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BACHELOR THESIS

Empirical Estimates of the Taylor Rule: A Meta-analysis

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Declaration of Authorship

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Signature

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Abstract

The central banks' reaction functions are commonly estimated in the empirical literature, but the results vary even for the same central bank. Meta-analysis is a tool used to uncover publication bias and explain the heterogeneity in estimates. In this thesis I analyse 1128 estimates from 88 primary studies. I examine the estimates of the coefficients from Taylor rule specification with and without interest rate smoothing and find statistically significant evidence of publication bias in all estimates of Taylor rule coefficients. Furthermore, the estimation of the effects beyond publication bias yields much lower estimates than commonly thought. I also managed to explain some of the heterogeneity in the estimates by accounting for different data characteristics used in the primary studies. E.g. different measures of inflation and output gaps significantly influence the estimates of the Taylor rule coefficients.

JEL Classification	C83, E52, E58
Keywords	meta-analysis, publication selection bias, Taylor rule, interest rate, inflation, output gap

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Abstrakt

Reakční funkce centrálních bank jsou běžně předmětem empirických odhadů, ale výsledky jednotlivých studií se liší i pro jednotlivé centrální banky. Meta-analýza je nástroj, který slouží k vysvětlování rozdílů v odhadech a odhalování vychýlení způsobeného publikační selektivitou. V této práci analyzuji 1128 odhadů z 88 primárních studií. Zkoumám odhady koeficientů Taylorova pravidla ve verzi s i bez vyhlazování úrokových měr, ve kterých jsem nalezl statisticky významnou evidenci publikační selektivity ve všech případech. Moje odhady koeficientů očištěné od vlivu publikační selektivity jsou pak výrazně nižší, než je v literatuře běžně uváděno. Dále se mi podařilo vysvětlit část variace v odhadech tak, že jsem vzal v úvahu různé charakteristiky dat, použitých v primárních studiích. Různé způsoby měření inflace a produkční mezery například významně ovlivňují odhady koeficientů Taylorova pravidla.

Klasifikace JEL	C83, E52, E58
Klíčová slova	meta-analýza, publikační selektivita, Taylorovo pravidlo, úroková míra, inflace, produkční mezera

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Acronyms

2SLS Two stage least squares

CPI Consumer price index

DSGE Dynamic stochastic general equilibrium

ECB European central bank

EU European Union

FAT Funnel asymmetry test

FDI Foreign direct investment

FED Federal Reserve

FGLS Feasible generalized least squares

GDP Gross domestic product

GDPCTPI Gross domestic product chain-type price index

GMM Generalized method of moments

HICP Harmonized index of consumer prices

HP Hodrick-Prescott (filter)

IV Instrumental variable

LS Least squares

MLE Maximum likelihood estimation

MRA Meta-regression analysis

NAIRU Non-accelerating inflation rate of unemployment

NLS Non-linear least squares

OLS Ordinary least squares

PCE Personal consumption expenditure

PEESE Precision-effect estimate with standard error

PET Precision-effect test

PPI Producer price index

RPI Retail price index

WPI Wholesale price index

Bachelor Thesis Proposal

Author	Jan Sviták
Supervisor	PhDr. Tomáš Havránek
Proposed topic	Empirical Estimates of the Taylor Rule: A Meta-analysis

Empirical studies, examining the same field of interest, often arrive due to various reasons at different results, which are sometimes even inconsistent with broadly accepted theory. Meta-analysis is a set of tools which enable us to obtain highly relevant results using the data from a great amount of empirical studies. Employing these methods we are able to reveal how much the results of these works are influenced by publication selection bias and numerous other factors. The aim of this thesis is to conduct a meta-analysis of empirical estimates of the Taylor rule, i.e. response of interest rate to inflation and output gap. One meta-analysis regarding this topic was already published, Chortareas, Magonis (2008). The main contribution of my work should be employment of up-to-date data and modern methods.

Outline

1. Method of meta-analysis (history, tools, benefits)
2. Taylor rule (definition, significance, usage)
3. Actual meta-analysis (summary of collected data, problem of publication selection bias and heterogenity)
4. Results and conclusions

Core bibliography

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Author Supervisor

Introduction

With the fast development of computers in recent decades empirical economic research has proliferated in size and complexity, because it suddenly became easier to use modern econometric methods. Nevertheless, the results of the studies often vary broadly across literature. This heterogeneity makes it difficult to draw any general conclusions from the literature. Another serious issue is publication bias caused by researchers' tendencies to publish only statistically significant results or results consistent with theory. Meta-analysis is a powerful quantitative tool able to uncover sources of heterogeneity and measure publication bias in contrast to narrative literature surveys.

One of the best known macroeconomic relationships is the Taylor rule proposed by Taylor (1993), a simple equation which endeavors to capture reaction functions of central banks. The original rule links the interest rate set by the central bank to levels of inflation and the output gap in the economy. The Taylor rule is a part of the vast majority of macroeconomic models, including the widely used New-Keynesian DSGE model among others. Given the huge importance of the Taylor rule, it is no wonder that its coefficients are very often within the scope of empirical research. Nevertheless, the heterogeneity of results is very similar to other areas of empirical research, so economists are not able to agree on exact values of the coefficients in question even for one particular central bank.

The objective of this thesis is to conduct a meta-analysis of the empirical estimates of the Taylor rule. By doing so it aims to explain the heterogeneity of results in empirical research on Taylor rules and attempts to find out, whether there is a significant publication bias associated with given area of literature. To my knowledge, the only meta-analysis on this topic is Chortareas & Magonis (2008). The main contribution of this thesis is the utilization of estimates from newer studies, and consequently a larger dataset, using modern methods used in meta-analysis including multilevel mixed effects meta-regression. The dataset consists of 1128 estimates from 88 studies including 61 journal articles and 27 working papers.

The remainder of the thesis is structured as follows. In Chapter 1, I introduce the Taylor rule and issues associated with its estimation. Chapter 2 summarizes the methodology used in meta-analysis. The meta-regression analysis of the estimates of Taylor rule coefficient is carried out in Chapter 3 and Chapter 4 summarizes the findings.

Chapter 1

Taylor rule

1.1 Original version

Macroeconomists have always been trying to create as precise a model of the economy as possible. Taylor (1993) proposes a simple model capturing monetary policy of central banks. One of the most powerful ways the central bank can influence the supply of money in the economy is by setting the interest rate. Thus, the Taylor rule attempts to explain the decision making process which leads to the resulting interest rate. The original simple Taylor rule takes the following form:

$$i = r^* + \alpha(\pi - \pi^*) + \beta\tilde{y} \tag{1.1}$$

where i is nominal interest rate, r^* is equilibrium real interest rate, π is inflation rate over the previous four quarters, π^* is the inflation target, $\tilde{y}$ is the output gap, defined as percentage deviation of real GDP from its potential, which is obtained as trend real GDP, $\tilde{y} = 100 \cdot \dfrac{y - y^*}{y^*}$.

To capture the monetary policy of the Federal Reserve, Taylor (1993) proposes utilizing the following weights:

$$i = 2 + 1.5(\pi - 2) + 0.5\tilde{y} \tag{1.2}$$

Thus, the target inflation $\pi^* = 2$ is assumed as well as stronger reaction of the central bank to changes in inflation than in the output gap.

To see straight ahead the influence of the inflation rate on the final decision about the interest rate, it is common in the literature to rewrite the equation such that the inflation target becomes a part of the intercept term. Thus, from now on, we will use the following specification:

$$i = \delta + \alpha\pi + \beta\tilde{y} \tag{1.3}$$

where $\delta = r^* - \alpha\pi^*$.

Values of the coefficients in (1.3) represent the preferences of the monetary authority. The Taylor rule is also very often referred to as monetary policy reaction function as it captures the reaction of the central bank to the values of the above stated variables.

1.2 Different specifications

The Taylor rule offers a simple tool which enables one to assess monetary policy given the data needed. Nevertheless, there are some issues associated with obtaining these data, especially output gaps. It is very difficult to estimate the level of GDP at the end of the year and also the determination of the potential output is not completely reliable. Therefore, a lot of studies utilizes, for instance, the Okun's law, defined by Okun (1962). It states a simple negative relationship between the output gap and unemployment gap. Consequently, the monetary policy rule becomes:

$$i = \delta + \alpha\pi + \beta_u(u - u^*) \tag{1.4}$$

where u^* is a natural rate of unemployment or the NAIRU and β_u is expected to be negative. Another solution to problematic measuring of the output gap is the use of output growth. Nevertheless, the vast majority of empirical literature still utilizes the output gap despite the uncertainty about correct measuring.

Other changes of specification of the monetary policy rule involve inclusion of numerous additional variables like exchange rates, money supply, financial indices, etc. By doing so researchers try to examine possible influence of these phenomena on interest rate set by the monetary authority. The rule, then, has the following form:

$$i_t = \delta + \alpha\pi + \beta\tilde{y} + \sum_{k=1}^{m} \gamma_k z_k \tag{1.5}$$

where z_k are possible variables that are expected to meaningfully extend the original Taylor rule. Specifications can also fundamentally differ in the functional form of the rule, as explanatory variables can acquire exponential form or become inputs of more complicated non-linear functions.

1.3 Backward-looking versus forward-looking rules

There has been a lot of discussion concerning the time horizon of data taken into account by the monetary authority. The question, therefore is, whether to use contemporaneous data, lagged variables or expectations about future development of inflation and the output gap, respectively. Taking various time periods into account the Taylor rule becomes:

$$i_t = \delta + \alpha\pi_{t+i} + \beta\tilde{y}_{t+j} \tag{1.6}$$

where i_t is the interest rate in period t and i, j are integers, that can be positive or negative depending on the backward- or forward-looking nature of the rule. The contemporaneous data are taken into account, when $i = j = 0$. Integers i and j does not have to be equal nor have the same sign, as we can, for instance, encounter rules estimated with forward-looking inflation and contemporaneous output gap. Forward looking version of the rule is used, for example, by Clarida *et al.* (1998; 2000), whereas the backward looking rule is estimated, for instance, by Carstensen (2006). Usage of both specifications can be reasonably justified.

1.3.1 Forward-looking rules

Some economists prefer forward-looking rules because of the presence of transmission lag between the introduction of the monetary policy and its effect on inflation and output. According to this approach, central banks make their decisions about the policy based on expectations about future development of followed indicators.

1.3.2 Backward-looking rules

On the other hand, some researchers also use backward-looking specification of the Taylor rule, even though the forward-looking and contemporaneous specifications seem to be more frequent in the literature. The argument for this type of reaction function is based on concerns about the availability of correct data at the time, when the decision has to be made. It sounds quite reasonable that monetary policy makers take into account past development of inflation and output as these are definitely more reliable than any kind of estimation of future levels of the variables in question.

1.4 Interest rate smoothing

It is often argued that central banks do not change interest rate as aggressively as the development of inflation and the output gap suggests. Among the reasons why monetary authorities dislike sudden and significant policy reversals are the risk of losing credibility and concerns about their negative impact on credit markets. Thus, central banks seem to smooth the changes in interest rates. For a detailed description of the reasons for interest smoothing see Goodfriend (1991). However, the rule as simple as (1.6) is not able to take this persistence of interest rates into account. As modeling of the variables determining the level of interest smoothing would be very difficult, Clarida *et al.* (1998) modify (1.6) in a following way:

$$i_t = (1-\rho)i_t^* + \rho i_{t-1} \tag{1.7}$$

where i_t is the actual nominal interest rate, $\rho \in \langle 0, 1 \rangle$ is the interest rate smoothing term capturing the level of interest rate persistence and i_t^* is the target interest rate, which can be written in the form of (1.6):

$$i_t^* = \delta + \alpha\pi_{t+i} + \beta\tilde{y}_{t+j} \tag{1.8}$$

Plugging (1.8) into (1.7), we obtain the simple version of Taylor rule taking into account interest rate smoothing:

$$i_t = (1-\rho)(\delta + \alpha\pi_{t+i} + \beta\tilde{y}_{t+j}) + \rho i_{t-1} \tag{1.9}$$

where α and β are long-term responses to inflation and output gap, respectively and ρ shows the gradual adjustment of the actual interest rate to the target interest rate. The above stated general equation (1.9) allows for contemporaneous, forward- and backward-looking specifications of monetary policy rules even though Clarida *et al.* (1998) use only forward- looking rule and utilize expectations.

