}_\pi(\tau)$ and $\tilde{\alpha}_y(\tau)$.[9] However, Chernozhukov and Hansen (2001) show that these estimates are only unbiased if changes in the endogenous variables do not affect the scale or shape of the distribution of the dependent variables, but only shift its location. This assumption is restrictive and excludes interesting cases. It is not fulfilled when estimating policy rules: if inflation decreases and thus interest rates decrease, the shape of the conditional distribution of the interest rate is altered as zero remains the lower bound of the interest rate.

Chernozhukov and Hansen (2001) developed inverse quantile regression that generates consistent estimates without restrictive assumptions.[10] They derive the following moment condition as the main identifying restriction of IVQR:

$$P(Y \le q_\tau(D,X)|X,Z) = \tau, \tag{6}$$

where $P(.|.)$ denotes the conditional probability, Y denotes the dependent variable i_t, D a vector of endogenous variables $\pi_{t+4|t}$ and y_t, X a vector of exogenous variables including a constant and i_{t-1} and Z a vector of instrument variables. This equation is similar to the definition of conditional quantiles given above except for conditioning on additional instrument variables. The main assumption for this moment condition is fulfilled if rank invariance holds: it requires that the expected ranking of observations by the level of the interest rate does not change with variations in the covariates. If for example inflation rises, the level of the interest rate would rise for all observations exposed to the change in inflation. Hence, it is likely that the ranking of these observations is not altered by the change in inflation.[11,12]

4.1. Inverse Quantile Regression

IVQR transforms equation (6) into its sample analogue. The moment condition is equivalent to the statement that 0 is the τ^{th} quantile of the random variable $Y - q_\tau(D,X)$ conditional on (X,Z).[13] Therefore, one needs to find parameters of the function $q_\tau(D,X)$ such that zero is the solution to the quantile regression problem, in which one regresses the error term $Y - q_\tau(D,X)$ on *any function* of (X,Z). Let $\lambda_D = [\alpha_\pi \;\; \alpha_y]'$

[9] I use a tilde to denote parameters and fitted values from quantile regression and a hat to denote least squares regression counterparts.

[10] Alternatively, one could use a control function approach as in Lee (2007). Results are likely to be similar to IVQR. However, using IVQR retains the simple structure of Taylor type rules. This facilitates the interpretation of the results. For a comparison of the two approaches see Chernozhukov and Hansen (2005).

[11] A weaker similiarity condition together with some other assumptions discussed in detail in Chernozhukov and Hansen (2001) is sufficient, too. Similarity requires that the distribution of the error term has to be equal for all values of each endogenous variable, holding everything else constant. Rank invariance is a stricter, but in the context of policy rule estimation also more intuitive condition than similarity.

[12] An additional advantage of IVQR is that it allows for measurement errors in the instruments. This will be the case in policy rule estimation using real-time data for the instruments as the data is revised later on. However, even using revised data will include measurement errors. Orphanides (2001) notes that mismeasurement is solved for many macroeconomic variables only slowly through redefinitions and rebenchmarks, but most likely never completely. Additionally, the output gap is an unobservable variable in practice and thus the output gap itself is an estimate.

[13] A simple example for unconditional quantiles may help to illustrate this equivalence: consider a sample $Y = \{2,5,6,9,10\}$ and the quantile at $\tau = 0.4$ that is computed to be $q_{0.4} = 5$. Now compute $Y - q_{0.4} = \{-3,0,1,4,5\}$. It is clear that 0 is the 0.4 quantile of this expression.

denote the parameters of the endogenous variables and $\lambda_X = [\alpha_0 \;\; \alpha_i]'$ denote a vector of parameters of the exogenous variables and Λ a set of possible values for λ_D. Write the conditional quantile as a linear function: $q_\tau(Y|D,X) = D'\lambda_D(\tau) + X'\lambda_X(\tau)$. The following algorithm implements IVQR:[14]

1. First stage regression: regress the endogenous variables on the exogenous variables and additional instruments using OLS. This yields fitted values $\hat{D}$.

2. Second stage regression: estimate for all $\lambda_D \in \Lambda$:

$$[\tilde{\lambda}_X(\lambda_D) \;\; \tilde{\lambda}_Z(\lambda_D)]' = \arg\min_{\{\lambda_X, \lambda_Z\}} \frac{1}{T}\sum_{t=1}^{T} \varphi_\tau(Y_t - D_t'\lambda_D - X_t'\lambda_X - \hat{D}_t'\lambda_Z), \tag{7}$$

   where $\varphi_\tau(u) = \tau - 1(u < 0)u$ is the asymmetric least absolute deviation loss function from standard quantile regression (see e.g. Koenker and Bassett, 1978) and λ_Z are additional parameters on $\hat{D}$.

3. Inverse step: find $\tilde{\lambda}_D$ by minimizing an Euclidian norm of $\tilde{\lambda}_Z(\lambda_D)$ over $\lambda_D \in \Lambda$:

$$\tilde{\lambda}_D = \arg\min_{\{\lambda_D \in \Lambda\}} \sqrt{\tilde{\lambda}_Z(\lambda_D)'\tilde{\lambda}_Z(\lambda_D)} \tag{8}$$

   This minimization ensures that $Y - q_\tau(D,X)$ does not depend on $\hat{D}$ anymore which is the above mentioned *function* of (X,Z).

Chernozhukov and Hansen (2001) call this procedure the inverse quantile regression as the method is inverse to conventional quantile regression: first, one estimates $\tilde{\lambda}_Z(\lambda_D)$ and $\tilde{\lambda}_X(\lambda_D)$ by quantile regression for all $\lambda_D \in \Lambda$. The inverse step (8) yields the final estimates $\tilde{\lambda}_D$, $\tilde{\lambda}_Z(\tilde{\lambda}_D)$ and $\tilde{\lambda}_X(\hat{\lambda}_D)$. The procedure is made operational through numerical minimization methods combined with standard quantile regression estimates. Through increasing τ from 0.01 to 0.99 one traces partial effects over the entire distribution of i_t conditional on i_{t-1}, $\pi_{t+4|t}$ and y_t including all the cases when the central bank deviates from a policy rule estimated at its conditional mean.

Throughout this study stationarity of all variables used in the regressions is assumed. It is reasonable to assume stationarity of the output gap. Using standard Dickey-Fuller tests Clarida et al. (1998) find that the federal funds rate and inflation are at the border between being I(0) and I(1). They proceed to estimate with an I(0) assumption under the argument that the Dickey-Fuller test lacks power in small samples.

4.2. Moving Blocks Bootstrap

Fitzenberger (1997) presents moving blocks bootstrap (MBB) as an estimator for standard errors in quantile regression that is robust to heteroskedasticity and autocorrelation of unknown forms. The MBB is modified in this study for usage with IVQR. Following Clarida et al. (1998) the autocorrelation considered is limited to one year. For each bootstrap blocks of the variables are drawn randomly from the whole sample. This includes the dependent variable, the endogenous variables, the exogenous variables and the instruments. For each of the 1000 bootstraps the IVQR estimates are computed. Finally, standard errors of the coefficients are computed as the standard deviation of the 1000 estimates of $\alpha_i(\tau)$, $\alpha_0(\tau)$, $\alpha_\pi(\tau)$ and $\alpha_y(\tau)$, respectively.

5. Estimation Results

Figure 2 shows the estimated coefficients of the inflation forecast, the output gap and the constant when restricting α_i to zero. The varying solid black lines show the IVQR coefficients over the conditional distribution of the federal funds rate denoted by the quantiles $\tau \in (0,1)$ on the horizontal axis. The shaded areas show 95% confidence bands. Conditional mean estimates (TSLS) together with 95% confidence intervals are denoted by straight horizontal lines. The IVQR coefficients for the inflation response and

[14] The dependence of the parameters on the quantile τ is omitted in the following equations to keep the notation simple.

the output gap response from 1979Q3 onwards vary significantly over the conditional distribution of the federal funds rate. The deviations of the parameter estimates from the TSLS coefficients reflect persistent deviations of the federal funds rate from a policy rule estimated at the mean. The systematic variations show that at least parts of the deviations from the policy rule are beyond unsystematic policy shocks.

