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How Robust are Money Demand Estimations?

A Meta-Analytic Summary of Findings about Income Elasticities

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I. Introduction

Money demand is certainly one of the best researched fields in economics. Over the last decades, literally thousands of articles have been published that contain empirical money demand estimations for numerous countries and time periods. However, despite these considerable efforts the results of this huge literature are quite diverse. The range of the estimated income and interest-rate elasticities is wide, and while some papers maintain that money demand is stable others come to the converse conclusion. In a survey article written in 1994, Martin Fase summarizes his results with a rather dismal note. "The present survey hardly shows any convergence of empirical findings, with clear outliers for certain coefficient values. This leads to the conclusion that the theoretical simplicity of the demand for money fades away in an empirical approach" (Fase (1994) p. 433). Since then, however, ten years have passed and we think that it is worthwhile to reconsider this conclusion: first, because in the meantime many more money demand studies have been undertaken which mostly apply fundamentally different econometric methods ("cointegration revolution"); and second, because the knowledge of the structure and specification of money demand is an important prerequisite for macroeconomic modeling and for the choice of a monetary policy strategy. For these purposes, it is vital to be able to assess the robustness and reliability of money demand estimations.

In this paper, we use a collection of almost 500 individual money demand estimations to investigate whether recent empirical findings

* The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Oesterreichische Nationalbank.

show a higher degree of convergence than ten years ago. To give a quick answer to this question right away, we observe again a wide variation of results. For the estimated (long-run) income elasticities – the main focus of our analysis – the estimates range from 0.01 to 2.46. Given this observation, we then search for factors that could explain the variation. For example, it might be due to the fact that studies differ from each other in various important dimensions, including the definition of monetary aggregates, scale variables, deflators, the inclusion or exclusion of specific interest rate, asset price variables, proxies for wealth or financial innovation and specificities of the estimation method.

An analysis of the implications of different study characteristics should be based on comparable models, which requires to control for all of these factors at the same time. A common method to deal with this issue is to look at the averages of estimated income elasticities for more and more disaggregated subsamples. Problems with data-availability, however, limit the scope of this approach and typically, only two or three variables can be analyzed at a time. In order to circumvent these problems, we conduct a number of meta-regressions. In particular, we regress the 500 estimated income elasticities on various study characteristics that could have an impact on their size. This approach allows to summarize these estimations in a systematic, quantifiable and multivariate manner and to detect similarities across studies – similarities that hold irrespective of the country, the time period, the estimation method or the money demand specification.

In addition, we investigate whether the variation in results could be caused by large confidence intervals of point estimates. For example, an estimated income elasticity of 1.3 does not necessarily imply that the hypothesis of a unitary income elasticity has to be rejected since, for example, the 95% confidence interval around 1.3 could well contain the value of 1.0. Thus, the common practice of presenting histograms of only the point estimates could cause misleading conclusions. Accordingly, we undertake an analysis of the frequency distribution of the confidence intervals associated with the point estimates.

The paper is structured as follows. In the next section, we give a brief overview of existing money demand theories and we develop a number of hypotheses about the possible influence of certain variables on the income elasticity of money demand. In section III., we describe the principles of meta-analyses and we present our data. In section IV., we test the hypotheses by undertaking a meta-regression analysis and in section

V., we deal with the role of the precision of point estimates. Section VI. concludes.

II. Theoretical Background and Basic Hypotheses

The starting point in most of the empirical literature on money demand is a specification of the form:

$$m_t - p_t = \gamma_0 + \gamma_1 y_t + \gamma_2 i_t^{own} + \gamma_3 i_t^{out} + \gamma_4 \pi_t + \gamma_5 w_t + \gamma_6 X_t + \varepsilon_t, \tag{1}$$

where $(m_t - p_t)$ is the logarithm of real money demand[1], y_t is the logarithm of the scale variable, i_t^{own} stands for nominal rates of return on those financial assets which are included in the definition of the respective monetary aggregate, i_t^{out} for the ones excluded from the definition, π_t for the rate of inflation, w_t for the logarithm of (real) wealth and X_t for a vector of other variables that – according to specific theories or to the conjecture of the respective author – might have a systematic impact on aggregate money demand.