The model can capture interest smoothing over more than one period. Clarida *et al.* (1998) suggest that second order partial adjustment model fits their

U.S. data better:

$$i_t = (1 - \rho_1 - \rho_2)(\delta + \alpha\pi_{t+i} + \beta\tilde{y}_{t+j}) + \rho_1 i_{t-1} + \rho_2 i_{t-2} \tag{1.10}$$

Thus, the general interest rate adjustment model of order n can be specified as follows:

$$i_t = (1 - \sum_{k=1}^{n} \rho_k)(\delta + \alpha\pi_{t+i} + \beta\tilde{y}_{t+j}) + \sum_{k=1}^{n} \rho_k i_{t-k} \tag{1.11}$$

However, some researchers, e.g. Aizenman *et al.* (2011) estimate the interest smoothing version of the rule in the following way:

$$i_t = d + a\pi_{t+i} + b\tilde{y}_{t+j} + \rho i_{t-1} \tag{1.12}$$

where a and b are short-term responses to inflation and output gap, respectively. When we compare equations (1.12) and (1.9) we can notice that short-term reaction coefficients can be rewritten in terms of the long-term responses as follows:

$$a = (1 - \rho)\alpha; \quad b = (1 - \rho)\beta \tag{1.13}$$

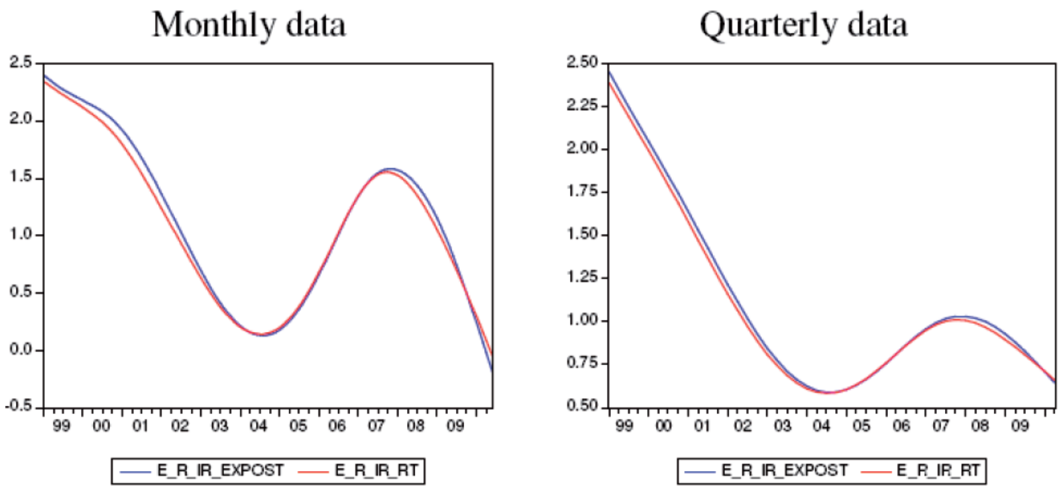
1.5 Estimation issues

When researchers estimate a Taylor-type policy rule, the first step they have to make is to choose one of the specifications described above. Then, it is necessary to obtain the dataset. Naturally, data for interest rates, inflation rates and output gaps are always needed. Furthermore, one can add data for whatever additional variables they decide to use. However, there are various sources and types of these data and each dataset can have several characteristics that can influence the actual values which is one of the major issues associated with estimating the Taylor as mentioned e.g. by Tchaidze & Carare (2004). For instance, data for all variables can be reported monthly, quarterly or yearly. We can also encounter real-time data as well as ex-post revised data. Possible differences in values obtained by different methods are for illustration depicted in figures below taken from Belke & Klose (2011). As we will see, some of the differences are quite significant, so they might seriously influence the results of estimation of the rule. Thus, some of the heterogeneity in the literature can be caused by usage of different datasets.

1.5.1 Interest rates

For the comparison of real-time and ex-post as well as quarterly and monthly data see Figure 1.1. We can notice that the difference between interest rates obtained ex-post or at the time, when the policy took place, is minimal. This is only natural as interest rates are in fact under control of the central bank. Therefore, revision of the data should not bring any dramatic changes. On the other hand, shapes of the curves representing data based on monthly and quarterly data, respectively, differ significantly.

Figure 1.1: Equilibrium real interest rates ex-post and in real time

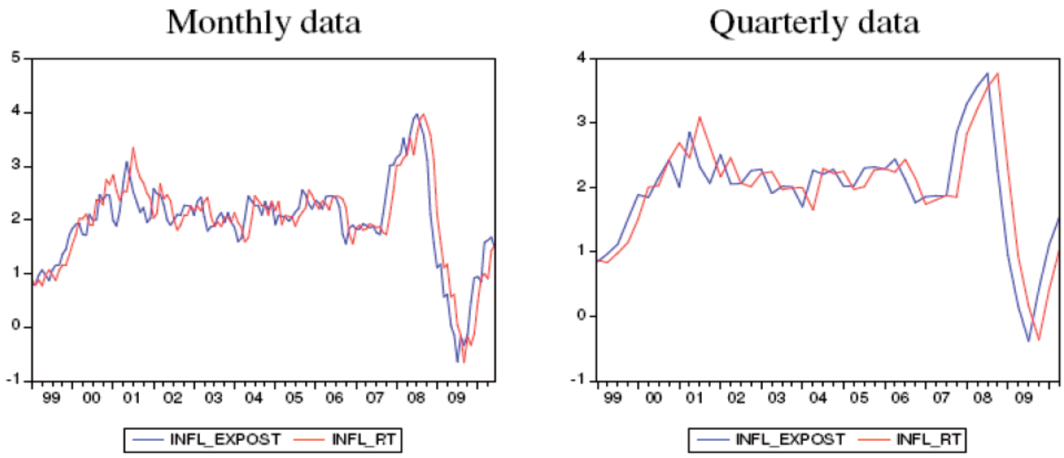


Source: Belke & Klose (2011)

1.5.2 Inflation

In case of inflation (Figure 1.2) the difference between revised and real-time data is bigger than in the previous case, but not dramatically so. This makes sense as there is some uncertainty in determining current inflation at a given time. Thus, revision of the data can lead to some changes. Contrary to interest rates, frequency of data does not seem to influence the data in such a significant way. This indicates that inflation does not fluctuate as much as interest rates on a monthly basis. Monthly data are just able to take into account small short-term fluctuations unlike the quarterly data.

Figure 1.2: Inflation rates ex-post and in real time

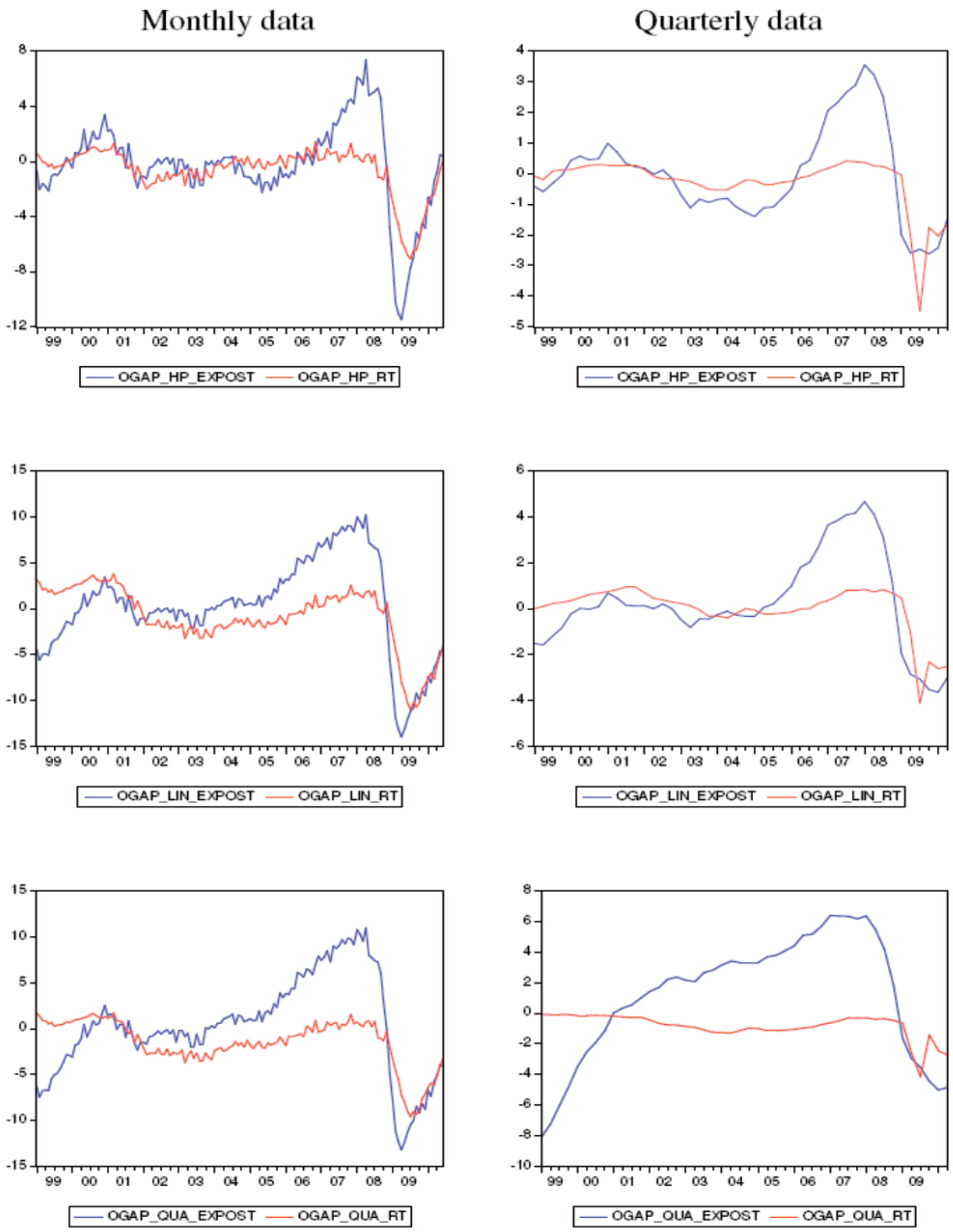


Source: Belke & Klose (2011)

1.5.3 Output gap

Besides the issues associated with frequency and origin of data, some more problems occur when the output gap data are concerned. Recall that the output gap is defined as $\tilde{y} = 100 \cdot \frac{y - y^*}{y}$. However, potential output y^* is not directly observable and, hence, has to be estimated. Since there are several techniques generating different values used in the literature, the resulting estimates of the Taylor rule can also differ with respect to the technique used to obtain a measure of the output gap. Several methods of estimating the output gaps and an evaluation of differences between them is extensively covered by Chagny & Döpke (2001). The data generated by the use of Hodrick-Prescott filter (Hodrick & Prescott 1997), linear trend and quadratic trend are depicted in Figure 1.3. Other methods that occur in the literature include, for instance, band-pass filter (Baxter & King 1999), Kalman filter (Kalman *et al.* 1960), Beveridge–Nelson filter (Beveridge & Nelson 1981), etc. The three approaches depicted in Figure 1.3 are, however, the most frequent ones in the literature on Taylor rules. In Figure 1.3 we can notice quite significant disparities between individual detrending methods used as well as huge differences between real-time and ex-post data. This might indicate that real-time estimations are not reliable enough and consequent revisions alter the data significantly. Differences between monthly and quarterly data are also apparent. Notice that scales of the axis of individual charts are not exactly the same.

Figure 1.3: Output gaps ex-post and in real time



Source: Belke & Klose (2011)

1.5.4 Linear and quadratic detrending

Ince & Papell (2010) use the three detrending methods emphasized above for estimating output gaps. According to the paper, all methods in question decompose a log of the output in a following way:

$$log(y_t) = g_t + c_t, \quad t = 1, \ldots, T \tag{1.14}$$

where y_t is the output measured either as real GDP or by industrial production at time t, g_t is a trend or growth component and c_t is a cyclical component. *log* is a natural logarithm. Linearly detrended output gaps can be derived from the respective residuals from the following regression:

$$log(y_t) = \underbrace{\alpha_0 + \alpha_1 t}_{\text{trend component}} + \underbrace{u_t}_{\text{cyclical component}} \tag{1.15}$$

where u_t are residuals constituting a deviation of $log(y_t)$ from trend. Quadratic detrending works very similarly. Naturally, we have to add a quadratic time trend term into the equation (1.15):

$$log(y_t) = \underbrace{\beta_0 + \beta_1 t + \beta_2 t^2}_{\text{trend component}} + \underbrace{v_t}_{\text{cyclical component}} \tag{1.16}$$

Obtained residuals v_t can be used to create output gaps in the estimation of the Taylor rule.

1.5.5 Hodrick-Prescott filter

HP filter is one of the most popular detrending techniques. It was proposed for the use in economics by Hodrick & Prescott (1997). The method was, however, proposed much earlier by Whittaker (1922). Contrary to linear and quadratic detrending, the HP filter allows for smooth varying of the trend over time. The sequence of growth terms $\{g_t\}$ (see (1.14)) is obtained as the solution of the following minimization problem:

$$\min_{\{g_t\}_{t=-1}^{T}} \left(\sum_{t=1}^{T} c_t^2 + \lambda \underbrace{\sum_{t=1}^{T} ((g_t - g_{t-1}) - (g_{t-1} - g_{t-2}))^2}_{\text{measure of smoothness}} \right) \tag{1.17}$$

where c_t represents deviations from g_t, sum of the squares of the second differences of g_t is a measure of smoothness of path $\{g_t\}$ and λ is a positive number penalizing variability in the series of growth components $\{g_t\}$. The bigger is

λ the smoother is the solution series. Asymptotically as $\lambda \to \infty$ the solution approaches the least squares fit of the linear trend model.

1.5.6 Different measures of output

Another issue is the choice of the measure of output. Some researchers simply use real GDP, but some rather utilize only industrial production. They often make their decision on the basis of availability of given data at the frequency demanded by the author. Nikolsko-Rzhevskyy & Papell (2012) use, for instance, output gaps obtained from the application of Okun's law on deviations of unemployment from its natural rate.

1.5.7 Considered specification

For the sake of analytical consistency, it is important to choose a concrete specification that will be considered in the following analysis. Based on the frequency of occurrence of individual specifications in the literature, I will conduct a meta-analysis of the estimates obtained from the Taylor rule of specification (1.9), while I allow for the inclusion of additional variables as in (1.5). Thus, I take into account interest rate smoothing and all possible time horizons of the variables. Therefore, the resulting specification is:

$$i_t = (1-\rho)(\delta + \alpha\pi_{t+i} + \beta\tilde{y}_{t+j} + \sum_{k=1}^{m}\gamma_k z_k) + \rho i_{t-1} \tag{1.18}$$

Rules with $\rho = 0$ are also included:

$$i_t = \delta + \alpha\pi_{t+i} + \beta\tilde{y}_{t+j} + \sum_{k=1}^{m}\gamma_k z_k \tag{1.19}$$

However, studies utilizing partial interest smoothing specification (1.12) are excluded, because coefficients a, b and α, β are clearly not explaining exactly the same effect.