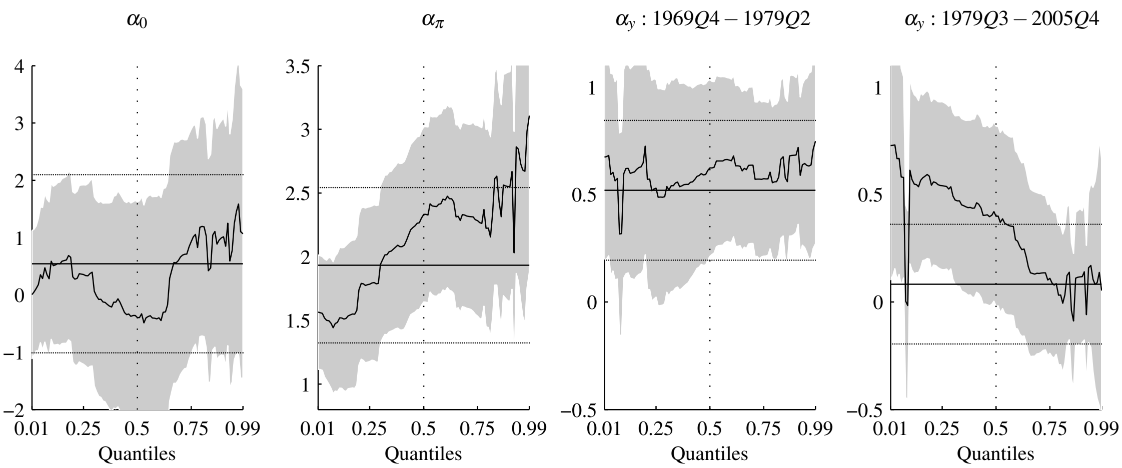

Figure 2: Estimated Coefficients ($\alpha_i = 0$). Notes: The solid line shows IVQR estimates of: $i_t = \alpha_0(\tau) + \alpha_\pi(\tau)\pi_{t+4|t} + (\alpha_{y,1}(\tau) + D\alpha_{y,2}(\tau))y_t + \varepsilon_t$ for $\tau \in (0,1)$. See table 4 for a description of the dummy variable D. Shaded areas denote 95% confidence bands of 1000 bootstraps. Solid straight horizontal lines show TSLS estimates together with 95% confidence bands.

The estimation results show that the Federal Reserve responded systematically to inflation. The IVQR inflation coefficient is significantly above one and increases from 1.5 to 3 over the conditional interest rate distribution. The estimation results confirm the finding of CKM that the Taylor principle is fulfilled over the whole conditional distribution of the federal funds rate using real-time instead of revised data and a different IV quantile estimation method. The upper part of the distribution covers periods where the interest rate has been set higher than the least squares policy rule estimates suggest and the lower part periods where it has been set lower. Therefore, the inflation response is stronger when the interest rate is set higher than on average and lower when the interest rate is set lower than on average. The least squares inflation response estimate is 1.93 and thus lower than the estimate of 2.30 at the conditional median. The estimated parameter at the median is more robust than at the mean as it is not prone to outliers.

The response to the output gap is higher in the first part of the sample than in the second part. In the first part of the sample the output gap response is significant and close to the estimated coefficient at the mean of 0.52. The estimates of the second subsample show that the output gap is significantly different from zero only for the lower range of the distribution. The Fed therefore did not always respond countercyclically to the output gap. The output gap reactions decrease significantly over the conditional distribution from 0.5 to about 0. While the decrease of the output gap coefficient found by CKM is less pronounced, they also find that the output gap response is significantly different from 0 only for the lower 50% of the conditional interest rate distribution. Least squares estimation results yield a lower output gap response parameter than at the conditional median. The estimated response at the conditional median is even at the upper bound of the 95% confidence band of the least squares estimates, which might be affected by outliers. In addition to not capturing the decreasing output gap coefficient, least squares estimates might thus underestimate the actual output gap response of the Fed.

The constant shows high variations over the conditional distribution of the federal funds rate, but also wide confidence bands. It varies between -0.5 and 1.5.

Figure 3 shows the estimated coefficients of the inflation forecast, the output gap, the constant and an interest rate smoothing term for the whole conditional distribution of the federal funds rate when allowing for a gradual adjustment of interest rates. As in the case without interest rate smoothing it is apparent that uniform coefficients of standard estimations of linear monetary reaction functions are an incomplete description of monetary policy. All IVQR parameter estimates vary significantly over the conditional distribution of the federal funds rate and support important nonlinearities of FOMC policy reactions. Although policy rules with an interest rate smoothing term show a high fit in general, the estimation results show that this is misleading and in fact high deviations from policy reaction parameters at the conditional mean of the interest rate appear.

The inflation response is significantly different from zero except for small outlier regions. The inflation coefficient is below the mean estimate of 0.39 between the 0.25 and the 0.75 quartile and increases strongly in the upper 25% of the distribution to 1.5. The upward kink above the 0.75 quartile shows that the mean estimate is only a rough approximation of the actual inflation response.

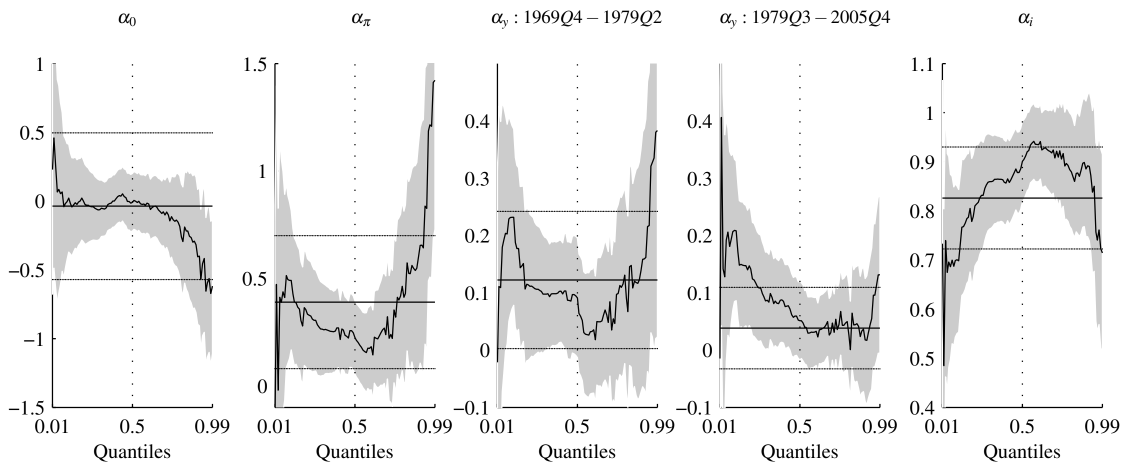

Figure 3: Estimated Coefficients ($\alpha_i \neq 0$). Notes: see figure 2 for a description of the different graphs. The estimated equation is $i_t = \alpha_0(\tau) + \alpha_i(\tau) i_{t-1} + \alpha_\pi(\tau)\pi_{t+4|t} + (\alpha_{y,1}(\tau) + D\alpha_{y,2}(\tau))y_t + \varepsilon_t$, for $\tau \in (0,1)$.

The response to the output gap is decreasing over the range of quantiles in the second subsample from values around 0.2 to 0.05. In the first subsample a decrease is visible in the interquartile range from values around 0.25 to 0.05 and an upward kink to 0.4 for estimates at the highest quantiles. The decrease of the output gap coefficient in the second subsample is highly significant. In both subsamples the estimates show that the output gap response is significantly different from 0 for the lower 50% of the conditional distribution only. At least after 1979Q3 the TSLS output gap response coefficent is not a good description of the actual output gap response. The Fed reacted more sensitive to the output gap at the lower half of the conditional interest rate distribution than the estimate at the conditional mean indicates.

The constant shows a large decline over the distribution from 0.5 to -0.5 with a mean estimate close to 0. The constant is not significantly different from 0 except for the highest quantiles.[15]

The interest rate smoothing parameter shows sizeable variations over the range of quantiles that take a hump-shaped pattern. With a mean estimate around 0.8 it increases from 0.7 to almost 1 at the median and decreases thereafter back to 0.7. The parameter is significantly different from zero over the whole range of quantiles suggesting that interest rate smoothing is a prevalent characteristic of monetary policy of the Federal Reserve. Interest rate smoothing is high at the median because the Fed sometimes does not change the federal funds rate for a number of FOMC meetings as shown in figure 1. However, when the Fed sets the interest rate higher than on average by reacting more to inflation, the FOMC seems to do that in a sequence of interest rate hikes leading to a lower interest rate smoothing coefficient than at the median. Similarly, when the Fed sets the interest rate lower than on average by reacting more to the (negative) output gap and less to inflation, this is also often done in a sequence of interest rate decreases leading to a lower than average interest rate smoothing coefficient. Estimates at the conditional mean are thus misleading as they average over times without changes in the federal funds rate and interest rate increases and decreases. The

[15]The constant can be written as $\alpha_0 = (1-\alpha_i)r^* + (1-\alpha_i-\alpha_\pi)\pi^*$ which shows that a large part of the decrease of α_0 is due to the increase of α_i until the median. The sharp decrease at the highest quantiles reflects the high increase of α_π in this region of the distribution.

conditional mean coefficient underestimates interest rate smoothing around the median of the conditional interest rate distribution and overestimates it at the tails of the distribution.