In this paper, we will focus on the size of the income elasticity – the single most important parameter of money demand estimations. Virtually all money demand theories expect a positive sign for γ_1, while there exists less agreement about its size. According to quantity-theory-based approaches, it should equal unity, whereas inventory theories suggest that it should be significantly lower.[2] In general, equilibrium approaches (as propagated, for example, by Milton Friedman) state that the demand for money of an individual depends on all (intratemporal and intertemporal) prices and on his or her wealth, including money, bonds, shares, real assets and human capital. Thus, these theories imply that the income elasticity of the demand for (broad) money can be different from 1.0. For example, as growth in income might well lead to an excessive increase in the demand for financial assets (including money balances), broad monetary assets might be a luxury good ($\gamma_1 > 1.0$). Since the inventory approaches mentioned above refer primarily to narrow money we can state our first main hypothesis.

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1 Some papers estimate nominal instead of real money, implying that the LHS of (1) is m_t while the RHS contains as an additional regressor $\gamma_7 p_t$.

2 In the seminal papers by *Tobin* (1956) and *Baumol* (1952) the income elasticity is 0.5, in other variants of the inventory model it ranges from 1/3 to 2/3 (e.g. *Miller & Orr* (1966)).

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Hypothesis 1 *Empirical money demand studies that use narrow concepts of money should lead to lower estimates for the income elasticity than studies that use broad concepts.*

Various theories of money demand assume that wealth plays an important role for the desire to hold monetary assets ($\gamma_5 > 0$). As we will see, however, most studies do not include measures for wealth. Noting that (at least in the aggregate) current income and total wealth are very likely to be positively correlated, the neglect of wealth would cause an omitted variable bias and lead to an overestimation of the income elasticity.[3] This can be expressed in the following hypothesis.

Hypothesis 2 *Money demand estimations that include a measure for wealth should – ceteris paribus – lead to lower estimated income elasticities than studies that exclude such a measure.*

It is frequently argued, that changes in a nation's payment system and payment habits should alter the income velocity (cf. Choi & Oh (2003)). In empirical studies, financial innovation is thereby proxied by a wide variety of variables including the number of ATMs, the dissemination of electronic payment cards, the ratio of currency to the total money stock, the ratio of population to bank offices, the degrees of monetization and financial development in general, etc. Taking the dissemination of electronic payment cards as an example, one would suspect that this innovation should tend to lower the demand for currency and other narrow concepts of money (cf. Stix (2004)). Since, on the other hand, the distribution of electronic payment systems is likely to be positively correlated with national income, the exclusion of proxies for these financial innovations will lead to an underestimation of the income elasticity. Other financial innovations, however, like bank concentration and the degree of financial development are probably better thought of as being proxies for the sophistication of available financial products which could well go hand in hand with a *larger* demand for (broad) money. In this case, the

3 If all variables are stationary, then this is straightforward to show in the context of OLS. Assume that the true model is given by: $Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + u_t$, while the following model is estimated: $Y_t = \beta_0 + \beta_1 X_{1t} + v_t$. In our case X_{1t} represents income and X_{2t} wealth. It can be shown that OLS estimation of the second ("wrong") model leads to a biased estimate of the coefficient: $E(\hat{\beta}_1) = \beta_1 + \beta_2 \frac{Cov(X_{1t}, X_{2t})}{Var(X_{1t})}$. Because $\beta_2 \neq 0$ (according to theory) $\hat{\beta}_1$ will be biased unless X_1 and X_2 are uncorrelated. The direction of the bias thus depends on the sign of β_2 and on whether X_1 and X_2 are positively or negatively correlated.

exclusion of the respective financial innovation variables would cause an upward bias in the estimation of the income elasticity.

Hypothesis 3 *The exclusion of variables proxying for financial innovation could lead to an omitted variable bias in the estimation of the income elasticity. The direction of the bias depends on the exact nature of the financial innovation variables used in the respective studies.*

The three hypotheses presented in this section are based on theoretical considerations that lead to unambiguous predictions about the possible effects. In section IV., we will use meta-regression techniques to investigate whether these hypotheses are in fact confirmed by the data. In subsequent sections, however, we will also include additional study characteristics as potential explanatory variables into the meta-regressions about which we do not have strong a priori expectations about the likely effects.

III. Empirical Methodology and Data Description

In this section, we briefly describe the principles of meta-analysis and we outline our procedure for paper selection, study retrieval, coding and estimation. Subsequently, we present descriptive statistics of the studies and their characteristics.