Chapter 2

Meta-analysis methodology

> "With meta-analysis, it is the research record itself, through objective statistical testing, that determines the research literature's message." Stanley *et al.* (2008)

Topics that garner a lot of attention among the researchers seem to offer a tremendous amount of empirical studies related to the topic. Thus, the results of such studies often vary a lot across studies on the same topic. Therefore, literature surveys are conducted in order to shed some light on the heterogeneity of results. Meta-analysis is a method that enables us to conduct such a review of literature in a quantitative way. Unlike narrative literature surveys, meta-analysis clearly states assumptions made in the process of the selection of studies and explains heterogeneity in the results using a logical statistical approach. Therefore, space for bias caused by possible personal opinions of the researcher conducting the review is substantially limited. In this chapter, we will go through the methodology recently used in meta-analysis. Emphasis is placed on methods used in Chapter 3.

Meta-analysis has been used for a long time in scientific literature. It has been very common, e.g. in medicine. Meta-analytic approach was first proposed by Glass (1976) and since then it has spread into various fields of scientific research. It was introduced also to the world of economics by Stanley & Jarrell (1989). Following the publication of this article meta-analysis became an important part of empirical economic research. The subject of meta-analysis can be, basically, any comparable effects estimated in the literature. Articles conducting meta-analysis include, for instance, Stanley (2004) on unemployment hysteresis, Jarrell & Stanley (1990) on the wage gap between union and non-union workers, Doucouliagos & Paldam (2009) on the development aid effectiveness, Chetty *et al.* (2011) on the difference between micro and macro labor supply elasticities, Havranek & Irsova (2011) on vertical spillovers from FDI or Havranek *et al.* (2012) on price-elasticity of demand for gasoline.

2.1 Publication bias

One of the biggest problems associated with reviewing empirical literature is publication selection bias, sometimes referred to as a "file drawer" problem (Rosenthal 1979). It is believed that researchers tend to seek statistical significance and results consistent with broadly accepted economic theory. The reason for this behavior is the fact that papers with statistically significant results consistent with theory are more likely to get published than those that lack statistical significance or fail to explain the results using conventional theory. As researcher's revenues and possible career advancement greatly depend on publications, every academic will try to publish as many articles as possible. As economists act rationally – as the agents are assumed to in numerous economic models – they want to be rewarded for their work by its publication. Researchers have, therefore, an incentive to juggle with the specification of estimated models or with data, they use for their estimation, in order to obtain the results, that are more likely to get published. Stanley (2005) recognizes two types of publication bias following the work by Card & Krueger (1995).

Type I publication bias results from the preferences of reviewers and publishers towards empirical results consistent with the conventional view and well-explained by broadly accepted theory. For instance, positive estimates of price-elasticity of gasoline – supposed to be negative by theory – are often discarded (see Havranek *et al.* (2012)).

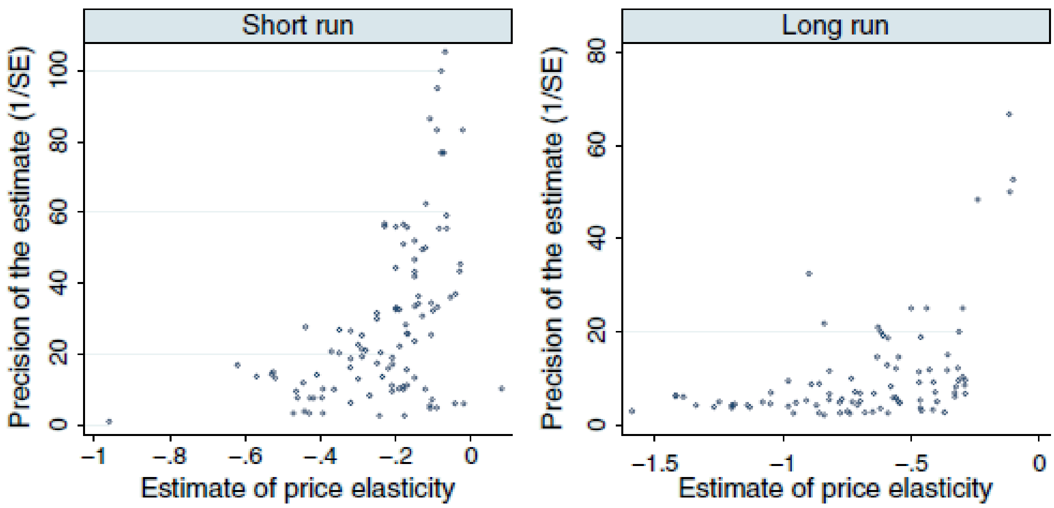
Type II publication bias is caused by the emphasis placed on statistical significance. Statistically insignificant results may, therefore, end up in "file drawer" and researchers may try to obtain as high t-statistics as possible to come up with absolutely significant and accurate results.

Both types of publication bias described above lead to scarcity of estimates that lack the qualities mentioned earlier. Hence, when we try to summarize outcomes from the whole literature and make a conclusion without correcting for publication bias, we will necessarily arrive at biased results. Typically, such a review exaggerates the true effect in question. Therefore, it is important to take publication bias into account.

2.1.1 Graphical analysis

To get the first notion about the extent of publication bias in the dataset consisting of estimates of effect sizes obtained from the literature, it is useful to picture it graphically. Stanley & Doucouliagos (2010) propose the use of a simple scatter diagram called a funnel plot. It is a simple figure plotting observations of effect sizes against the measure of precision of the estimates, e.g. inverse of their standard errors. The name "funnel plot" follows from the fact, that data without publication bias should constitute an inverted funnel. This shape follows from the assumption that without publication selection the estimates should be distributed randomly, i.e. evenly, around the most precise estimates which form the tip of the inverted funnel. When a part of the funnel is missing or the funnel is skewed in one direction, it is an indication of presence of publication bias. For illustration, in Figure 2.1 taken from Havranek *et al.* (2012) we can notice apparent skewness. Hence, based on these scatter plots we can expect publication bias in literature on price-elasticity of demand for gasoline, which was, indeed, found in the conducted meta-analysis.

Figure 2.1: Funnel plots of the estimates of price-elasticity of demand for gasoline

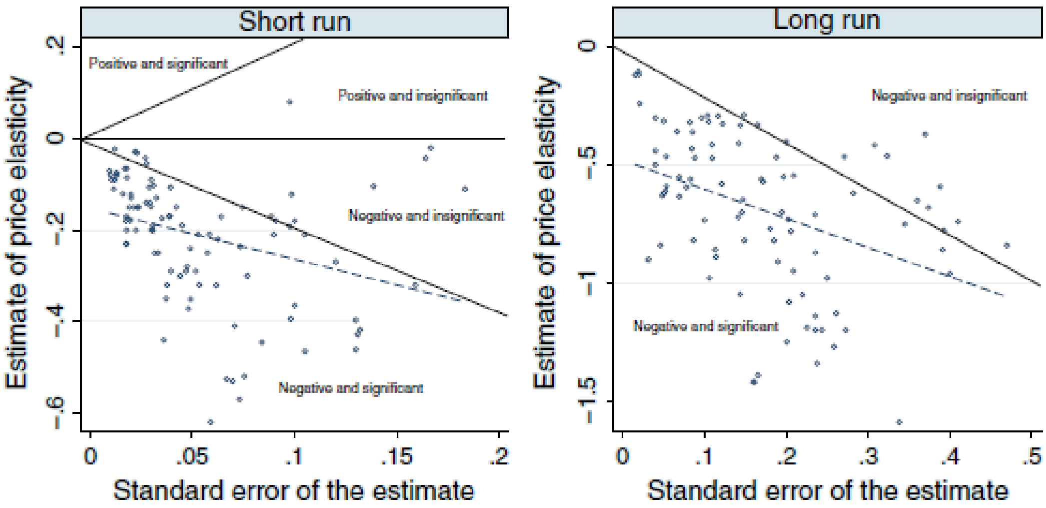


Source: Havranek *et al.* (2012)

Figure 2.2 shows another type of scatter plot used in meta-analysis. It is basically a modified funnel plot and it is a visualization of the funnel asymmetry test, which will be described later in terms of an econometric model. In Figure 2.2 we can clearly see indication of both types of publication bias.

Overwhelming majority of estimates is significant (type I) and positive, hence, consistent with broadly accepted theory (type II).

Figure 2.2: Visualization of the funnel asymmetry test of the estimates of price-elasticity of demand for gasoline



Source: Havranek *et al.* (2012)

2.1.2 Funnel asymmetry test

As described above, researchers may try to solve insignificant coefficients and large standard errors by trying to make the effects larger in order to obtain a significant estimate. The correlation between effect sizes and their standard errors is a sign of publication bias. Hence, the econometric model for uncovering publication bias has the following form (Stanley 2005):

$$b_i = \beta_1 + \beta_0 se_i + \epsilon_i \tag{2.1}$$

where b_i is the estimated effect size, se_i is its standard error and ϵ_i is a disturbance term. The reader can now notice similarity with the funnel plots described above. Results with no publication selection will be distributed randomly around the intercept β_1. However, given the nature of our dataset, consisting of estimates collected from numerous studies, the residuals ϵ_i are likely to be heteroskedastic. Hence, the statistical inference from the obtained results might not be valid as standard errors will not be estimated correctly. As a remedy Stanley (2005) uses WLS estimation and divides the equation by standard errors.

$$\frac{b_i}{se_i} = t_i = \beta_0 + \beta_1 \frac{1}{se_i} + e_i \tag{2.2}$$

where t_i is a t-statistic of the estimate b_i resulting from the division of the estimate by its standard error and e_i is a new disturbance term. The intercept β_0 represents the extent of publication bias and the coefficient β_1 represents the size of the effect in question. Consequently, testing for significance of β_0 is called funnel asymmetry test (FAT) and testing for significance of β_1 is then called precision-effect test (PET).

2.1.3 Heckman meta-regression

While PET seems to be a reliable test for the presence of a genuine effect – as shown by simulations by Stanley (2008) – it is important to be able to precisely estimate the magnitude of the effect in question beyond the publication bias. To accomplish that, it is useful to point out the similarity of publication selection with the sample selection problem examined by Heckman (1979). Stanley & Doucouliagos (2007) work with this similarity. The problem is usually being solved by Heckman's two equation system:

$$b = Z\beta + \varepsilon \tag{2.3}$$

$$P^* = \boldsymbol{K}\alpha + u \tag{2.4}$$

where P^* is the probability that the estimated effect b will be reported, and hence observable for the meta-analysis, $\boldsymbol{K}$ is a matrix of variables influencing P^* and Z is a vector of moderator variables. Estimation of Equation 2.4 by probit is usually the first step. Nevertheless, also unreported variables are needed. These are not available when publication selection is present. Hence, we have to move to the second step of Heckman's method.

$$b = Z\beta + \rho\sigma I(\boldsymbol{K}\hat{\alpha}) + e \tag{2.5}$$

where $I(\boldsymbol{K}\hat{\alpha})$ is the inverse Mills ratio, ρ is the correlation between ε and u, and σ is the standard error of ε. We miss the estimate $\hat{\alpha}$, so we treat $I(\boldsymbol{K}\hat{\alpha})$ as an omitted variable in estimation of β. Thus, Stanley & Doucouliagos (2007) identifies the Equation 2.5 by replacing the inverse Mills ratio with αse. Use of standard errors of b works, because standard errors are likely to vary widely between individual studies. Nevertheless, inverse Mills ratio depends on the standard errors and, therefore, the relationship between the reported estimate and its standard error will be nonlinear, when publication selection is present. As nonlinear relationships are typically estimated using power series, Stanley & Doucouliagos (2007) constructs precision-effect estimate with standard error (PEESE) model:

$$b_i = \beta + \alpha se_i^2 + \epsilon_i \tag{2.6}$$

The vector of moderator variables Z is omitted as they do not explain publication bias, but heterogeneity is covered in section 2.2. Again, we need to correct for heteroskedasticity using WLS:

$$t_i = \alpha se_i + \beta \frac{1}{se_i} + e_i \tag{2.7}$$

According to the Monte Carlo simulations conducted by Stanley & Doucouliagos (2007) $\hat{\beta}$ gives precise estimate of the effect size b beyond publication bias.

2.2 Heterogeneity

Discovering publication bias and estimating the true effect beyond is, however, not the only thing that meta-analysis can tackle. As mentioned several times above, empirical estimates in the literature typically show quite a high level of heterogeneity. The main purpose of meta-analysis besides dealing with publication bias is, therefore, explaining the heterogeneity in estimated effect sizes. We can explain the reasons for such variation in results by means of moderator variables that are incorporated into the econometric model following Stanley & Jarrell (1989):

$$b_i = \beta + \sum_{k=1}^{K} \alpha_k Z_{ki} + \epsilon_i \tag{2.8}$$

where Z_{ki} are moderator variables that represent characteristics of individual studies or even individual estimates assumed to affect variation in estimates b_i. Such characteristics typically include estimation methods, model specifications or type and origin of data used for estimation. Of course, we need to take into account publication bias and obvious heteroskedasticity, so we make use of the equation for FAT (2.1) and use WLS, again. By doing so, we obtain:

$$t_i = \beta_0 + \beta_1 \frac{1}{se_i} + \sum_{k=1}^{K} \alpha_k \frac{Z_{ki}}{se_i} + e_i \tag{2.9}$$

Furthermore, following Stanley *et al.* (2008) we can also examine heterogeneity in publication bias by adding moderator variables that are suspected of affecting the extent of publication selection. Such variables usually represent characteristics like gender or employer of the researcher or date of publication of the study.

$$t_i = \beta_0 + \beta_1 \frac{1}{se_i} + \sum_{k=1}^{K} \alpha_k \frac{Z_{ki}}{se_i} + \sum_{l=1}^{L} \gamma_l S_{li} + e_i \tag{2.10}$$

When interpreting the results it is crucial to distinguish between the two sets of moderator variables Z_{ki} and S_{li}. Variables weighted by standard errors explain heterogeneity in estimates of the effect size, whereas the variables S_{li} explain possible variation in the extent of publication selection.