The graphs for the inflation and output gap response are roughly U-shaped, while the interest rate response graph is hump-shaped. The variations of the interest rate smoothing parameter directly affect the reduced form inflation response and the output gap response: $\alpha_\pi = \beta(1-\alpha_i)$ and $\alpha_y = \gamma(1-\alpha_i)$. The U-shaped inflation and output gap response graphs therefore reflect the hump-shaped interest rate smoothing graph. Figure 4 shows the structural parameters β and γ (see equations (1) and (2)).[16]

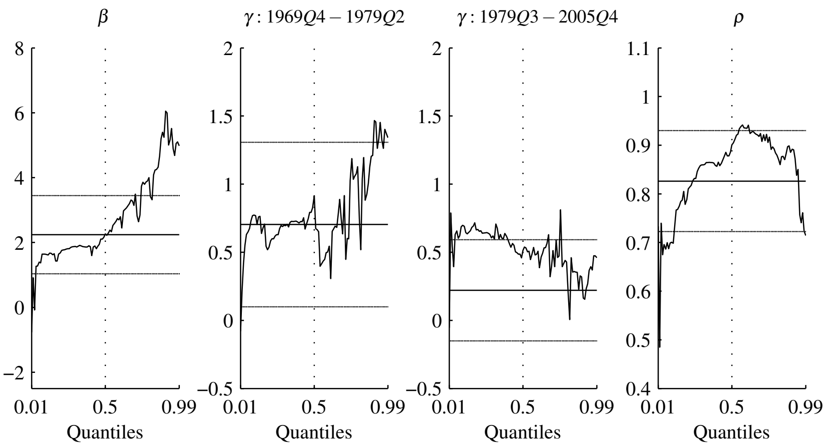

Figure 4: Estimated Structural Coefficients. Notes: see figure 2 for a description of the different graphs. The coefficients are computed as follows: $\beta(\tau) = \alpha_\pi(\tau)/(1-\alpha_i(\tau))$ and $\gamma(\tau) = \alpha_y(\tau)/(1-\alpha_i(\tau))$, for $\tau \in (0,1)$. $\rho(\tau)$ is directly obtained from the estimation.

The increase in the structural inflation response over the conditional interest rate distribution is much clearer than in figure 3. The inflation response increases from 0 to 6 with an estimate of 2.24 at the conditional mean. The least squares estimate of the inflation response coefficient is thus only a rough approximation of the actual inflation response over the conditional interest rate distribution. Except for the extreme left tail the Taylor principle of moving the interest rate more than one-to-one in response to changes in inflation is satisfied over the whole conditional interest rate distribution. The structural output gap response increases over the conditional interest rate distribution for the first subsample and decreases for the second subsample. For the Volcker-Greenspan sample, the structural coefficients thus confirm the finding from the specification without interest rate smoothing: when the interest rate is set higher than implied by the conditional mean of standard policy rule estimates, the Fed reacted stronger to inflation and less to the output gap and vice versa when the interest rate is set below the rate implied by standard policy rule estimates.

In summary, the estimation results for specifications with and without interest rate smoothing suggest that the Federal Reserve responded more aggressive to inflation and less to the output gap during upward deviations from a monetary policy reaction function estimated at the mean and the other way around during downward deviations. For the first part of the sample variations in the output gap response are limited especially in the case without a gradual adjustment of interest rates. For the specification with a gradual adjustment of the federal funds rate the interest rate smoothing parameter amplifies the higher weight of inflation relative to the output gap during upward deviations from a policy rule. During downward deviations the lower smoothing parameter diminishes the relatively low inflation reaction further. This leads to a high increase of the structural inflation response coefficient over the conditional interest rate

[16]The confidence bands are unreasonably wide at those parts of the conditional interest rate distribution where the interest rate smoothing parameter is close to 1. In the bootstrap procedure I have to devide the reduced form coefficients by $1-\alpha_i$ for each bootstrap to get the confidence bands of the structural coefficients. When α_i is close to 1, this leads to explosive estimates. This problem has been pointed out by CKM and is the reason, why they only estimate a specification without interest rate smoothing. However, in my case the point estimate of the interest rate smoothing parameter is sufficiently far from 1, so that the point estimates of the structural parameters are in a reasonable range. Therefore, I only show here the point estimates, but not the confidence bands.

distribution. Least squares estimates of the interest rate smoothing coefficient cannot capture important differences between the degree of smoothing at the tails of the conditional interest rate distribution and around the median. Smoothing is higher around the median as there are periods without any change in the federal funds rate. When the Fed starts changing the interest rate in a sequence of hikes or decreases, this possibly leads to deviations from average policy reactions and a lower degree of interest rate smoothing. Systematic deviations from policy rule parameters estimated at the mean are strong. Mean estimates are not a good approximation to actual policy reponses as the IVQR coefficients are not uniform across the conditional interest rate distribution. Furthermore, in several cases the mean estimate is affected by outliers and deviates from more robust estimates at the conditional median.

5.1. Robustness

For a proper comparison with the results by CKM I use revised data. Figure 5 shows estimation results without interest rate smoothing for the period 1979Q3-2005Q4, which is the sample used by CKM. The dashed line shows the point estimates by CKM and the dotted varying lines 90% confidence bands reported by CKM. The solid lines show my estimation results.

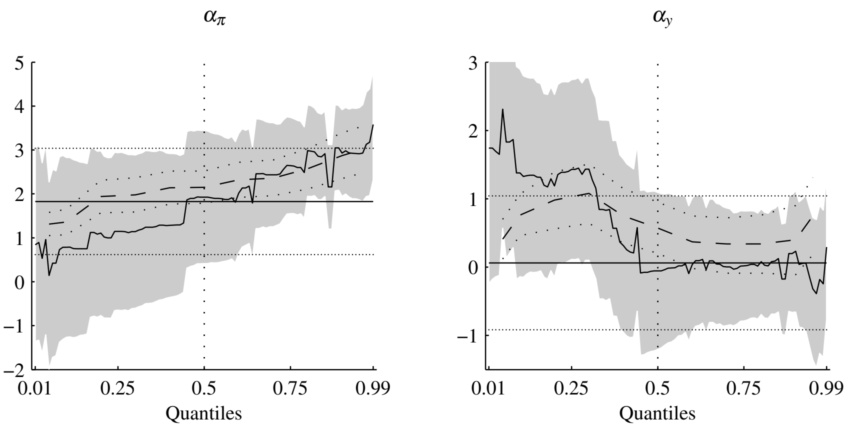

Figure 5: Revised Data, 1979Q3-2005Q4, Estimated Coefficients ($\alpha_i = 0$). Notes: The solid line shows IVQR estimates of: $i_t = \alpha_0(\tau) + \alpha_\pi(\tau)\pi_{t+4|t} + \alpha_y(\tau)y_t + \varepsilon_t$ for $\tau \in (0,1)$. Shaded areas denote 90% confidence bands of 1000 bootstraps. Solid straight horizontal lines show TSLS estimates together with 90% confidence bands. Dashed lines show estimates by CKM together with 90% confidence bands.

The point estimates for the inflation response are roughly similar. Both of them increase from values around 1 to 3. The confidence bands are much wider for my results. One reason is the bootstrap algorithm that takes into account serial correlation of the error terms and another reason is that CKM use monthly data resulting in 312 observations compared to 108 quarterly observations for my revised dataset. The results for the output gap are roughly similar, too. Both estimation results show that the output gap response is significantly different from 0 only for the lower 50% of the conditional interest rate distribution. My results show a clearer decline of the output gap response until the median and a zero output gap response for the higher 50% of the distribution, while the variations in the output gap response coefficient are limited in the CKM case.