1. The Concept of Meta-Analysis

"Meta-analysis" is the collective name for quantitative methods of combining the results of separate but related studies on a specific topic to extract common features of these studies (cf. Lipsey & Wilson (2001); Stanley (2001)). A special form of a meta-analysis is a meta-regression analysis, where "the dependent variable is a summary-statistic, perhaps a regression parameter, drawn from each study, while the independent variables may include characteristics of the method, design and data used in these studies" (Stanley (2001) p. 131 f.). Thus, the difference to the more traditional surveys on a specific topic ("narrative literature reviews") is that the meta-analysis involves less subjective reasoning and judgmental arguments about what represents an acceptable empirical method, a "state-of-the-art" treatment of the question at hand, etc. A (multiple) meta-regression analysis allows to analyze the joint impact of various study characteristics on the point estimates, to compare and quantify these effects and to use statistical tools to test for their significance.

2. Data

In order to avoid possible selection and availability biases in compiling our sample, we follow a rule-based strategy to retrieve relevant studies. In particular, we have searched in the EconLit Database for articles that met certain criteria. In the end, we arrived at a sample of 79 papers published in academic journals after 1994 that form our basic sample.[4] Most of these studies contain more than one money demand estimation yielding 559 estimations.[5] For each of these estimations, we extracted and coded information about the estimated coefficients and about a number of potential explanatory variables (see Table 1).

Our sample shows the typical wide variability of money demand estimations. This variability is multi-dimensional, e.g. reflected in differences in estimated income elasticities, interest rate (semi-)elasticities and other coefficients, the number of cointegrating vectors found, the lag structure employed, etc. (cf. Knell & Stix (2004)).

After adjusting for outliers, our data set comprises 491 point estimates of income elasticities for which summary statistics are shown in Table 2.[6] Although these figures refer only to unconditional means, they already reveal some interesting results. First, the average estimated income elasticity over all point estimates is 0.98, being astonishingly close to the

4 First, we had looked for entries that contained the words "money demand" and one of the following word parts: "empiric*", "estimat*", "stab*" or "instab*". In addition to this, it was required that studies were published in one of 232 leading economic journals, that they included an abstract (in order to check whether they contain empirical estimates) and that they were included in Econlit as of July 2002. This left us with a total of 386 papers. This number was further narrowed down by considering only papers published after 1994 that had either "mon* demand" or "mon* stability" in the title. After reading the abstracts of all remaining entries and excluding all papers that were not appropriate for our purpose (since they contained only theoretical models, cross-section analyses, purely econometric analyses, etc.), we arrived at a sample of 94 articles. During the process of coding another 15 papers were excluded (e.g. for missing empirical results) leaving us finally with 79 papers. A complete list of these papers is available from us upon request.

5 We did not distinguish between the different estimations within a paper following the suggestion that in a meta-regression analysis the differences in the results should (at least partly) be explained by the particularities of the specifications. We will come back to this issue, however, when we turn to the question of weighting.

6 We discard the estimates in the lower and upper five percentiles of our data. More elaborated techniques result in quite similar adjusted samples. Furthermore, we eliminate models where the income elasticity has been restricted to be 1.0 without statistical testing.

Table 1

Meta-Independent Variables

Income Elasticity = the point estimates of long-run income elasticities	
Monetary Aggregates	
M0	= 1 ... if a study uses M0 or MB
M1	= 1 ... if a study uses M1
M2	= 1 ... if a study uses M2
M2M	= 1 ... if a study uses M2M (M2 less small time deposits)
MZM	= 1 ... if a study uses MZM (money at zero maturity)
M3	= 1 ... if a study uses M3
M4	= 1 ... if a study uses M4
Money Broad	= 1 ... if a study uses either M2, MZM, M2M, M3 or M4
Money Narrow	= 1 ... if a study uses M1
Money Currency	= 1 ... if a study uses M0
Nom. Money	= 1 ... if a study uses nominal money as the dep. variable
Scale Variables	
GDP	= 1 ... if a study uses either GDP, GNP or Net National Income as a scale variable
Consumption	= 1 ... if a study uses either consumption, personal income or private GDP (GDP less government component) as a scale variable
Indices	= 1 ... if a study uses either an index of industrial production or of coincident indicators as a scale variable
Expenditure	= 1 ... if a study uses a measure of expenditures (real total transactions, total final expenditures, etc.) as a scale variable
Data Frequencies	
Monthly Data	= 1 ... if a study uses monthly data
Quarterly Data	= 1 ... if a study uses quarterly data
Annual Data	= 1 ... if a study uses annual data
Estimation Method	
ADL	= 1 ... if a study uses a distributed lag estimation method
EG	= 1 ... if a study uses the Engle-Granger estimation method
DOLS	= 1 ... if a study uses the dynamic OLS or GLS estimation method
FMOLS	= 1 ... if a study uses the fully modified OLS estimation method
CP	= 1 ... if a study uses the Cooley-Prescott estimation method
Random Coeff.	= 1 ... if a study uses the random coefficients estimation method
Spectral	= 1 ... if a study uses the spectral regression method
Johansen	= 1 ... if a study uses the Johansen system estimation method
CCR	= 1 ... if a study uses the canonical correlation estimation method