2.3 Estimation

In Chapter 3, I estimate FAT (2.2) model and Heckman meta-regression model (2.7) in order to examine the presence of publication bias and estimate the true effect beyond. As far as heterogeneity is concerned, the model using two sets of moderator variables (2.10) is considered. Nevertheless, there is one issue left which needs to be addressed. The numbers of estimates reported by individual studies vary broadly. There are studies reporting only one estimate as well as studies reporting dozens of estimates of the effect size in question. Hence, it does not seem right to treat all the estimates in the same way because studies with a higher number of estimates would end up with an extremely great influence on the final results, especially compared to the studies with only one or just a few estimates reported. This becomes an even bigger problem, when we realize that estimates from the same study often share the same characteristics and are, therefore, likely to be correlated. As a remedy, the multilevel mixed effects estimation able to take into account between study heterogeneity is commonly used. Therefore, following Havranek & Irsova (2011) and Havranek *et al.* (2012) I modify the models (2.2), (2.7) and (2.10) in the following way:

$$t_{ij} = \beta_0 + \beta_1 \frac{1}{se_{ij}} + \zeta_j + \epsilon_{ij} \tag{2.11}$$

$$t_{ij} = \alpha se_{ij} + \beta \frac{1}{se_{ij}} + \zeta_j + \epsilon_{ij} \tag{2.12}$$

$$t_{ij} = \beta_0 + \beta_1 \frac{1}{se_{ij}} + \sum_{k=1}^{K} \alpha_k \frac{Z_{kij}}{se_{ij}} + \sum_{l=1}^{L} \gamma_l S_{lij} + \zeta_j + \epsilon_{ij} \tag{2.13}$$

$$\zeta_j | se_{ij} \sim N(0, \Psi), \quad \epsilon_{ij} | se_{ij}, \zeta_j \sim N(0, \theta)$$

where i and j represent i-th estimate from j-th study, ζ_j is a study-level disturbance term and ϵ_{ij} is an error term of the estimate. Ψ represents the between study heterogeneity and θ the variation within study. The composite error term can be written as $\xi_{ij} = \zeta_j + \epsilon_{ij}$. Assuming the independence of both components, the composite variance is a sum of the two variances, $var(\xi_{ij}) = \Psi + \theta$. As Ψ approaches zero, the mixed effects estimation becomes close to OLS because of the lack of between study heterogeneity. To justify the utilization of mixed effects model I carry out the likelihood-ratio tests. Null hypothesis of the test states, that there is no between study heterogeneity in the data and, therefore, the mixed effects estimation has no advantage over OLS.

Chapter 3

MRA of empirical estimates of the Taylor rule

In this chapter the actual meta-regression analysis is conducted. I was able to find only two studies that might be considered as Taylor rule literature reviews. Neither Hamalainen (2004) or Tchaidze & Carare (2004) come up with the conclusion based on the literature. Both mainly discuss issues associated with estimating Taylor-type monetary policy reaction functions. The only meta-analysis of empirical estimates of the Taylor rule up to date known to the author is the work by Chortareas & Magonis (2008). In this study researchers reveal the presence of publication selection bias in the literature, find a genuine effect of inflation on interest rates but fail to do so in case of the output gap. They use FAT and PET and estimate the model by simple OLS and IV and try to explain the heterogeneity in the estimates.. This work, hence, aims to contribute by estimation of the true effect using PEESE, further clarification of the causes of heterogeneity of the estimates using some additional moderator variables and use of multilevel mixed effects model instead of OLS.

3.1 Data description

The first step in conducting a meta-analysis is a search for estimates of the effect size in empirical literature. Typically, there is a huge amount of studies dealing with the effect in question, so the search through the literature is the most time consuming part of work associated with meta-analysis. After an extensive search on Google Scholar 1128 estimates of the Taylor rule from 88 studies are utilized in the analysis. 680 estimates come from 52 studies that were not included in the previous meta-analysis by Chortareas & Magonis (2008). To make the dataset as representative as possible, I decided to also include studies used by Chortareas & Magonis (2008). However, the authors were not willing to provide their data, so I went through the studies listed as references in their article and added another 448 estimates from 36 studies into the dataset. The studies include 61 published journal articles and 17 working papers. I discarded studies using specification other than the one specified in subsection 1.5.7 as well as studies that do not report standard errors or t-statistics of the estimates. Furthermore, some studies do not use the output gap, but rather the unemployment gap or output growth for their estimation of Taylor rules, so these estimates are not included in the dataset, whereas the estimates of response to inflation remain in the dataset. You can find the complete list of primary studies in Appendix B.

Characteristics of the data are summarized in Table 3.1. Specifications with and without interest rate smoothing are treated separately, such that only estimates absolutely consistent with each other are pooled together. Basic intuition suggests that coefficients from the rule with interest smoothing represent a rather long-term target of the monetary authority, whereas coefficients from the original Taylor rule represent immediate short-term responses of the interest rate to inflation and output gap, respectively. In both cases we can notice indications of significant variation in the data.

Table 3.1: Summary statistics

	Count	Mean	Std. dev.	Median	Min	Max
Inflation ($\rho \neq 0$)	860	1.23	0.78	1.28	-6.13	6.98
Output gap ($\rho \neq 0$)	794	0.68	0.55	0.51	-4.63	7.89
Inflation ($\rho = 0$)	268	1.28	0.60	1.26	-0.42	3.70
Output gap ($\rho = 0$)	223	0.38	0.34	0.33	-1.38	1.75

In case of the data for the rule without interest smoothing I detected and discarded one outlier with an extremely low standard error. Reasons for dropping the observation are justified in detail in the Appendix A. Furthermore, various characteristics of the studies and also of the individual estimates were collected and coded mainly using dummy variables. These moderator variables are necessary for conducting a heterogeneity analysis. Characteristics coded include:

- Year of publication of the study (base year is 1998)
- Dummy for studies published in peer-reviewed journals
- Average year of data used in the estimation (base year is 1955)
- Central bank examined (FED, ECB, AR, AT, AU, BE, BR, CA, CL, CN, CZ, DE, ES, FI, FR, GR, HU, IE, IN, IT, JP, MX, NL, PL, PT, SE, SK, TR, UK, VE)[1]
- Specification (forward- or backward-looking nature of Taylor rule coefficients)
- Estimation method (LS, GMM, 2SLS, MLE, FGLS, IV)
- Measures of inflation (CPI, HICP, GDPCTPI, GDP deflator, RPI, PCE, WPI, PPI, Wages)
- Measure of output (real GDP, industrial production, output derived from Okun's law)
- Method for estimating potential GDP (HP filter, linear trend, quadratic trend)
- Frequency of the data (monthly, quarterly)
- Real-time or ex-post data

Dummy moderator variables with very few positive values are not included in the heterogeneity analysis and one dummy from each group is naturally dropped because of collinearity. To compare this meta-analysis with other studies, we can use information from the survey of meta-analyses by Nelson & Kennedy (2009). According to this survey, meta-analyses on average consist of 42 primary studies and 191 observations with 6.9 observations per study. The following meta-regression utilizes 1128 estimates of the Taylor rule from 88 studies. Thus, each study reports 12.81 estimates on average. Hence, the extent of the dataset is significantly above average. Furthermore, the number of observations per study and the large difference between the minimum (1) and maximum (62) number of estimates reported in one article was one of the key arguments for the use of multilevel mixed effects model.

[1]Apart from the FED and the ECB, the countries are coded according to ISO 3166-1-alpha-2 standard developed by the International Organization for Standardization

3.2 Publication bias

I begin the meta-regression analysis by examining the presence and extent of publication bias in the dataset consisting of estimates of Taylor rules coefficients described in previous section. The chosen approach closely follows the methodology described in Chapter 2.

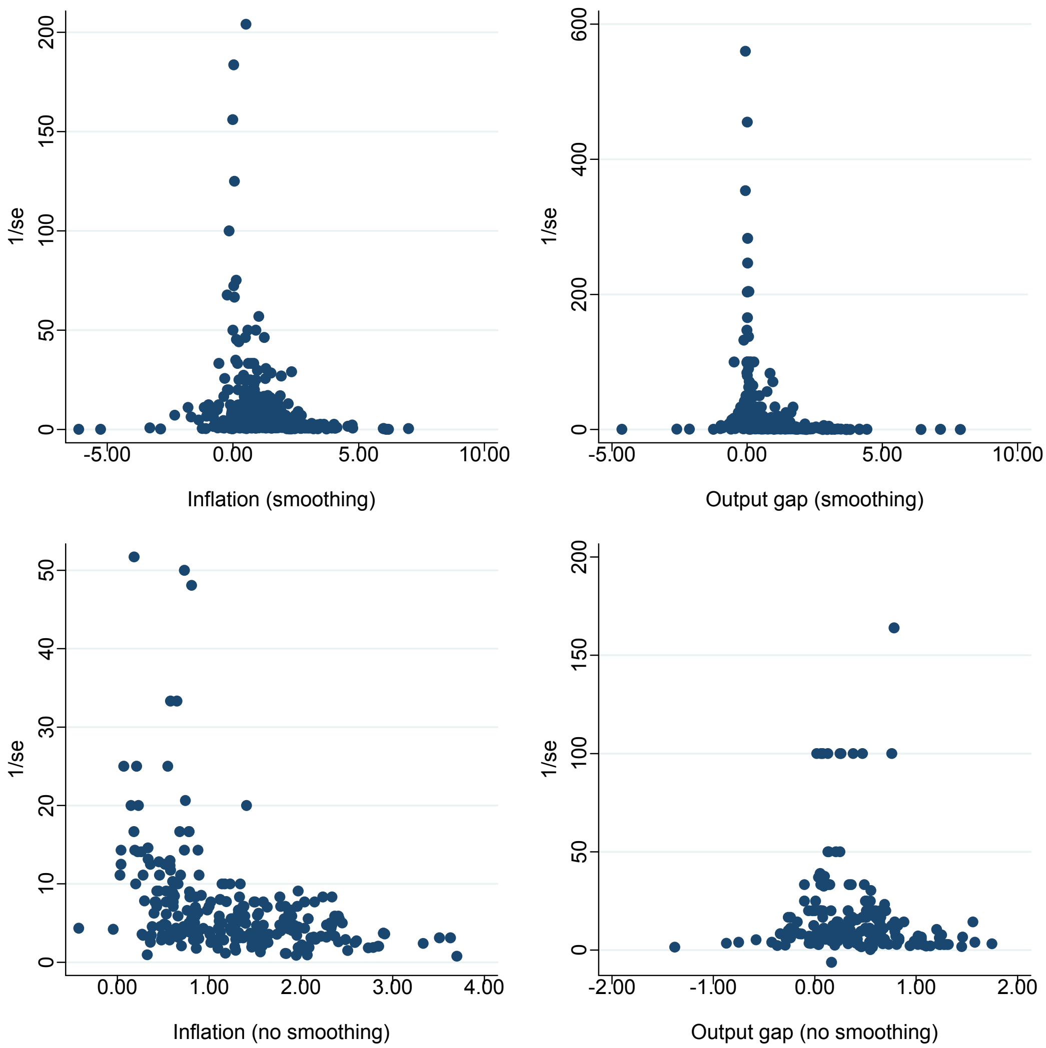
3.2.1 Funnel plots

First, I carry out a graphical analysis so we can get an idea about the extent and direction of publication bias before proceeding with econometric methods. In Figure 3.1 we can see funnel plots as proposed by Stanley & Doucouliagos (2010). As mentioned earlier, estimates from the specifications of the Taylor rule with and without interest rate smoothing are treated separately. Therefore, the first row in the figure shows funnel plots of the estimates of the Taylor rule of the interest smoothing specification, while the second row pictures the funnel plots of the version of the monetary policy without interest rate smoothing, i.e. the original version of the rule proposed by Taylor (1993).

As far as the coefficients from the interest rate smoothing version of the Taylor rule are concerned the data are not so far from resembling a funnel. The estimates are distributed quite evenly around the points around zero with the lowest standard errors and, consequently the highest value of our measure of precision, the inverse of standard error. Nevertheless, we can notice that right parts of the two funnels are somewhat denser, i.e. they contain more estimates. This might hint at possible positive publication selection bias. We can expect the extent of publication to be larger in case of the inflation coefficient as the corresponding funnel plot appears to be more asymmetric.

The funnel plots for the coefficients from the original version of the rule differ quite significantly from the plots in the first row. The scatter plot representing the inflation response estimates in particular does not look like a funnel at all. The left part of the prospective funnel is completely missing, which suggests quite a large extent of positive publication bias in the estimates. On the other hand, the funnel plot for the output gap coefficient seems to be the most symmetric of all. Note that the line of observations with precision 100 is probably caused by the rounding of standard errors in primary studies. The left side of the inverted funnel looks a little thinner, but the extent of the bias appears to be lower than in other cases, maybe nearly non-existent.