Comparing the results with revised data to the real-time counterparts, I find that with revised data the increase in the inflation response coefficient is more pronounced. The lower tail inflation response coefficients starts at 1 compared to 1.5 for real-time data. For the output gap response the lower-tail estimates are much higher with revised data with estimates around 2 compared to real-time estimates of about 0.75. Revised data, thus, overestimates the parameter variations over the conditional interest rate distribution.

In figure 6 I use the same sample with revised data, but allow for interest rate smoothing. In this way one can get a rough idea how the results by CKM would look like with interest rate smoothing. The results show an increase of the inflation response over the range of quantiles, a decrease in the output gap response and the constant and an increasing interest rate smoothing parameter with a slight hump in the upper quartile. The main results from the real-time dataset are thus confirmed with revised data: the FOMC responds more aggressive to inflation and less to the output gap during upward deviations from a monetary policy reaction function estimated at the mean and the other way around during downward deviations. While the point estimate of the interest rate smoothing coefficient is always below 1 for real-time data, this is not the case with revised data. CKM note that it is therefore difficult to interpret the structural coefficient $\beta = \alpha_\pi(1-\alpha_i)$ and $\gamma = \alpha_y(1-\alpha_i)$ as they are explosive.

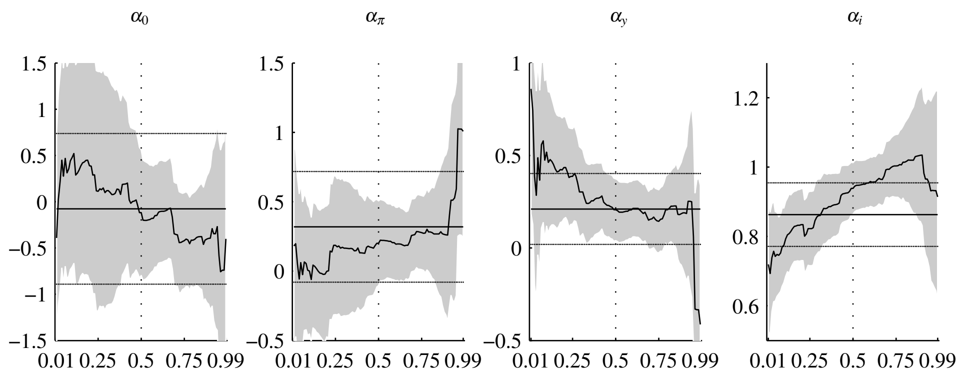

Figure 6: Revised Data, 1979Q3-2005Q4, Estimated Coefficients ($\alpha_i \neq 0$). Notes: see figure 2 for a description of the different graphs. The estimated equation is $i_t = \alpha_i(\tau)i_{t-1} + \alpha_0(\tau) + \alpha_\pi(\tau)\pi_{t+4|t} + \alpha_y(\tau)y_t + \varepsilon_t$, for $\tau \in (0,1)$.

Using revised data an extension of the sample beyond 2005Q4 is possible. I have computed results up to 2008Q4. I do not show these here, as they are very similar to the results until 2005Q4. The only difference is that the output gap response in the lower quantiles decreases. The quick decrease of the federal funds rate from 2006 onwards may have let to a lower federal funds rate than conditional mean estimates would imply, i.e. the federal funds rate has been set at the lower tail of the conditional interest rate distribution. However, between 2005Q4 and 2008Q4 the output gap has been positive. The high output gap response at the lower tail of the conditional interest rate distribution until 2005Q4 would lead to a higher interest rate than observed. Hence, the Fed did not react much to the output gap and this leads to the insignificant output gap reaction in the lower tail of the conditional interest rate distribution when extending the sample to 2008Q4.[17]

5.1.1. Subsamples and Quarterly Data

To ensure robustness of the results I repeat the estimations for quarterly spaced data, for the subsamples 1979Q3-2005Q4 and 1983Q1-2005Q4. The subsamples starting in 1979 and in 1983 are widely used in the literature on policy rules (see e.g. Clarida et al., 2000). Repeating regressions of the baseline specification with quarterly data yields results similar to the baseline specification, while the confidence bands are wider. Estimation results for the different subsamples confirm the findings of the baseline case showing that the baseline results are not driven by the high inflation period of the 70's.

6. Testing for Shifting Policy Preferences

Varying policy parameters over the conditional interest rate distribution might reflect systematic policy deviations from a linear policy rule framework, i.e. asymmetric policy preferences. An alternative explanation is that quantile regression wrongly assigns different parameter values at different parts of the conditional interest rate distribution and that these parameter variations only reflect instabilities of estimated policy parameters over time. The sample includes monetary policy of four different Fed chairmen (Burns, Miller, Volcker and Greenspan) who might have had different policy preferences. The monetary policy committee changes over time and thus there might be various preference shifts of unknown timing.

[17]Extending the sample beyond 2008 is problematic as the zero lower bound on interest rates becomes binding. This changes the conditional interest rate distribution, which would lead to biased estimates. To avoid this, one could either model a structural break at the end of 2008 or use censored quantile regression. For the former not enough data points are available yet. The latter is a very interesting task for future research, but goes beyond the scope of this paper. Censored quantile regression is a suitable method to take into account the lower bound of the conditional interest rate distribution. However, idealy one would model other measures of the Fed like quantitative easing to fully characterize monetary policy actions during the recent financial crisis.

In this section I test whether parameter variations over the range of conditional quantiles might simply reflect some kind of shifting preferences. Preference changes can include for example shifting to more or less weight on inflation stabilization relative to output stabilization. This would lead to changes in the inflation and output response coefficients.[18]

The tests for structural change in the conditional mean in section 3.1 cannot detect preference shifts that alter the shape of the conditional interest rate distribution without significantly shifting its mean.[19] In this section I test shifting preferences that might show up in any part of the conditional interest rate distribution. Qu (2008) and Oka and Qu (2011) have developed tests for structural change with unknown timing in regression quantiles. The tests are subgradient based and have good properties in small samples. For the break test, I estimate the policy parameters at the different conditional quantiles under the null of no structural break. If a structural break exists, then the estimated parameter under the null hypothesis will not be close to the true values for at least one subset of the sample. The estimated residuals will persistently fall below (or above) the true quantile, forcing the subgradient to take a large value.

The test is run in two stages as recommended by Qu (2008) and Oka and Qu (2011). First, I test whether there is structural change across a range of quantiles using the *DQ*-test. This is a general test for change in the conditional distribution of the interest rate. As I do not have any prior information in which part of the conditional interest rate distribution such a change is likely to occur I test for the whole range $\tau \in (0,1)$. The disadvantage of this large range is that the power of the test decreases as opposed to the case where prior information is used to trim the range of quantiles. Therefore, in a second step I test for structural change occuring in prespecified individual quantiles using the SQ_τ-test. If the *DQ*-test rejects the null hypothesis of no structural break, the SQ_τ-test can reveal possible heterogeneity of the structural break in different parts of the conditional interest rate distribution. In this way I can detect in which parts of the distribution the actual change takes place.

The tests allow for multiple structural breaks with unknown timing. The test procedure runs sequentially: first, for a given number of breaks, the break dates and the policy parameters are estimated jointly by minimizing the quantile check function over all permissible break dates. I repeat this procedure for 1 to 3 structural breaks. Second, I use the *DQ*- and SQ_τ-test to test the existence of one structural break against the null hypothesis of no structural break. If the null hypothesis of no structural change is rejected, I test afterwards in sequential steps the null hypothesis of 1 break against the alternative hypothesis of 2 breaks. If I find evidence in favor of 2 breaks I finally check the null hypothesis of 2 breaks against the alternative hypothesis of 3 breaks. Tables for critical values are provided in Qu (2008).

I run the tests for the case without and with interest rate smoothing. Tables 5 and 6 show the estimated break dates for the 10%, 5% and 1% siginificance level.

Table 5: Tests for Structural Breaks in Regression Quantiles (no interest rate smoothing)

Quantile	DQ-Test 0.01-0.99	SQ-Test 0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
1st Break date	80Q4***	80Q3**	80Q3***	80Q4***	80Q4**	80Q4***	80Q4***	80Q4***	80Q4***	80Q4***	80Q4***	-
2nd Break date	87Q2***	-	-	88Q2***	88Q2***	87Q2***	87Q2***	87Q2***	87Q2***	87Q2***	88Q3***	-
3rd Break date	01Q3***	-	-	-	92Q4*	92Q4*	92Q4*	01Q3***	01Q3***	01Q3***	01Q3***	-

Notes: *, ** and *** indicate significance of the estimated break dates on the 10%, 5% and 1% significance level, respectively.