Note: See continuation on next page.

Table 1

Meta-Independent Variables (continued)

Other Variables	
Dummies	= 1 ... if a study includes at least one dummy variable as an explanatory variable
Wealth	= 1 ... if a study includes a measure of wealth
Fin. Innov.	= 1 ... if a study includes a measure of financial innovations
Time	= the sample mid-point year of an individual estimation
No. of Obs.	= the number of observations of individual estimations
No. of Years	= the number of years in the sample used for individual estimations

Table 2

Descriptive Statistics for Income Elasticities

	Mean	Std. Dev.	Min.	Max.	Obs.
Total	0.98	0.40	0.16	2.10	491
OECD Countries	1.01	0.40	0.16	2.10	392
Non-OECD Countries	0.89	0.39	0.19	2.05	99
USA	0.85	0.33	0.18	1.97	206
GBR	0.99	0.41	0.22	2.03	25
DEU	1.17	0.20	0.60	1.52	45
EU Multicountry	1.34	0.32	0.86	1.96	44

Note: The table summarizes descriptive statistics for the estimated income elasticities. "EU Multicountry" refers to studies that combine data on various European countries to derive some aggregate money demand estimation.

prediction of the basic quantity theory. Second, however, there exists substantial variation across point estimates. For the total sample, e.g., the standard deviation is 0.40. This implies that an approximate 95% confidence interval of estimated point estimates ranges from around 0.2 to 1.8, a sizeable range including basically all values for income elasticities implied by theoretical models.

In traditional money demand surveys (cf. Fase (1994); Sriram (2001)), the variety of estimates is usually illustrated in histograms. We perform a similar exercise for our sample in Figure 1 where we have used kernel

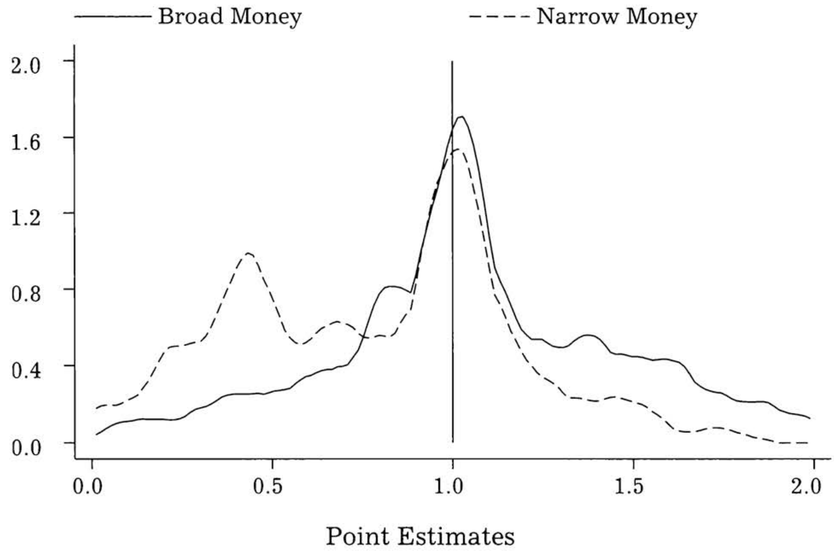

Figure 1: Smoothed Histogram of Point Estimates

density estimations to "smooth" the histograms (separately for broad and narrow monetary aggregates). We see the expected peak at 1.0 and for narrow money estimations also a second peak around 0.5. In addition, it is clearly visible how strongly the point estimates of the income elasticities differ across studies. Furthermore, as the distribution of income elasticities for narrow money is more skewed to the right than the one for broad money, Figure 1 provides some first support for hypothesis 1. This evidence, however, is only based on a "univariate" comparison and it is not clear whether it still holds if one corrects for other potential explanatory variables.