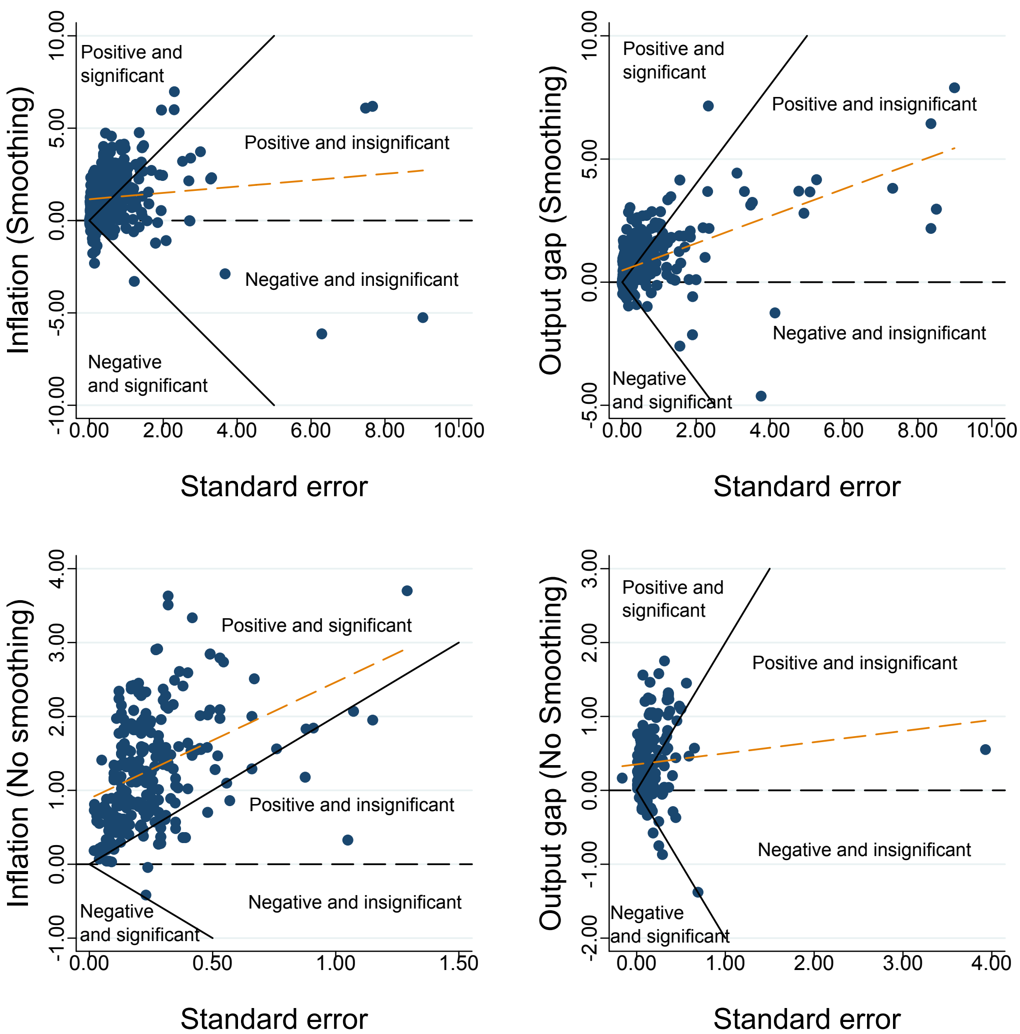
Figure 3.1: Funnel plots of coefficients of the Taylor rule with and without interest smoothing



3.2.2 Visualizations of funnel asymmetry tests

Figure 3.2 consists of visualizations of FATs of the estimates of respective coefficients constructed following Havranek *et al.* (2012). These plots confirm that FAT captures both types of publication bias. The solid lines represent t-statistics equal to 2 in absolute value and, therefore, suggest statistical significance of the estimates at approximately a 5% level. The dashed sloped lines represent the linear fits of Equation 2.1. The organization of plots in the figure is the same as in case of funnel plots. In case of no publication bias the estimates should form an isosceles triangle pointing to the value of the most precise estimate. None of the plots reminds us of the triangle shape. Nevertheless, in case of the estimates of the Taylor rule with interest rate smoothing we can notice that a significant number of statistically insignificant estimates is reported, which hints at a not so dramatic extent of type II publication bias. On the other hand, negative estimates are visibly underreported and the observations do not seem to be randomly distributed around the most precise estimates. Furthermore, linear fits of both datasets have a positive slope suggesting publication bias.

Figure 3.2: Visualization of the funnel asymmetry test for the coefficients of the Taylor rule with and without interest smoothing



Figures depicting plots of the coefficients from the original Taylor rule tell us a similar story as far as non-random distribution of datapoints around the most precise estimate is concerned. We can also notice a significant positive slope of linear fits of data in both cases. However, the visualization of FAT for the response to inflation shows large extent of publication bias – by far the largest among the examined estimates – which is consistent with the analysis of funnel plots. We can see that the line representing the t-statistic of value 2 basically forms a border to the cloud of data above it. Furthermore, the slope of the linear fit of the observations suggests very significant positive publication bias.

3.2.3 Histograms of t-statistics

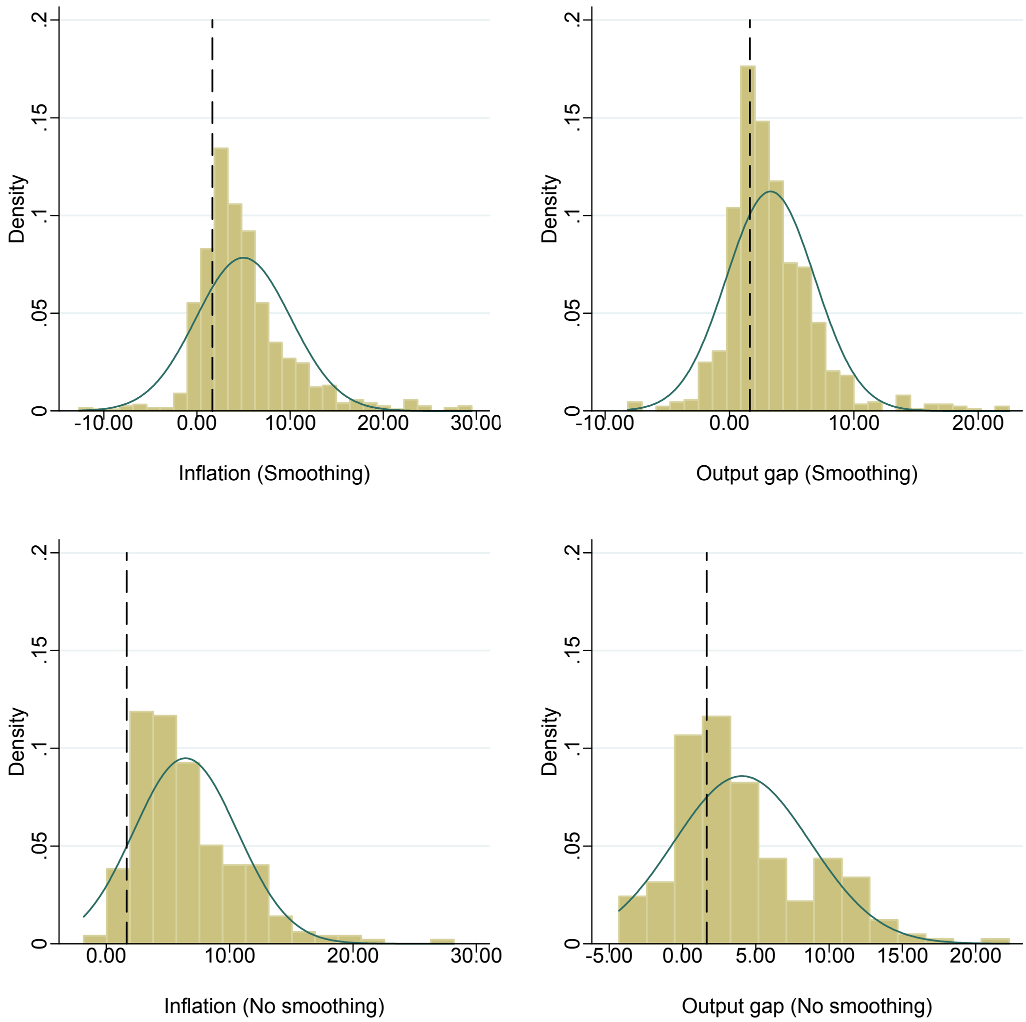
To further examine the presence and extent of type II publication bias concerning preference of publishers for statistically significant estimates Figure 3.3 depicts the histograms of t-statistics of reported estimates following Havranek (2013). The common assumption is that if there was no publication bias present in the literature t-statistics of reported estimates would follow normal distribution. Therefore, I added a curve representing normal distribution into the histograms. Furthermore, the dashed lines mark the t-statistics of 1.645 commonly used as a critical value for statistical significance at a 10% level.

In all cases the density of the t-statistics is the highest around the critical value for statistical significance. In case of both coefficients from the Taylor rule with interest rate smoothing the densities of t-statistics of estimates around the critical value are much higher than densities implied by normal distribution. There can be also seen a significant drop in the densities on the left side of the reference line in both histograms.

The most dramatic difference between densities on the left and right hand-side of the reference line can be, however, noticed in case of the response to inflation from the original version of the Taylor rule in the bottom left corner of the figure. This evidence strongly supports our notion about type II publication bias in the literature as estimates just below the threshold of 1.645 are heavily underreported, especially compared to estimates with corresponding t-statistics just above the critical value. On the other hand, this difference is negligible in case of the output gap coefficient from the original rule. Hence, we might not find evidence of publication bias in this case as neither of the graphical approaches employed in previous subsections suggests a large extent of publication bias in the estimates of response to output gap from the original specification of the Taylor rule.

Overall, the findings obtained from all three types of figures constructed in the last three subsections are consistent with each other as far as the presence and extent of publication in estimates of individual coefficients are concerned. Hence, we can expect to find further evidence of publication bias at least in some of the datasets in question.

Figure 3.3: Histograms of the corresponding t-statistics



3.2.4 Funnel asymmetry test

We gained an idea about the extent of publication selection bias thanks to the graphical analysis conducted above. Nevertheless, in order to claim the presence of publication bias, it is necessary to employ a more formal approach, the meta-regression analysis. Its role can also play the fact, that while estimating the econometric models described in section 2.1 it is accounted for clustering of data in individual studies. My preferred method to use is a multilevel mixed effects estimation. Nevertheless, to check the robustness of results to different approaches to estimation of the model, I also report the results of the estimation using OLS with standard errors clustered at a study level.

I run the funnel asymmetry test (FAT) and precision-effect test (PET) to uncover the extent of publication bias and determine whether the responses to inflation and output gap are, indeed, significant. I estimate the model with variables weighted by standard errors to solve the heteroskedasticity problem (Equation 2.2). The reader can examine the results in Table 3.2.

Table 3.2: Funnel asymmetry test

	Smoothing		No smoothing	
	Inflation	Output gap	Inflation	Output gap
Multilevel mixed effects				
Constant *(publication bias)*	4.310***	3.897***	4.036***	2.166*
	(0.470)	(0.606)	(0.734)	(1.275)
1/se	0.200***	0.031***	0.492***	0.235***
	(0.017)	(0.003)	(0.038)	(0.021)
Clustered OLS				
Constant *(publication bias)*	3.863***	3.235***	3.845***	1.067
	(0.904)	(0.545)	(0.700)	(1.644)
1/se	0.233***	0.029*	0.419***	0.238***
	(0.071)	(0.016)	(0.097)	(0.059)
Likelihood-ratio test (χ^2)	98.32***	82.38***	87.31***	59.93***
Observations	854	788	267	222

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

First, let me evaluate the differences between estimates obtained by the two estimation methods. We can see that in general the estimates differ only marginally and their magnitudes and significance are quite similar. The most notable difference is in the estimates of publication bias in case of the output gap coefficient from the original Taylor rule. Hence, the choice of the estimation technique does not seem to significantly affect the result in most cases. Furthermore, values of the likelihood-ratio test support the choice of the multilevel mixed effects model as the null hypothesis of no heterogeneity between studies is rejected at 1% significance level. Thus, we can focus on the inference from the results from the preferred estimation procedure.

As far as the coefficients from the rule allowing for interest rate smoothing are concerned, all variables are statistically significant at a 1% level. Thus, there is evidence supporting the presence of publication bias in the empirical literature utilizing interest rate smoothing version of the monetary policy rule. Moreover, the value of the FAT coefficient of the MRA model is around 4 in both cases. According to Doucouliagos & Stanley (2011), absolute values of the estimate of the model intercept higher than 2 indicate 'severe' publication selection activity. The logic behind this statement is straightforward. If the effect in question was non-existent in reality, the FAT coefficient equal to 2 or higher would make it become significant in the empirical literature, because the t-statistics equal to 2 is high enough to ensure statistical significance at 5% level.

Furthermore, both PET coefficients are significant at a 1% significance level suggesting a genuine effect of inflation and the output gap, respectively, on interest rates set by a monetary authority. Nevertheless, both estimates are quite low – especially the estimate of the response to the output gap. To assess the magnitude of the effects more precisely, I run the precision-effect estimation with standard error (PEESE) further on.

Based on the graphical analysis conducted earlier, we got an impression that data on response to output gap from the original Taylor rule contain the least amount of publication bias. Indeed, the FAT coefficient is significant only at a 10% level. Thus, the extent of publication bias is probably lower than in other cases. On the other hand, the funnel plot of the inflation coefficient suggested quite a large extent of publication bias. Unsurprisingly, this notion is confirmed by the estimate of the FAT coefficient as its magnitude also suggests 'severe' publication selection bias.