The results for the specification without interest rate smoothing indicate that at least part of the parameter variations found in section 5 might reflect shifting policy preferences. The *DQ*-test finds three structural breaks on the 5% significance level: 1980Q4, 1987Q2 and 2001Q3. The SQ_τ-test shows that the first break is present over large parts of the conditional interest rate distribution. The second break is not

[18] For example the change in the output gap response in the early eighties that has been detected in section 3.1 could either mean that the Fed has put more weight on inflation stabilization relative to output stabilization or that the (real-time) output gap has been viewed as a poor indicator of future inflation and the output gap response has thus decreased.

[19] Examples for such a structural change is a symmetric widening or tightening of the conditional distribution. With a highly dispersed conditional interest rate distribution, many deviations from a policy rule estimated at the conditional mean would occur. A tight distribution would indicate a strict rule-based policy with slight deviations from a linear policy rule only.

present in the lower tail and the third break is only present in the upper part of the conditional interest rate distribution. The 1980Q4 break falls in the time range of Paul Volcker's aggressive anti-inflationary policy, the non-borrowed reserve targeting period and a NBER-defined recession. The second break is estimated to be shortly before Alan Greenspan took over as Fed chairman and the 1987 stock market crash. The third break point coincides with a series of interest rate decreases and the September 11 terrorist attacks. At least the timing of the first two breaks makes it likely that they reflect shifting policy preferences. Figure 7 shows the constant and the inflation and output gap response parameters for the four estimated regimes.

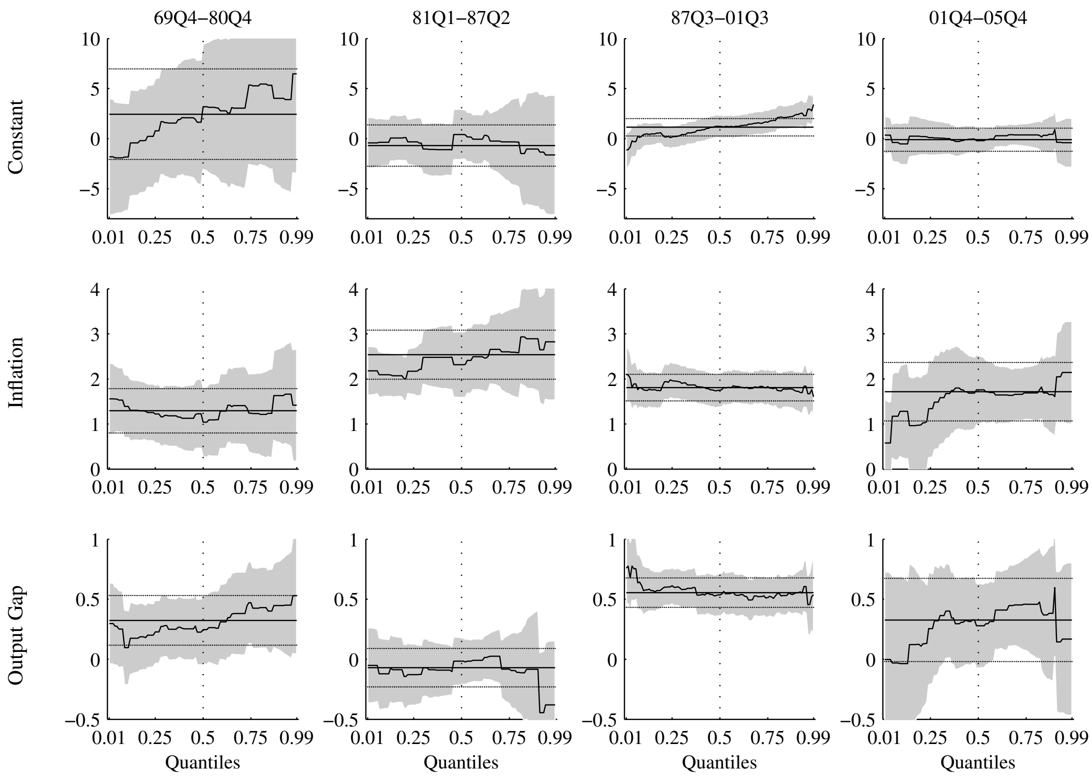

Figure 7: Estimated Coefficients for Different Subsample ($\alpha_i = 0$).

One can see that the conditional interest rate distribution has changed quite a lot over time. The average inflation responses were higher from 1981-1987 than in the other three regimes, while the output gap responses were lower. There exist structural breaks that tests at the conditional mean cannot detect. For example the conditional mean estimates are similar for the 1987-2001 and the 2001-2005 regimes. However, the inflation response parameter is uniform over the range of quantiles for the former regime and increasing for the latter regime. For the case without interest rate smoothing, it is thus likely that the parameter variations found in section 5 reflect at least partly structural breaks in the conditional interest rate distribution. For example the increase of the inflation response parameter over the range of quantiles is present in the second and fourth subsample, while the inflation response parameter is uniform for the first and third subsample.

Table 6 shows the structural break test results for the specification with interest rate smoothing. The results are very different from the specification without interest rate smoothing. The DQ-test does not detect any structural break on the 10%, 5% and the 1% significance level. As the power of the DQ-test might be not very high due to the large considered range of quantiles $\tau \in (0,1)$, I run in addition the SQ_τ test. There is some evidence for structural change in the extreme low tail of the conditional interest rate distribution. However, the overall picture shows that there is clearly no preference change. Furthermore, the main estimation results in section 5 have allowed for a break in the output gap reaction in 1979, so that they are robust to shifting preferences regarding the output gap at the beginning of the Volcker era in the early 1980s. The structural break results in section 3.1 clearly rejected structural breaks in other parameters in 1979.

Table 6: Tests for Structural Breaks in Regression Quantiles (with interest rate smoothing)

Quantile	DQ-Test 0.01-0.99	SQ-Test 0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
1st Break date	-	80Q3***	80Q3**	-	-	-	-	-	89Q1*	-	-	-
2nd Break date	-	86Q1**	86Q1**	-	-	-	-	-	-	-	-	-
3rd Break date	-	98Q3**	98Q3**	-	-	-	-	-	-	-	-	-

Notes: *, ** and *** indicate significance of the estimated break dates on the 10%, 5% and 1% significance level, respectively.

The results for the specifications with and without interest rate smoothing contradict each other. However, the estimation results in section 5 showed clear evidence for a large degree of interest rate smoothing over the whole conditional interest rate distribution. As discussed above large parts of the empirical literature confirm this view. The results indicate that the structural breaks for the case without interest rate smoothing are due to a misspecified monetary policy rule. The fluctuations of the interest rate smoothing parameter as shown in figure 3 are very strong. Thus, the structural breaks in the case without interest rate smoothing reflect most likely that the degree of interest rate smoothing is not constant over the conditional interest rate distribution. The specification without interest rate smoothing cannot capture these variations and thus shows instead evidence for structural breaks in the constant, the inflation and the output gap response. The specification with interest rate smoothing is more reliable. The test results show that parameter variations in this case are not caused by shifting preferences, but by stable asymmetric policy responses that cannot be detected when estimating the policy parameters at the conditional mean only. These asymmetric policy reactions will be analysed in more detail in the next section.

7. Asymmetric Policy Reactions and the Business Cycle

The strong variations of policy coefficients raise the question if these are connected to inflation and/or the stance of the business cycle. For example, central bankers might be more averse to the danger of running into a recession than to accepting higher inflation during an expansion (Blinder, 1998). Thus, if the probability of a recession rises they might favor to decrease the interest rate by reacting more to the output gap compared to other times (Cukierman and Muscatelli, 2008). To investigate systematically whether those kinds of asymmetric central bank preferences exist, I need to determine on which part of the conditional interest rate distribution the federal funds rate has been set at each point in time. Afterwards I can check whether these specific interest rate reactions are correlated with the level of inflation or economic activity.

To estimate at which part of its conditional distribution the federal funds rate is set at each point of the sample, I first compute for each observation fitted values of the interest rate. Doing this for all different quantiles $\tau \in (0,1)$ using the parameters from IVQR, I get a whole set of fitted values $\tilde{i}_t(\tau), \tau \in (0,1)$. I then choose for each observation in the sample the quantile $\tilde{\tau}_t$ that minimizes the squared difference of the fitted value and the actual value of the federal funds rate in period t: $\tilde{\tau}_t = \min_{\{\tau\}}(\tilde{i}_t(\tau) - i_t)^2$.[20] In this way I generate a time series of quantiles $\tilde{\tau}_t$ that shows the path of the position of the federal funds rate on its conditional distribution.[21] Figure 8 shows this estimated series of quantiles for the case without interest rate smoothing. I plot for comparison the federal funds rate and its implied value by a standard estimated policy rule with TSLS methods as in table 4.