Analyzing the summary statistics of specific subsamples of countries, one can observe that there also seems to be a high degree of between-country diversity. For OECD countries, the average point estimate of the income elasticity is exactly unity, while non-OECD countries have a significantly lower value (0.89). The average estimates for the U.S. are considerably lower (0.84) than for Germany (1.16) or for multi-country studies of European economies (1.34).[7]

[7] The subsample "EU Multicountry" refers to studies that combine data on various European countries to derive some aggregate money demand estimation.

The discussion thus far did not take the differences between studies explicitly and systematically into consideration. As the variation across subsamples and the different pictures for broad and narrow monetary aggregates indicate, it can be expected that the point estimates of income elasticities are influenced by certain specific characteristics of individual studies. As shown in Table 3, the empirical specifications do in fact differ considerably across studies. For example, about 40% of all models use narrow concepts of money (*MB*, *M*0 or *M*1) while the rest takes broader aggregates. In studies which analyze non-OECD countries, narrow money concepts are used more often than broader concepts. Furthermore, only 2% of all estimations include a measure for wealth and only 3% a proxy for financial innovation. In the following, we will therefore analyze whether some of these different study characteristics have a systematic impact on the estimated income elasticities.

IV. Results

1. Basic Specification

In the following regressions, the income elasticities estimated in the individual studies are regressed on the small set of explanatory ("meta-independent") variables that were discussed in the previous section. The results are summarized in Table 4 for six different specifications. The specifications differ with respect to the use of OLS or weighted LS, the inclusion or exclusion of country dummies and for the sample of countries considered.

Columns 1 to 3 report the results of specifications without individual country dummies. In the first colum we estimate the model with OLS, while in columns 2 and 3 we use weighted LS. The weights which are used in column 2 are based on the sample size of the individual studies reflecting the idea that the "quality" of the point estimates should increase with the number of observations.[8] In the context of studies on

Thereby, special emphasis has to be laid on the question how the data are aggregated (fixed exchange rate, flexible exchange rate or PPP method) and how cross-border holdings are treated (*Wesche* (1997)). In our sample we have 44 EU Multicountry estimations, ranging from an EC-3 (Germany, France, the Netherlands) to an EU 15 sample.

[8] The question of whether meta-regressions should be weighted is controversial (*Weichselbaumer* & *Winter-Ebmer* (2001); *Wolf* (1986), 39; *Krueger* (2003)). Econometrically, weighted least squares should correct for heteroscedasticity in the er-

Table 3

Characteristics of the Studies by Sub-Groups

	Total	OECD	Non-OECD	USA
MB	1	1		1
M0	6	2	22	1
M1	32	29	45	30
M2	29	31	20	48
M2M	2	3		6
MZM	6	8		15
M3	21	24	12	
M4	3	4		
Sum	100	100	100	100
GDP, GNP, NNI	62	60	69	29
Consumption	16	18	10	33
Indices	19	19	19	35
Expenditure	3	4	2	4
Sum	100	100	100	100
Monthly Data	26	30	11	57
Quarterly Data	57	54	72	21
Annual Data	16	16	17	22
Sum	100	100	100	100
ADL	16	15	21	5
EG	10	5	30	3
DOLS	8	10	1	10
FMOLS	7	9		2
CP	1		7	
Random Coeff.	2	2		3
Spectral	1	1		2
Johansen	54	57	40	73
CCR	1	1		2
Sum	100	100	100	100
Nom. Money	7	9		1
Wealth	2	2		
Fin. Innov.	3		12	
Dummies	21	23	13	4
Obs.	491	392	99	206

Note: The table shows the frequencies (in percent) of the various characteristics of the studies. For a definition of variables, see Table 1.