Similarly to the case of the rule accounting for interest smoothing, both coefficients from the original Taylor rule seem to be significant and have genuine effect on the interest rates, because both PET coefficients are statistically significant at 1% level.

3.2.5 Heckman meta-regression

To examine the genuine effects of inflation and the output gap on interest rates more precisely, I employ the PEESE. This allows us to uncover the real estimate of the effect size beyond publication bias. The Heckman meta-regression corrected for heteroskedasticity by means of weighted least squares is used for the estimation (Equation 2.7). Again, I use the multilevel mixed effects estimation to account for possible heterogeneity between the individual primary studies. The outcome is compared to the results from the OLS estimation with standard errors clustered at study level. As in the previous case, the results do not differ dramatically. Moreover, we can reject the null hypothesis of the likelihood-ratio test in case of all estimates. Therefore, there is some between study heterogeneity present and the use of the multilevel mixed effects estimation is justified. The results obtained from the regression can be examined in Table 3.3.

Table 3.3: Heckman meta-regression

	Smoothing		No smoothing	
	Inflation	Output gap	Inflation	Output gap
Multilevel mixed effects				
1/se *(true effect)*	0.191***	0.030***	0.416***	0.234***
	(0.017)	(0.003)	(0.041)	(0.022)
se	-1.294***	-0.631 **	-5.670***	-0.182
	(0.362)	(0.267)	(1.437)	(1.252)
Clustered OLS				
1/se *(true effect)*	0.217***	0.028*	0.362***	0.236***
	(0.074)	(0.016)	(0.119)	(0.061)
se	-1.670**	-0.843***	-3.833	-0.434
	(0.769)	(0.250)	(2.434)	(0.911)
Likelihood-ratio test (χ^2)	91.85***	78.84***	96.60***	59.88***
Observations	854	788	267	222

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

In case of the specification of the rule with interest rate smoothing the response of the nominal interest rate to inflation beyond publication bias is significant at 1% level and equal to 0.191. When we compare the magnitude of the estimate with the simply computed average or median, which might be taken into account by a person unfamiliar with more rigorous methods, the difference is enormous (see, Table 3.4). The mean and median of the estimates from the primary studies are equal to 1.23 and 1.28, respectively. Thus, both values are consistent with the commonly accepted opinion that response to inflation from the Taylor principle should be higher than 1. However, after correcting for publication bias the true value drops way below 1. Hence, based on our sample including reaction functions estimates of several central banks, the response of monetary authorities to inflation seems to be lower than quite often argued.

The mean and median of the output gap coefficient with values 0.68 and 0.51 are also very close to the value proposed by Taylor (1993), but after accounting for publication bias the response to output gap is very close to zero with value 0.03. Hence, the response of central banks to fluctuations in output while setting interest rates seems to be negligible. At the moment we are examining the Taylor rule with the interest smoothing term. Thus, the logical explanation for very low responses to both inflation and output gap might be great attention of monetary authorities to a smooth path of the interest rates[2].

On the other hand, estimates of both coefficients of the original Taylor rule are significant at 1% level and larger than zero even after correcting for publication bias. Nevertheless, the response to inflation is much lower than a simple mean of the datapoints which illustrates the extent of publication bias. Furthermore, it is lower than 1 and, hence, not consistent with the original proposal by Taylor (1993).

The estimate of the output gap coefficient from the rule without interest smoothing beyond publication bias is significantly lower then both mean and median computed from the data. Furthermore, the effect size is lower than the value 0.5 proposed by Taylor (1993). You can compare the results from Heckman meta-regression with the simple mean and median in Table 3.4.

The estimates of all coefficients beyond publication yielded significantly lower values than often mentioned in literature. Nevertheless, the dataset contains estimates of many central banks' reaction functions, so I also carried out the Heckman meta-regression separately for the Federal Reserve and the European Central Bank to obtain the Taylor rule estimates for individual monetary authorities. The results reported in Appendix D are quite similar to the findings from the whole dataset.

[2]Estimates of the lagged interest rate are almost always very significant and often close to unity.

Table 3.4: Comparison of the results

	Estimate	Mean	Median
Inflation ($\rho \neq 0$)	0.19	1.23	1.28
Output gap ($\rho \neq 0$)	0.03	0.68	0.51
Inflation ($\rho = 0$)	0.42	1.28	1.26
Output gap ($\rho = 0$)	0.23	0.38	0.33

3.3 Heterogeneity

Apart from publication bias, meta-analysis is a powerful tool for explaining the heterogeneity of the estimates in the literature. In this section I estimate the model (2.10), which is weighted by inverse standard errors to solve heteroskedasticity, once again, employing the multilevel mixed effects procedure. The sets of moderator variables Z_k and S_l include study and estimate characteristics described below.

3.3.1 Data characteristics

Central banks

I include dummy variables for individual central banks to account for possible differences among them. The central banks of the following countries are included: FED, ECB, AR, AT, AU, BE, BR, CA, CL, CN, CZ, DE, ES, FI, FR, GR, HU, IE, IN, IT, JP, MX, NL, PL, PT, SE, SK, TR, UK, VE

Specification

Furthermore, I take into account the forward- or backward-looking nature of both coefficients.

Time dimensions

To capture possible variation of responses to inflation and the output gap in time, the average year of data used in the primary study is included in the model. Furthermore, as illustrated in Figure 1.2 and Figure 1.3, the data may differ given the frequency at which they are reported. Hence, I construct dummy variables for data reported on monthly and quarterly basis. Variable capturing ex-post nature of the data is also included to assess the difference compared to the real-time data.

Measures of output gap and inflation

As can be seen from Figure 1.3 the method of detrending output may significantly alter the data on output gaps. Therefore, I include dummy variables for the HP filter and quadratic detrending in the model. Moreover, the output itself may be defined variously as some studies use output gaps based on real GDP and some rely on industrial production. Hence, the industrial production dummy variable is incorporated into the model. Inflation can be also measured in different ways. I account for indices based on consumer prices (CPI and HICP [3]) and GDP based indices (GDPCTPI and GDP deflator).

Estimation methods

Econometric methods used in the literature include GMM, LS, 2SLS, MLE, IV and rarely several others. Thus, I include dummy variables for GMM, 2SLS, MLE and IV to distinguish them from the least squares estimation.

Study characteristics

Finally, the year of publication and dummy indicating the study's publication in a journal are used. They are not weighted by standard errors, because this way we can assess their effect on the extent of publication bias. The year of publication is included both weighted and unweighted to see also its influence on effect sizes.

3.3.2 Results

Results of the meta-regression analysis can be found in Table 3.5. We can once again strongly reject the null hypothesis of the likelihood-ratio test. Hence, the use of multilevel fixed effects estimation is justified. I do not report numerous significant central banks' dummy variables in Table 3.5 as variation between individual monetary authorities seems natural. Complete results obtained from the estimation can be found in Appendix C along with the robustness checks.

[3] CPI and HICP were not included separately because HICP is used in the EU. Hence, the dummy for HICP would have the same values as the ECB dummy

Study characteristics

The unweighted variables seem to influence the extent of publication bias only in some cases. The dummy variable for publication of the study in a journal is significant only in one case and the year of publication has somewhat ambigous effect on the coefficients. Therefore, it is difficult to draw any convincing conclusions. Furthermore, the newer studies tend to report lower estimates with the exception of inflation coefficient from the interest smoothing version of the Taylor rule.

Data characteristics

We can see that data reported on a quarterly basis tend to have a positive influence on the estimates of the output gap coefficient in both specifications of the reaction function. The utilization of the data for inflation based on consumer prices then appears to lead to understating of the coefficient estimates. With regard to the measure of the output gap, we can notice that usage of industrial production tends to lower the estimates of the response to the output gap in both variants of the Taylor rule.

Furthermore, the estimates of the coefficients in case of the interest smoothing rule seem to get lower as more recent data are utilized. According to the estimates of the monthly and quarterly dummy variables, it seems that the more frequent the data are reported the higher is the response to the output gap in the interest smoothing rule. On the other hand, the inflation coefficient from the original Taylor rule seems to get lower. The forward-looking specification of the rule seems to affect one coefficient in each version of the rule, while the backward-looking variants do not appear to yield estimates significantly different from the contemporaneous ones. Finally, quadratic detrending and HP filter each proved to affect the estimates of one coefficient compared to the linear detrending method.

Estimation methods

The interest smoothing version of the reaction function seems to be quite robust to estimation techniques as only the GMM dummy variable is significant in case of the output gap coefficient. On the other hand, the original specification of the Taylor rule does not appear to be as robust to estimation methods, because all three dummy variables included in the model are statistically significant in case of one or both coefficients. Moreover, all estimation method variables are positive and GMM, 2SLS and IV estimation, therefore, tend to overstate the values of the Taylor rule coefficients compared to LS, which is consistent with findings from the previous meta-analysis conducted on this topic by Chortareas & Magonis (2008).

Table 3.5: Heterogeneity analysis

	Smoothing				No smoothing			
	Inflation		Output gap		Inflation		Output gap	
1/se	0.507***	(0.102)	0.655***	(0.0986)	2.938***	(0.341)	0.753***	(0.0771)
Constant	5.186***	(0.882)	-0.538	(1.135)	2.461***	(0.521)	-2.026	(2.136)
Study characteristics								
published							-3.607**	(1.653)
year	-0.226**	(0.0871)	0.317***	(0.115)			0.725***	(0.171)
year/se	0.0537***	(0.00656)	-0.0469***	(0.00639)	-0.0613***	(0.0119)	-0.0855***	(0.00558)
Data characteristics								
avgyear/se	-0.0211***	(0.00231)	-0.00768***	(0.00204)				
forward/se			-0.221***	(0.0320)	0.694***	(0.0980)		
monthly/se			0.296***	(0.0509)	-0.719***	(0.150)		
quarterly/se	0.120***	(0.0397)	0.178***	(0.0453)	-0.459***	(0.136)	0.189***	(0.0167)
expost/se			0.0840**	(0.0412)				
CPbased/se	-0.162**	(0.0686)			-0.632***	(0.172)		
GDPbased/se					-0.361**	(0.173)		
industrial/se			-0.475***	(0.0544)			-0.337***	(0.0417)
quadratic/se			-0.129***	(0.0392)				
HP/se							0.138***	(0.0220)
Estimation methods								
GMM/se			0.237***	(0.0410)	0.343***	(0.0785)	0.152***	(0.0400)
SLS/se					0.554**	(0.237)		
IV/se					0.308*	(0.166)		
Likelihood-ratio test (χ^2)	141.09***		256.90***		28.05***		38.21***	
Observations	854		788		267		222	

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Chapter 4

Conclusion

The Taylor rule is without a doubt an appealing and simple tool for describing monetary policy. Nevertheless, its simplicity may be a little problematic. Some might argue that such a simple equation cannot capture the behavior of the central bank. There is a debate still underway concerning the exact specification of the rule as it can be forward- or backward-looking or contemporaneous and include numerous additional variables believed to influence the decision of the monetary authority about the interest rates. Furthermore, some economists prefer the version of the rule which accounts for smoothing of the interest rates.

However, the estimates of the Taylor rule coefficients can differ not only because of different specifications. The results also depend on the data employed in the estimation. Data can differ in frequency at which they are reported or whether they are real-time or revised. Furthermore, there are several measures of both inflation and the output gaps.

In my heterogeneity analysis I confirmed that data characteristics really matter and influence magnitudes of estimates. Inflation measured by changes in consumer prices causes the estimates to be lower than when measured e.g. by GDP based indices. Different measures of output gap also proved to have effect on the outcome of the estimation as the usage of industrial production as a measure of output will likely lead to lower estimates of the response to output gap than in case of the output measure based on real GDP.

Furthermore, I addressed the issue of publication bias. Publication selection bias was found in the empirical literature on a lot of different topics and literature on the Taylor rule is no exception. I found evidence of severe extent of positive publication bias in the estimates of inflation coefficients from both specification of the rule and in estimates of the response to output gap in case of the policy rule with interest smoothing. Moreover, evidence of publication bias was also found in the estimates of the output gap coefficient from the original version of the Taylor rule. Researchers, thus, tend to publish rather larger estimates in order to obtain estimates consistent with well-known theory.

To obtain the 'true' effect sizes beyond publication bias, I employed the Heckman meta-regression. I arrived at the estimate of 0.19 for the inflation coefficient and 0.03 in case of response to output gap when I examined the data for interest smoothing version of the monetary policy rule. My estimates of the coefficients of the original Taylor rule yielded values 0.42 and 0.23 for inflation and the output gap, respectively.

Hence, we can conclude that values of the coefficients beyond publication bias are much lower than commonly thought. My estimate of the original Taylor rule suggests that central banks might not respond to inflation and output gap in such an extent and, therefore, supports the assumption that central banks tend to employ interest rate smoothing or pay great attention to several other indicators. Even though the sample includes estimates of the reaction function of numerous central banks, the estimation of the Taylor rule coeffients individually for the ECB and the FED supports these findings.

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Appendix A

Outlier analysis

The outlier was spotted while constructing a funnel plot for estimates of the inflation coefficient from the Taylor rule without interest smoothing. The observation comes from Aklan & Nargelecekenler (2008) and contains the extremely low standard error of 0.0015 which causes t-statistics and our measure of precision (1/se) to be extremely high. Furthermore, it has a considerable effect on the final outcome of the estimation, as shown below. Figure A.1 shows a scatter plot of t-statistics and the measure of precision, which are used in all MRA models corrected for heteroskedasticity by the means of WLS. We can spot the outlier in the right upper corner. The figure also contains linear fits of data with and without the problematic point illustrating the influence of the point on the outcome of the estimation. In order to be fully able to assess the difference between the slopes of both fits, I extended the linear fit of the data without the outlier by the dashed line.