[20] I find that this minimization problem is well behaved and features a unique minimum. Minimizing alternatively absolute deviations yields exactly the same quantile assignment at each point of the sample.

[21] I check robustness of the results using probit, logit and nonparametric estimation methods to estimate realized quantiles. Probit and logit estimates give similar results to the ones reported here. Nonparametric regression yields by trend similar results though showing some high frequency jumps of the estimated quantiles that might be caused by the low number of observations.

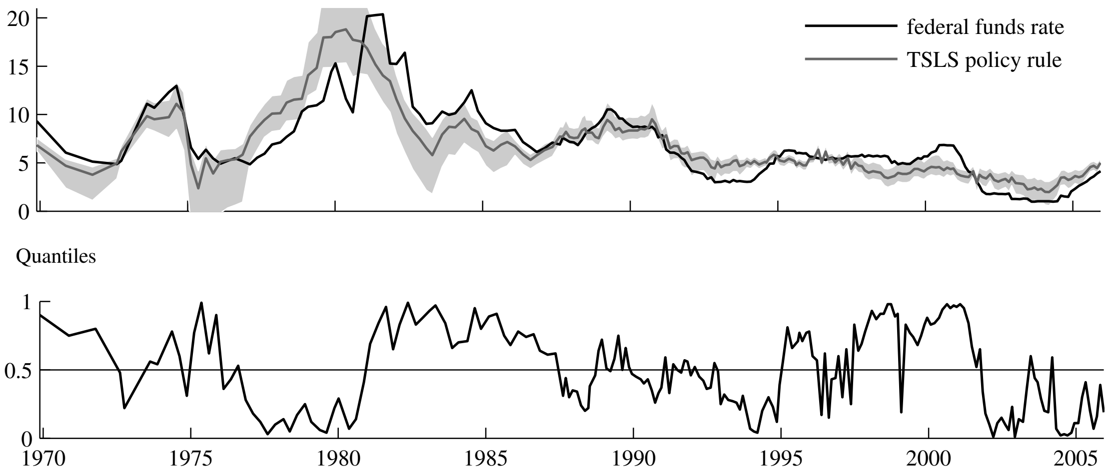

Figure 8: Federal Funds Rate, Estimated Policy Rule and Estimated Quantiles ($\alpha_i = 0$). Notes: Row 1 shows the federal funds rate and fitted values of the estimated policy rule using TSLS together with a 95% confidence band. Row 2 shows a series of estimated quantiles $\tilde{\tau}_t$.

The graph shows that this procedure translates the observed deviations from a policy rule estimated at the mean—i.e. the TSLS error term—into a similar series of estimated quantiles on the conditional interest rate distribution. Using this estimated series of quantiles, one can decompose the deviations of the federal funds rate from the values implied by a linear policy rule ($i_t - \hat{i}_t$) into deviations from average reponses to inflation and the output gap:

$$i_t - \hat{i}_t = [\tilde{\alpha}_0(\tilde{\tau}_t) - \hat{\alpha}_0] + [\tilde{\alpha}_\pi(\tilde{\tau}_t) - \hat{\alpha}_\pi]\pi_{t+4|t} + [\tilde{\alpha}_y(\tilde{\tau}_t) - \hat{\alpha}_y]y_t + \xi_t, \tag{9}$$

where $\hat{\alpha}_0$, $\hat{\alpha}_\pi$ and $\hat{\alpha}_y$ denote parameters from a linear policy rule estimated with TSLS as reported in table 4 and $\hat{i}_t$ denotes the fitted values of the interest rate from the same estimation. $\tilde{\alpha}_0(\tilde{\tau}_t)$, $\tilde{\alpha}_\pi(\tilde{\tau}_t)$ and $\tilde{\alpha}_y(\tilde{\tau}_t)$ refer to the IVQR results. The remaining error term ξ_t is negligible small so that $i_t \approx \tilde{i}_t(\tilde{\tau}_t)$.[22] For example the second term on the right side shows how much the central bank's reaction to expected inflation deviates at time t from the reaction implied by a linear policy rule.[23]

Figure 9 shows this decomposition of deviations from an average constant, the average inflation response and the average output gap response over time. The sum of the different deviations yields the overall deviations from the average responses, i.e. the TSLS error term.

[22]The major advantage of the methodology used here in comparison to logit and nonparametric approaches is that the estimated terms of the right hand side sum up almost exactly to the overall deviations on the left side. This is not the case when switching to other methods for estimating the quantile series. A disadvantage is that policy shocks do not show up anymore, but are absorbed in the variations of the parameters.

[23]The methodology is easily expanded to analyze deviations of the federal funds rate from benchmark policy rules. Deviations from Taylor's rule can be for example decomposed as follows: $i_t - i_t^{Taylor} = [\tilde{\alpha}_0(\tilde{\tau}_t) - 1] + [\tilde{\alpha}_\pi(\tilde{\tau}_t) - 1.5]\pi_{t+4|t} + [\tilde{\alpha}_y(\tilde{\tau}_t) - 0.5]y_t$.

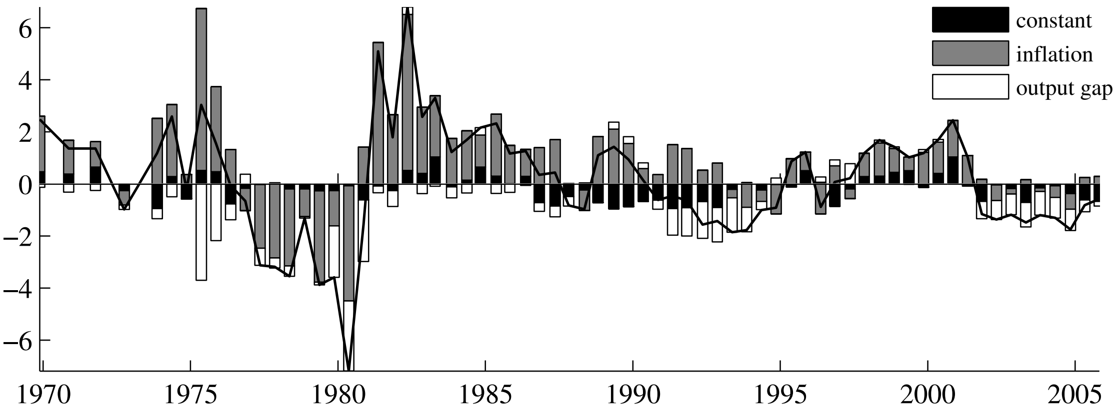

Figure 9: Decomposition of Policy Deviations from the Values Implied by a Policy Rule Estimated at the Conditional Mean. Notes: The solid line shows the difference between the federal funds rate and the TSLS estimate of a policy rule: $i_t - \hat{i}_t$. The bars denote differences between estimated policy reactions and policy reactions implied by a policy rule estimated at the conditional mean (constant: $\tilde{\alpha}_0(\tilde{\tau}_t) - \hat{\alpha}_0$, inflation: $[\tilde{\alpha}_\pi(\tilde{\tau}_t) - \hat{\alpha}_\pi]\pi_{t+4|t}$, output gap: $[\tilde{\alpha}_y(\tilde{\tau}_t) - \hat{\alpha}_y]y_t$). Summing up the values from the bars approximately yields the black solid line.

One can see that deviations of the IVQR constant from the TSLS constant are small. Major deviations from the conditional mean policy rule are mainly due to persistent deviations in the inflation response and to a lower extent in the output gap response. For example from 1981 to 1987 Paul Volcker reacted much more to inflation than implied by a linear policy rule. Between 1990 and 1995 and after 2001 the Fed responded more to the output gap than a linear policy rule would suggest. This resulted in a lower federal funds rate than when the Fed would have strictly followed a linear policy rule. To investigate systematically whether deviations from average responses are linked to inflation or the output gap I compute correlations with inflation and the output gap. First, I compute correlations between the overall deviations from average policy responses with inflation and the output gap. Afterwards I compute correlations for deviations with respect to the constant, the inflation response and the output gap response with inflation and the output gap. Table 7 shows the results.