A common measure for assessing influence of the point on the regression is Cook's distance proposed by Cook (1977). It combines two problematic features of the point, its leverage and size of the residual. There is no consensus on the value of Cook's D that would be sufficient to delete the point from the dataset. Common indicator of high level of influence on regression is Cook's D greater than median of F distribution with p and $(n-p)$ degrees of freedom, where p is a number of regressors and n is a number of observations (Cook & Weisberg 1982). Bollen & Jackman (1985) suggest the critical value equal to $4/n$. Furthermore, Cook (1977) mentions the value 1. In our case, $F_{p,n-p}(0.5) = F_{2,266}(0.5) = 0.695$. Thus, the lowest critical value is $4/n$. In Table A.1 are observations with Cook's distance higher than $4/n$, so we are able to examine all possible outliers. We can see that only the observation from Aklan & Nargelecekenler (2008) exceeds all cut-off values found in the literature. Neither of the other points arising suspicions overcomes even a single other critical value of Cook's distance. Based on this analysis the observation was discarded. It is not included in the STATA *.dta file, but it was left in the Excel file, where it is marked red.

Figure A.1: Scatter plot of t-statistics and 1/se

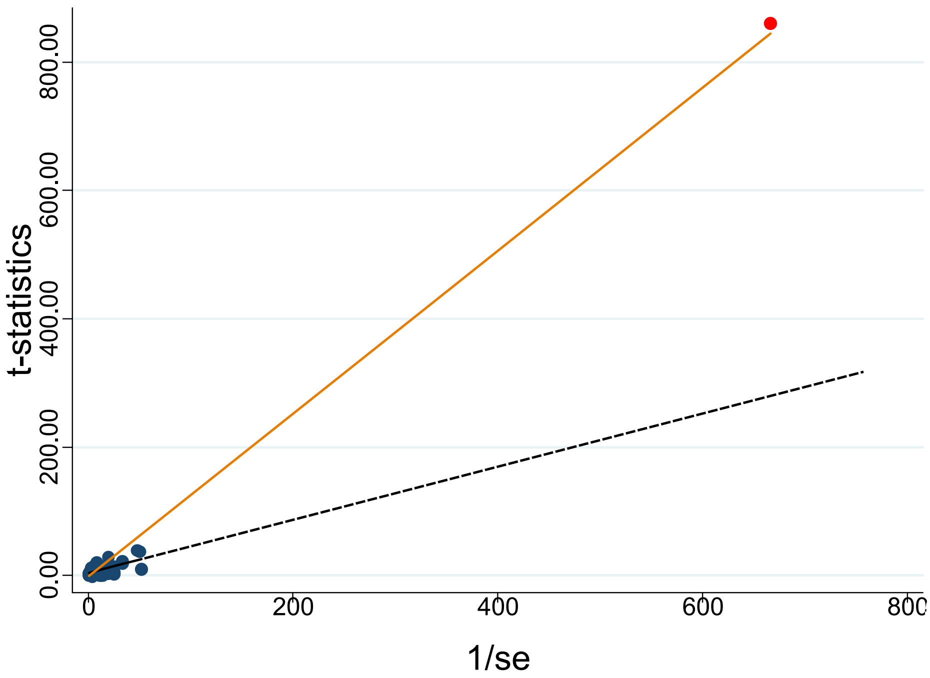

Table A.1: Observations with $D > 4/n$

t-stat	1/se	Cook's D
38.97	48.08	0.029
860.13	**666.67**	**3215.012**
19.33	33.33	0.023
21.67	33.33	0.018
1.75	25.00	0.034
3.00	20.00	0.017
36.50	50.00	0.048
5.25	25.00	0.026
9.41	51.69	0.232

Appendix B

List of primary studies

Table B.1: List of primary studies

Aklan & Nargelecekenler (2008)	Frenkel *et al.* (2011)	Martin & Milas (2012)
Angeloni & Dedola (1999)	Gamber & Hakes (2006)	Milas & Naraidoo (2012)
Ashley *et al.* (2011)	Zheng *et al.* (2012)	Mirza & Storjohann (2011)
Belke & Klose (2011)	Gerberding *et al.* (2005)	Mitchell & Pearce (2010)
Belke & Klose (2012)	Gerdesmeier & Roffia (2003)	Molodtsova *et al.* (2008)
Belke & Potrafke (2012)	Gerdesmeier & Roffia (2005)	Munoz & Schmidt-Hebbel (2012)
Beyer *et al.* (2005)	Gerlach-Kristen (2003)	Murray *et al.* (2008)
Blattner & Margaritov (2010)	Giordani (2004)	Nikolsko-Rzhevskyy (2011)
Bleich & Fendel (2012)	Gorter *et al.* (2008)	Nikolsko-Rzhevskyy & Papell (2012)
Bouvet & King (2011)	Gorter *et al.* (2012)	Orlowski (2010)
Branch (2011)	Hayo & Hofmann (2006)	Orphanides (2001)
Carstensen (2006)	Hutchison *et al.* (2010)	Orphanides & Wieland (2008)
Castelnuovo (2007)	Chevapatrakul *et al.* (2009)	Österholm (2005)
Castro (2011)	Choi & Wen (2010)	Otto & Voss (2010)
Cecchetti & Li (2008)	Chortareas (2008)	Peersman & Smets (1999)
Clarida *et al.* (1998)	Jansen & De Haan (2009)	Perez (2001)
Clarida *et al.* (2000)	Jondeau *et al.* (2004)	Pierdzioch *et al.* (2012)
Conrad & Eife (2012)	Jovanović (2012)	Romer & Romer (2002)
Consolo & Favero (2009)	Kahn (2012)	Rudebusch (2001)
Doménech *et al.* (2002)	Kim & Mizen (2010)	Rudebusch (2002)
Dornbusch *et al.* (1998)	Kim & Ogakib (2011)	Sauer & Sturm (2007)
Eleftheriou *et al.* (2006)	Klose (2011)	Singh (2010)
English *et al.* (2003)	Koustas & Lamarche (2012)	Smant (2002)
Faust *et al.* (2001)	Lee & Crowley (2009)	Smith & Taylor (2009)
Favero & Marcellino (2001)	Lee *et al.* (2011)	Surico (2003)
Favero & Monacelli (2003)	Leigh (2005)	Tchaidze (2001)
Fendel *et al.* (2011)	Levin & Taylor (2010)	Tchaidze (2004)
Fendel & Frenkel (2009)	L'œillet & Licheron (2012)	Tillmann (2011)
Fendel & Frenkel (2006)	Yagihashi (2011)	
Forte (2010)	Martin & Milas (2010)	

Appendix C

Robustness check

To be absolutely sure about the effects of variables in question I extend the models used for the heterogeneity analysis by gradually adding other variables. In the following tables, we can see that the significant variables preserve their statistical significance and magnitude and, therefore, seem robust to the specification of the model.

Table C.1: Robustness check: Inflation (Smoothing)

	Dependent variable: t-statistics			
	(1)	(2)	(3)	(4)
Constant	5.186*** (0.882)	4.934*** (0.834)	4.891*** (0.852)	4.563*** (1.005)
1/se	0.507*** (0.102)	0.699*** (0.161)	0.662*** (0.165)	1.145*** (0.301)
Significant variables				
year	-0.226*** (0.0871)	-0.208** (0.0820)	-0.202** (0.0836)	-0.195** (0.0865)
year/se	0.0537*** (0.00656)	0.0394*** (0.00863)	0.0416*** (0.00865)	0.0295** (0.0125)
avgyear/se	-0.0211*** (0.00231)	-0.0211*** (0.00337)	-0.0211*** (0.00337)	-0.0241*** (0.00371)
quarterly/se	0.120*** (0.0397)	0.372*** (0.0660)	0.384*** (0.0669)	0.234** (0.113)
CPbased/se	-0.162** (0.0686)	-0.179*** (0.0692)	-0.191*** (0.0709)	-0.292** (0.117)
IN/se	-0.473** (0.200)	-0.634*** (0.226)	-0.629*** (0.227)	-0.610** (0.242)
ECB/se	0.349*** (0.0323)	0.362** (0.140)	0.347** (0.140)	0.428*** (0.149)
DE/se	0.876*** (0.0591)	0.614*** (0.127)	0.585*** (0.128)	0.609*** (0.129)
UK/se	0.615*** (0.144)	0.428*** (0.165)	0.432*** (0.165)	0.475*** (0.165)
TR/se	0.699*** (0.0758)	0.710*** (0.151)	0.725*** (0.153)	0.970*** (0.180)
ES/se	1.271*** (0.0688)	1.002*** (0.133)	0.990*** (0.133)	1.014*** (0.135)
AR/se	0.480*** (0.0921)	0.500*** (0.162)	0.521*** (0.167)	0.759*** (0.191)
BR/se	0.752*** (0.161)	0.805*** (0.213)	0.823*** (0.216)	1.050*** (0.233)
MX/se	0.360* (0.189)	0.426* (0.237)	0.442* (0.239)	0.665*** (0.253)
JP/se	1.492*** (0.335)	1.235*** (0.344)	1.213*** (0.343)	1.212*** (0.343)
FR/se	0.826*** (0.0876)	0.636*** (0.130)	0.648*** (0.130)	0.702*** (0.133)
IT/se	1.296*** (0.0654)	1.077*** (0.123)	1.078*** (0.122)	1.122*** (0.126)
BE/se	0.928*** (0.148)	0.665*** (0.186)	0.651*** (0.186)	0.676*** (0.186)
GR/se	1.008*** (0.0986)	0.733*** (0.152)	0.719*** (0.152)	0.930*** (0.173)
IE/se	-0.0993*** (0.0272)	-0.404*** (0.123)	-0.419*** (0.123)	-0.401*** (0.125)
Central banks				
FED/se		-0.278** (0.138)	-0.294** (0.137)	-0.217 (0.142)
CZ/se		0.164 (0.170)	0.187 (0.174)	0.337* (0.197)
PL/se		0.247 (0.264)	0.263 (0.265)	0.448 (0.277)
FI/se		-0.238* (0.134)	-0.252* (0.134)	-0.232* (0.136)
CL/se		0.0392 (0.145)	0.0304 (0.145)	0.388** (0.197)
VE/se		0.146 (0.158)	0.168 (0.163)	0.406** (0.189)
HU/se		0.0484 (0.219)	0.0651 (0.221)	0.278 (0.236)
SK/se		-0.334 (0.260)	-0.317 (0.261)	-0.0938 (0.274)
CA/se		-0.732* (0.385)	-0.370 (0.526)	-0.0224 (0.546)
CN/se		0.0811 (0.585)	0.0502 (0.583)	0.282 (0.601)
NL/se		-0.0684 (0.163)	-0.0801 (0.162)	-0.0553 (0.163)
SE/se		0.228 (0.582)	0.502 (0.630)	0.504 (0.626)
AT/se		-0.336*** (0.123)	-0.350*** (0.123)	-0.145 (0.148)
PT/se		0.0362 (3.085)	0.0190 (3.074)	0.0453 (3.054)
Estimation methods				
MLE/se			-0.372 (0.400)	-0.599 (0.415)
GMM/se			0.0343 (0.0521)	0.0404 (0.0529)
2SLS/se			0.419* (0.230)	0.359 (0.259)
IV/se			0.605 (0.450)	0.554 (0.451)
Study & data characteristics				
published				0.523 (0.700)
backwardinflation/se				-0.273*** (0.105)
forwardinflation/se				-0.188** (0.0857)
GDPbased/se				-0.0696 (0.151)
expost/se				-0.0352 (0.105)
monthly/se				-0.148 (0.118)
Likelihood-ratio test (χ^2)	141.09	95.98	95.92	86.65
Observations	854	854	854	854

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table C.2: Robustness check: Inflation (No smoothing)

	Dependent variable: t-statistics							
	(1)		(2)		(3)		(4)	
Constant	2.461***	(0.521)	2.502***	(0.524)	3.150*	(1.670)	3.184**	(1.524)
1/se	2.938***	(0.341)	3.045***	(0.363)	3.093***	(0.364)	2.966***	(0.396)
Significant variables								
year/se	-0.0613***	(0.0119)	-0.0617***	(0.0120)	-0.0652***	(0.0136)	-0.0617***	(0.0136)
forward/se	0.694***	(0.0980)	0.684***	(0.102)	0.705***	(0.102)	0.674***	(0.104)
monthly/se	-0.719***	(0.150)	-0.742***	(0.154)	-0.758***	(0.152)	-0.650***	(0.157)
quarterly/se	-0.459***	(0.136)	-0.478***	(0.139)	-0.487***	(0.136)	-0.438***	(0.133)
CPbased/se	-0.632***	(0.172)	-0.635***	(0.170)	-0.595***	(0.171)	-0.638***	(0.175)
GDPbased/se	-0.361**	(0.173)	-0.357**	(0.171)	-0.328*	(0.172)	-0.293*	(0.176)
GMM/se	0.343***	(0.0785)	0.345***	(0.0791)	0.319***	(0.0792)	0.318***	(0.0768)
2SLS/se	0.554**	(0.237)	0.531**	(0.238)	0.519**	(0.239)	0.516**	(0.240)
IV/se	0.308*	(0.166)	0.307*	(0.165)	0.314*	(0.165)	0.292*	(0.165)
ECB/se	-0.845***	(0.187)	-0.924***	(0.240)	-0.941***	(0.233)	-1.040***	(0.219)
FED/se	-1.212***	(0.178)	-1.297***	(0.232)	-1.346***	(0.228)	-1.358***	(0.214)
DE/se	-0.783***	(0.225)	-0.916***	(0.267)	-0.939***	(0.264)	-0.954***	(0.256)
UK/se	-0.865***	(0.301)	-0.952***	(0.312)	-0.959***	(0.310)	-0.993***	(0.307)
TR/se	-0.558***	(0.201)	-0.637**	(0.251)	-0.643***	(0.243)	-0.746***	(0.274)
CA/se	-1.396***	(0.313)	-1.490***	(0.329)	-1.525***	(0.326)	-1.526***	(0.319)
SE/se	-1.655***	(0.534)	-1.756***	(0.551)	-1.748***	(0.546)	-1.731***	(0.533)
AU/se	-1.430***	(0.241)	-1.517***	(0.282)	-1.551***	(0.278)	-1.588***	(0.263)
Central banks								
BE/se			-0.0557	(1.058)	-0.0192	(1.047)	-0.00883	(1.016)
IE/se			-4.214	(3.002)	-4.075	(2.969)	-4.142	(2.884)
FR/se			-0.918	(1.406)	-0.863	(1.392)	-0.866	(1.351)
IT/se			-0.729	(0.640)	-0.715	(0.633)	-0.687	(0.612)
NL/se			-0.159	(1.410)	-0.104	(1.395)	-0.108	(1.355)
ES/se			-0.311	(0.636)	-0.297	(0.629)	-0.270	(0.609)
JP/se			-0.0550	(0.314)	-0.0850	(0.310)	-0.0861	(0.295)
AT/se			-1.624	(1.495)	-1.564	(1.479)	-1.571	(1.437)
PT/se			-0.815	(0.610)	-0.803	(0.603)	-0.775	(0.583)
FI/se			-0.122	(1.003)	-0.0883	(0.992)	-0.0758	(0.963)
Study characteristics								
published					-1.606	(1.114)	-1.654	(1.011)
year					0.0689	(0.142)	0.0699	(0.131)
Other								
avgyear/se							0.00377	(0.00316)
backward/se							-0.0501	(0.139)
expost/se							-0.0824	(0.0659)
MLE/se							-0.447	(1.474)
Likelihood-ratio test (χ^2)	28.05***		27.17***		19.96***		12.27***	
Observations	267		267		267		267	

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table C.3: Robustness check: Output gap (Smoothing)

	Dependent variable: t-statistics							
	(1)		(2)		(3)		(4)	
Constant	-0.538	(1.135)	-0.757	(1.142)	-0.576	(1.151)	-0.815	(1.327)
1/se	0.655***	(0.0986)	0.555***	(0.110)	0.564***	(0.114)	0.585***	(0.115)
Significant variables								
year	0.317***	(0.115)	0.335***	(0.116)	0.319***	(0.117)	0.314***	(0.118)
year/se	-0.0469***	(0.00639)	-0.0493***	(0.00663)	-0.0504***	(0.00715)	-0.0484***	(0.00742)
avgyear/se	-0.00768***	(0.00204)	-0.00720***	(0.00209)	-0.00707***	(0.00210)	-0.00793***	(0.00220)
forward/se	-0.221***	(0.0320)	-0.232***	(0.0338)	-0.236***	(0.0368)	-0.233***	(0.0382)
monthly/se	0.296***	(0.0509)	0.280***	(0.0523)	0.282***	(0.0545)	0.269***	(0.0566)
quarterly/se	0.178***	(0.0453)	0.191***	(0.0470)	0.187***	(0.0471)	0.159***	(0.0539)
expost/se	0.0840**	(0.0412)	0.116***	(0.0445)	0.120***	(0.0451)	0.124***	(0.0464)
industrial/se	-0.475***	(0.0544)	-0.429***	(0.0588)	-0.428***	(0.0589)	-0.458***	(0.0660)
quadratic/se	-0.129***	(0.0392)	-0.110***	(0.0403)	-0.116***	(0.0408)	-0.0960**	(0.0436)
GMM/se	0.237***	(0.0410)	0.210***	(0.0446)	0.199***	(0.0498)	0.219***	(0.0555)
ECB/se	0.413***	(0.0318)	0.518***	(0.0617)	0.524***	(0.0624)	0.495***	(0.0705)
DE/se	0.323***	(0.0373)	0.379***	(0.0538)	0.383***	(0.0556)	0.383***	(0.0561)
UK/se	0.301***	(0.0598)	0.334***	(0.0709)	0.336***	(0.0709)	0.335***	(0.0710)
TR/se	0.241***	(0.0700)	0.338***	(0.0858)	0.339***	(0.0857)	0.316**	(0.127)
ES/se	0.195*	(0.102)	0.223**	(0.107)	0.223**	(0.107)	0.224**	(0.107)
AT/se	-0.318***	(0.0432)	-0.230***	(0.0674)	-0.221***	(0.0721)	-0.222***	(0.0744)
BR/se	0.399***	(0.0835)	0.485***	(0.0956)	0.481***	(0.0958)	0.471***	(0.0984)
CL/se	0.387**	(0.195)	0.471**	(0.205)	0.467**	(0.206)	0.459**	(0.209)
MX/se	0.355***	(0.0797)	0.440***	(0.0921)	0.437***	(0.0923)	0.427***	(0.0949)
VE/se	0.648***	(0.0506)	0.734***	(0.0663)	0.731***	(0.0663)	0.719***	(0.0686)
CZ/se	0.377***	(0.0575)	0.459***	(0.0721)	0.455***	(0.0733)	0.447***	(0.0761)
HU/se	0.377***	(0.0606)	0.459***	(0.0749)	0.455***	(0.0759)	0.446***	(0.0788)
PL/se	0.379***	(0.0598)	0.461***	(0.0742)	0.458***	(0.0753)	0.449***	(0.0781)
SK/se	0.520***	(0.0850)	0.606***	(0.0960)	0.603***	(0.0961)	0.592***	(0.0983)
IT/se	0.161***	(0.0545)	0.211***	(0.0682)	0.218***	(0.0688)	0.219***	(0.0691)
NL/se	-0.478***	(0.0362)	-0.401***	(0.0556)	-0.396***	(0.0567)	-0.394***	(0.0573)
BE/se	0.104*	(0.0621)	0.177**	(0.0752)	0.182**	(0.0761)	0.184**	(0.0765)
IE/se	-0.453***	(0.0301)	-0.374***	(0.0525)	-0.369***	(0.0537)	-0.367***	(0.0544)
FI/se	-0.529***	(0.0297)	-0.449***	(0.0524)	-0.444***	(0.0536)	-0.442***	(0.0543)
Central banks								
IN/se			0.442	(0.367)	0.444	(0.367)	0.393	(0.374)
AR/se			0.117	(0.262)	0.113	(0.263)	0.105	(0.266)
CA/se			-0.242	(0.382)	-0.269	(0.383)	-0.310	(0.384)
CN/se			-0.328	(0.809)	-0.311	(0.809)	-0.399	(0.816)
FR/se			-0.0154	(0.0693)	-0.00940	(0.0695)	-0.0106	(0.0697)
SE/se			0.248	(0.297)	0.309	(0.301)	0.300	(0.300)
FED/se			0.117**	(0.0578)	0.125**	(0.0585)	0.0919	(0.0667)
JP/se			0.0620	(0.0738)	0.0646	(0.0738)	0.0662	(0.0739)
GR/se			0.0443	(0.132)	0.0533	(0.134)	0.0522	(0.135)
PT/se			-0.320	(2.712)	-0.316	(2.709)	-0.343	(2.705)
Estimation methods								
MLE/se					-0.197	(0.159)	-0.174	(0.162)
2SLS/se					-0.0233	(0.151)	0.0125	(0.156)
IV/se					0.0772	(0.237)	0.106	(0.238)
Study & data characteristics								
published							0.474	(1.056)
HP/se							0.0495	(0.0393)
backward/se							-0.00623	(0.0786)
Likelihood-ratio test (χ^2)	256.90		249.61		247.26		227.42	
Observations	788		788		788		788	

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table C.4: Robustness check: Output gap (No smoothing)

	Dependent variable: t-statistics							
	(1)		(2)		(3)		(4)	
Constant	-2.026	(2.136)	-1.826	(2.073)	-1.934	(2.046)	-1.744	(2.180)
1/se	0.753***	(0.0771)	0.812***	(0.0824)	0.810***	(0.0822)	0.751***	(0.194)
Significant variables								
published	-3.607**	(1.653)	-3.788**	(1.605)	-3.756**	(1.587)	-4.031**	(1.671)
year	0.725***	(0.171)	0.704***	(0.166)	0.720***	(0.165)	0.725***	(0.170)
year/se	-0.0855***	(0.00558)	-0.0858***	(0.00544)	-0.0862***	(0.00544)	-0.0874***	(0.00581)
quarterly/se	0.189***	(0.0167)	0.187***	(0.0163)	0.187***	(0.0163)	0.217*	(0.114)
industrial/se	-0.337***	(0.0417)	-0.348***	(0.0409)	-0.346***	(0.0410)	-0.346***	(0.0429)
HP/se	0.138***	(0.0220)	0.139***	(0.0216)	0.139***	(0.0217)	0.133***	(0.0234)
GMM/se	0.152***	(0.0400)	0.147***	(0.0393)	0.152***	(0.0401)	0.149***	(0.0435)
ECB/se	0.310***	(0.0628)	0.262***	(0.0709)	0.266***	(0.0703)	0.264***	(0.0759)
FED/se	0.259***	(0.0608)	0.203***	(0.0705)	0.207***	(0.0702)	0.222***	(0.0781)
DE/se	0.477***	(0.0810)	0.400***	(0.0980)	0.403***	(0.0977)	0.432***	(0.126)
TR/se	0.650***	(0.146)	0.615***	(0.147)	0.612***	(0.146)	0.801***	(0.302)
IE/se	1.085***	(0.258)	1.142***	(0.300)	1.136***	(0.299)	1.158***	(0.303)
Central banks								
UK/se			0.208	(0.270)	0.208	(0.270)	0.206	(0.269)
ES/se			-0.0284	(0.844)	-0.0438	(0.842)	0.00486	(0.844)
JP/se			0.0366	(0.211)	0.0383	(0.211)	0.0426	(0.212)
CA/se			-0.192*	(0.113)	-0.188*	(0.112)	-0.160	(0.132)
FR/se			0.942	(1.404)	0.917	(1.401)	0.992	(1.402)
IT/se			0.0237	(1.118)	0.00317	(1.116)	0.0650	(1.117)
NL/se			0.792	(1.076)	0.773	(1.074)	0.832	(1.076)
SE/se			-0.563	(0.378)	-0.561	(0.378)	-0.566	(0.377)
BE/se			0.323	(0.556)	0.313	(0.555)	0.347	(0.557)
AT/se			0.942	(0.684)	0.930	(0.683)	0.971	(0.685)
PT/se			-0.457	(0.777)	-0.472	(0.775)	-0.426	(0.777)
FI/se			0.192	(1.252)	0.170	(1.249)	0.238	(1.250)
AU/se			-0.372	(0.335)	-0.369	(0.335)	-0.375	(0.334)
Estimation methods								
MLE/se					-0.300	(0.570)	-0.290	(0.576)
2SLS/se					0.0390	(0.0815)	0.0386	(0.0813)
IV/se					-0.000757	(0.0521)	-0.00377	(0.0522)
Data characteristics								
quadratic/se							-0.0166	(0.0177)
forward/se							0.154	(0.180)
backward/se							-0.185	(0.260)
expost/se							0.00863	(0.0206)
monthly/se							0.0274	(0.117)
avgyear/se							0.00104	(0.00335)
Likelihood-ratio test (χ^2)	38.21		31.81		29.13		22.90	
Observations	222		222		222		222	

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Appendix D

Results for the ECB and the FED

I run the Heckman regression for the FED and the ECB individually to obtain estimates of their reactions to inflation and output gap. Again, I employ the multilevel mixed-effects estimation. Nevertheless, the inflation coefficient for the ECB reaction function without interest smoothing was estimated by OLS, because the null hypothesis of likelihood-ratio test justifying the use of mixed-effects estimation cannot be rejected[1].

[1] P-value equal to 1.00

Table D.1: Heckman meta-regression for the ECB and the FED

	Smoothing		No smoothing	
	Inflation	Output gap	Inflation^{+}	Output gap
European Central Bank				
1/se *(true effect)*	0.400***	0.047***	0.623***	0.241***
	(0.029)	(0.003)	(0.075)	(0.048)
se	0.595	-2.290 **	6.824	18.186
	(0.856)	(1.034)	(4.230)	(26.357)
Likelihood-ratio test (χ^2)	14.39***	85.47***	0.00	7.65***
Observations	164	134	52	51
Federal Reserve				
1/se *(true effect)*	0.490***	0.079**	0.111*	0.412***
	(0.044)	(0.037)	(0.059)	(0.048)
se	-0.729**	-0.522	-7.593***	0.239
	(0.345)	(0.322)	(1.523)	(0.772)
Likelihood-ratio test (χ^2)	160.42***	44.15***	33.71***	8.24***
Observations	333	304	144	100

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

$^{+}$ Regression for ECB estimated by OLS

Appendix E

Content of Enclosed DVD

There is a DVD enclosed to this thesis which contains empirical data and Stata source codes.

- Thesis.pdf: PDF version of the thesis
- dataset.xls: Data obtained from the primary studies.
- data.dta: STATA dataset used for the estimation.
- code.do: STATA do-file including the code used to obtain the outcome presented in the thesis.