Table 7: Correlations between Policy Deviations from Average Responses and Macroeconomic Variables ($\alpha_i = 0$)

	$\pi_{t+4\|t}$	y_t
	1969Q4-2005Q4	
$i_t - \hat{i}_t$	-0.13 (0.06)	0.00 (0.95)
$\tilde{\alpha}_0(\tilde{\tau}_t) - \hat{\alpha}_0$	-0.07 (0.34)	-0.01 (0.89)
$[\tilde{\alpha}_\pi(\tilde{\tau}_t) - \hat{\alpha}_\pi]\pi_{t+4\|t}$	0.11 (0.09)	**-0.19 (0.01)**
$[\tilde{\alpha}_y(\tilde{\tau}_t) - \hat{\alpha}_y]y_t$	**-0.17 (0.02)**	**0.26 (0.00)**
	1969Q4-1979Q2	
$i_t - \hat{i}_t$	**-0.43 (0.02)**	**-0.38 (0.04)**
$\tilde{\alpha}_0(\tilde{\tau}_t) - \hat{\alpha}_0$	-0.22 (0.25)	-0.02 (0.92)
$[\tilde{\alpha}_\pi(\tilde{\tau}_t) - \hat{\alpha}_\pi]\pi_{t+4\|t}$	-0.31 (0.10)	**-0.48 (0.01)**
$[\tilde{\alpha}_y(\tilde{\tau}_t) - \hat{\alpha}_y]y_t$	-0.17 (0.98)	**0.46 (0.01)**
	1979Q3-2005Q4	
$i_t - \hat{i}_t$	-0.05 (0.51)	0.03 (0.70)
$\tilde{\alpha}_0(\tilde{\tau}_t) - \hat{\alpha}_0$	-0.07 (0.37)	0.00 (0.99)
$[\tilde{\alpha}_\pi(\tilde{\tau}_t) - \hat{\alpha}_\pi]\pi_{t+4\|t}$	**0.29 (0.00)**	**-0.19 (0.01)**
$[\tilde{\alpha}_y(\tilde{\tau}_t) - \hat{\alpha}_y]y_t$	**-0.15 (0.04)**	**0.26 (0.00)**
	1983Q3-2005Q4	
$i_t - \hat{i}_t$	**0.22 (0.00)**	**0.29 (0.00)**
$\tilde{\alpha}_0(\tilde{\tau}_t) - \hat{\alpha}_0$	-0.27 (0.00)	**0.18 (0.02)**
$[\tilde{\alpha}_\pi(\tilde{\tau}_t) - \hat{\alpha}_\pi]\pi_{t+4\|t}$	**0.53 (0.00)**	-0.04 (0.60)
$[\tilde{\alpha}_y(\tilde{\tau}_t) - \hat{\alpha}_y]y_t$	**0.27 (0.00)**	**0.52 (0.00)**

Notes: The entries show correlations between deviations of policy responses from average responses (conditional mean estimates). p-values are shown in brackets. Results are shown for the whole sample and three different subsamples.

While overall deviations of the federal funds rate from values implied by a policy rule estimated with TSLS show no correlation with inflation or the output gap for the whole sample 1969Q4-2005Q4, looking at subsamples gives more insights. Overall deviations are negatively correlated with the business cycle and inflation for the pre-Volcker period, but positively correlated for the post-Volcker period. Thus, the Federal Reserve deviated from the policy responses proposed by a simple linear policy rule procyclically for the pre-Volcker period and anticyclically for the post-Volcker period.

One can check further if these correlations of policy responses with macroeconomic variables correspond to inflation responses or output gap responses. Inflation response deviations from linear symmetric rule implied responses are significantly positively correlated with the level of inflation for the Volcker-Greenspan era. Thus, during times of high inflation the Fed reacted more to inflation than during times of low inflation. This has been called a inflation avoidance preference in the literature.

Results are much clearer for correlations between deviations with respect to the output gap response and the business cycle. The correlation is positive and significant for all subsamples. Federal Reserve policy responses to the output gap deviated anticyclically from a linear policy rule. Recalling that the IVQR coefficient of the output gap response is only positive for the lower part of the conditional interest rate distribution and is zero for the upper part, implies that the Fed's output gap response during expansions corresponds to the parameter estimates in the upper part of the conditional interest rate distribution and the Fed's output gap response during downturns corresponds to the parameter estimates at the lower part of the conditional interest rate distribution. The Fed reacted a lot to the output gap during recessions, but little during expansions. This led to lower interest rates than proposed by a linear policy rule during downturns (reaction to negative output gap) und thus confirms a recession avoidance preference of the Federal Reserve found by Rabanal (2004) and Cukierman and Muscatelli (2008).

Cukierman and Muscatelli (2008) estimate an interest rate rule with smooth-transisition models for inflation deviations from a target and the output gap to capture nonlinearities in the reaction to these two variables. Rabanal (2004) estimates a policy rule with Markov-Switching and finds a higher output gap response parameter during contractions than during expansions. Gerlach (2000) and Surico (2007) also find that the Federal Reserve responded more strongly to recessions than to expansions, but only between 1960 and 1980 and not afterwards. Gerlach (2000) uses a nonlinear policy reaction function and a HP-filtered output gap, while Surico (2007) uses the CBO output gap and squared inflation and output gap terms in a linear policy rule. The differences to my results might be due to the different methodological approach and the usage of real-time data in this study.

Figure 9 reflects the anticyclicality for important episodes of monetary policy: for example during the downturn of the early nineties due to FOMC concerns about "financial headwinds" (Poole, 2006) the output gap response is high. As the real-time output gap is negative for most of the time (see figure 1) this high output gap reaction brings about an anticyclical decrease in the interest rate. Another example is the period 2001-2005: after the September 11 terrorist attacks the Fed decreased the federal funds rate by reacting more to the output gap than on average.

Figure 10 shows the federal funds rate and the fitted values from a policy rule *with* interest rate smoothing together with estimated quantiles. Even though differences between the federal funds rate and the fitted values from the policy rule are hardly visible, the series of quantiles shows that deviations from the policy rule are persistent for several quarters during some periods.

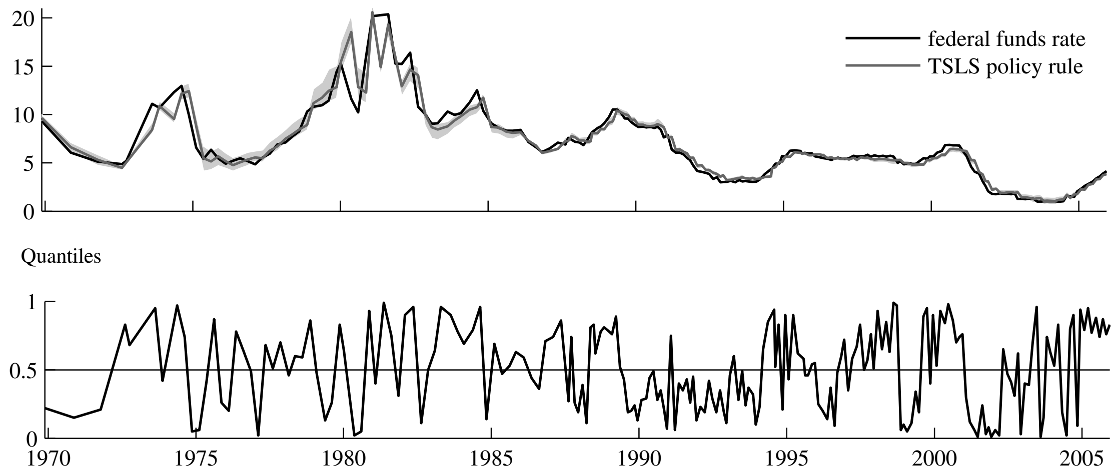

Figure 10: Federal Funds Rate, Estimated Policy Rule and Estimated Quantiles ($\alpha_i \neq 0$). Notes: see figure 8 for a description of the different graphs.

For example the decrease of interest rates from 1990 to 1995 and from 2001 to 2003 is associated with interest rates at the lower 50% of its conditional distribution, while the interest rate increases around 1995, 2000 and in 2004/2005 are associated with interest rates at the higher 50% of the conditional interest rate distribution. These examples also give some support for the earlier interpretation of the interest rate smoothing coefficient. Interest inertia is lower at the tails of the conditional interest rate distribution, which corresponds to sequences of interest rate hikes and decreases.

Figure 11 shows the same decomposition for the case with interest rate smoothing as previously discussed for a rule without interest rate smoothing.

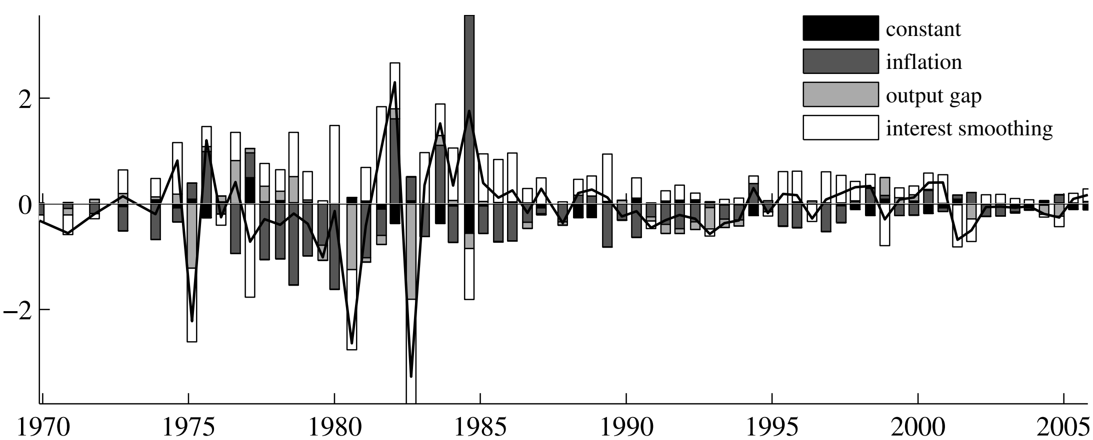

Figure 11: Decomposition of Policy Deviations from the Values Implied by a Policy Rule Estimated at the Conditional Mean. Notes: The solid line shows the difference between the federal funds rate and the TSLS estimate of a policy rule: $i_t - \hat{i}_t$. The bars denote differences between estimated policy reactions and policy reactions implied by a policy rule estimated at the conditional mean (constant: $\tilde{\alpha}_0(\tilde{\tau}_t) - \hat{\alpha}_0$, inflation: $[\tilde{\alpha}_\pi(\tilde{\tau}_t) - \hat{\alpha}_\pi]\pi_{t+4|t}$, output gap: $[\tilde{\alpha}_y(\tilde{\tau}_t) - \hat{\alpha}_y]y_t$, interest smoothing: $[\tilde{\alpha}_i(\tilde{\tau}_t) - \hat{\alpha}_i]i_{t-1}$). Summing up the values from the bars approximately yields the black solid line.

While deviations from a linear policy rule in figure 10 look small, figure 11 shows that these even take values between -4% and 4% during the reserve targeting period in the early 1980's. The decomposition shows that the Fed deviated mainly in its reactions to inflation, the lagged interest rate and during some periods in the reaction to the output gap from the conditional mean policy rule.

Table 8 shows that these deviations are systematic. Deviations in the output gap response from the linear policy rule are highly anticyclical for the Volcker-Greenspan period. The correlations are 0.37 for the subsample 1979Q3-2005Q4 and 0.43 for 1983Q3-2005Q4. Both values are significant on the 1% level. This confirms the main result of a recession avoidance preference found for the case without interest rate smoothing. An inflation avoidance preference as found in the results without interest rate smoothing cannot be confirmed. One can conclude that even though the deviations from a policy rule are small when allowing for a gradual adjustment of interest rates, quantile regression is still useful as it allows a more precise description of monetary policy that is otherwise hidden behind the high degree of interest rate smoothing.

Table 8: Correlations between Policy Deviations from Average Responses and Macroeconomic Variables ($\alpha_i \neq 0$)

	$\pi_{t+4\|t}$	y_t
	1969Q4-2005Q4	
$i_t - \hat{i}_t$	0.01 (0.6)	0.06 (0.41)
$\tilde{\alpha}_0(\tilde{\tau}_t) - \hat{\alpha}_0$	0.00 (0.95)	-0.05 (0.52)
$[\tilde{\alpha}_\pi(\tilde{\tau}_t) - \hat{\alpha}_\pi]\pi_{t+4\|t}$	0.11 (0.13)	-0.08 (0.24)
$[\tilde{\alpha}_y(\tilde{\tau}_t) - \hat{\alpha}_y]y_t$	**-0.13 (0.05)**	0.10 (0.15)
$[\tilde{\alpha}_i(\tilde{\tau}_t) - \hat{\alpha}_i]i_{t-1}$	-0.09 (0.20)	0.08 (0.27)
	1969Q4-1979Q2	
$i_t - \hat{i}_t$	-0.07 (0.74)	0.18 (0.35)
$\tilde{\alpha}_0(\tilde{\tau}_t) - \hat{\alpha}_0$	-0.01 (0.98)	-0.15 (0.45)
$[\tilde{\alpha}_\pi(\tilde{\tau}_t) - \hat{\alpha}_\pi]\pi_{t+4\|t}$	-0.10 (0.60)	0.00 (0.99)
$[\tilde{\alpha}_y(\tilde{\tau}_t) - \hat{\alpha}_y]y_t$	-0.17 (0.39)	-0.16 (0.40)
$[\tilde{\alpha}_i(\tilde{\tau}_t) - \hat{\alpha}_i]i_{t-1}$	-0.20 (0.31)	0.23 (0.23)
	1979Q3-2005Q4	
$i_t - \hat{i}_t$	0.01 (0.93)	0.05 (0.53)
$\tilde{\alpha}_0(\tilde{\tau}_t) - \hat{\alpha}_0$	-0.03 (0.71)	-0.01 (0.93)
$[\tilde{\alpha}_\pi(\tilde{\tau}_t) - \hat{\alpha}_\pi]\pi_{t+4\|t}$	0.11 (0.14)	-0.11 (0.15)
$[\tilde{\alpha}_y(\tilde{\tau}_t) - \hat{\alpha}_y]y_t$	**-0.28 (0.00)**	**0.37 (0.00)**
$[\tilde{\alpha}_i(\tilde{\tau}_t) - \hat{\alpha}_i]i_{t-1}$	-0.03 (0.69)	-0.03 (0.72)
	1983Q3-2005Q4	
$i_t - \hat{i}_t$	0.09 (0.27)	**0.17 (0.03)**
$\tilde{\alpha}_0(\tilde{\tau}_t) - \hat{\alpha}_0$	0.00 (0.99)	-0.14 (0.07)
$[\tilde{\alpha}_\pi(\tilde{\tau}_t) - \hat{\alpha}_\pi]\pi_{t+4\|t}$	-0.13 (0.10)	0.04 (0.64)
$[\tilde{\alpha}_y(\tilde{\tau}_t) - \hat{\alpha}_y]y_t$	-0.03 (0.73)	**0.43 (0.00)**
$[\tilde{\alpha}_i(\tilde{\tau}_t) - \hat{\alpha}_i]i_{t-1}$	**0.22 (0.01)**	-0.09 (0.28)

Notes: The entries show correlations between deviations of policy responses from average responses (conditional mean estimates). p-values are shown in brackets. Results are shown for the whole sample and three subsamples.

8. Conclusion

Using quantile regressions to estimate monetary policy rules appears to be useful: without including additional variables, one obtains more detailed estimates than with standard estimation techniques without violating the robustness property of simple rules. Deviations of the federal funds rate from standard policy rule estimates are caused to a large extent by systematic changes in the inflation and output gap reaction parameters and the interest rate smoothing parameter over the conditional distribution of the federal funds rate, rather than by policy shocks. Inflation reactions increase and output gap responses decrease over the conditional distribution of the interest rate. Interest rate smoothing is highest at the conditional median and lower at the tails of the conditional interest rate distribution. Allowing for a gradual adjustment of interest rates pretends a high fit of an estimated linear policy rule, while quantile regression reveals systematic and significant movements of monetary policy reaction coefficients over the conditional distribution of the federal funds rate. Structural break tests in regression quantiles show that the conditional interest rate distribution is stable for the realistic specification with interest rate smoothing. Parameter variations can thus not be attributed to preference shifts of policymakers. Mapping parameter variations over the conditional interest rate distribution into the time domain shows that deviations of the output gap response from a linear policy rule are anticyclical for the Volcker-Greenspan era. The anticyclical output gap response together with a decreasing output gap coefficient over the conditional distribution of the interest rate for the second part of the sample implies at least a mild recession avoidance preference of the Federal Reserve for the period 1980-2005.

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