Table 4

Meta-Regression – Simple Specification

	Dependent Variable: Income Elasticity					
	(1)	(2) (1) wgt. w. # of obs.	(3) (1) wgt. w. # of years	(4)	(5) OECD	(6) Non-OECD
Country Dummies	No	No	No	Yes	No	No
M1	–0.120*	–0.072	–0.169**	–0.063	–0.081	–0.078
	(0.068)	(0.081)	(0.084)	(0.077)	(0.114)	(0.097)
M2	0.083	0.039	0.226***	0.225***	0.125	0.174
	(0.069)	(0.077)	(0.083)	(0.078)	(0.114)	(0.116)
M2M	–0.059	–0.009	–0.061	0.167	–0.001	–
	(0.119)	(0.098)	(0.147)	(0.118)	(0.149)	
MZM	0.126	0.176**	0.124	0.353***	0.184	–
	(0.089)	(0.082)	(0.104)	(0.096)	(0.127)	
M3	0.322***	0.330***	0.210**	0.171**	0.396***	0.097
	(0.073)	(0.087)	(0.091)	(0.087)	(0.116)	(0.212)
M4	0.519***	0.529***	0.479***	0.385**	0.577***	–
	(0.110)	(0.133)	(0.145)	(0.157)	(0.142)	
Nom. Money	0.034	0.108	0.109	0.055	0.012	–
	(0.066)	(0.085)	(0.088)	(0.076)	(0.066)	
Wealth	–0.396***	–0.356**	–0.378**	–0.480***	–0.391***	–
	(0.126)	(0.149)	(0.165)	(0.159)	(0.124)	
Fin. Innov.	–0.548***	–0.488***	–0.455***	–0.149	–	–0.371*
	(0.102)	(0.115)	(0.127)	(0.157)		(0.197)
Const.	0.925***	0.875***	0.926***	0.155	0.867***	0.927***
	(0.062)	(0.074)	(0.078)	(0.359)	(0.110)	(0.080)
R^2	0.23	0.17	0.21	0.45	0.26	0.12
$\bar{R}^2$	0.22	0.16	0.20	0.40	0.24	0.08
Obs.	491	491	491	491	392	99

Note: Standard errors in parentheses. *** (**) [*] indicate significance at a 1% (5%) [10%] level. Columns (1) and (4)–(6) are estimated by OLS, columns (2) and (3) by weighted LS. “wgt. w.” stands for “weighted with”. See Table 1 for a definition of variables.

long-run money demand, one could also argue that the estimates of the *long-run* income elasticity are the more accurate the longer the time span a study covers.[9] Following this line of reasoning, we use the number of years a study covers as a weighting scheme in column 3. In general, the results of the meta-regressions in columns 1 to 3 suggest that different weighting schemes do not cause fundamental changes in the results. The signs of all estimated coefficients are consistent across the three specifications and also their sizes and levels of significance are quite similar. In contrast, the inclusion of country dummies (column 4) makes a non-negligible difference.[10] Some explanatory variables change their level of significance, while at the same time the explanatory power of the regression (as measured by $\bar{R}^2$) increases considerably (from 0.22 to 0.4). The significance of many of the individual country dummies thus implies that there are important differences between countries, even if individual study characteristics are controlled for.

In a next step, we analyze whether this important role of country-specific effects can be related to the role of different country groupings. For example, it could be argued that the countries in our sample are very inhomogenous and that country difference will not play a role if more homogenous groups of countries are analyzed. To account for this possibility, columns 5 and 6 present the results for OECD and non-OECD countries in a specification without country dummies, respectively. For the rather homogenous group of OECD countries, we obtain an $\bar{R}^2$ that is much lower than in a comparable specification with country dummies while the other explanatory variables remain, by and large, unaffected.[11] For the inhomogenous group of non-OECD countries, the explanatory power of the regression is even lower. These findings provide strong evidence that country-specific effects are important in determining the sensitivity of money in reaction to changes in income. Therefore, we con-

ror term. If the source of heteroscedasticity is known or if there are strong theoretical reasons for assuming such a relation, this is straightforward. In many situations, however, as in our framework, weighting expresses a priori beliefs about the "quality" of studies with certain characteristics (like the rank of the publishing journal, reputation of the authors, comprehensiveness of the study etc.). Thus, the weighting scheme reflects to a lesser degree theoretical presumptions and remains to some extent arbitrary.

9 In the unit root literature some evidence suggests that the power of unit root tests depend on the span of the data rather than on the number of observations (cf. *Maddala* & *Kim* (1998) p. 129 f.).

10 The coefficients for the country dummies are not shown.

11 Running the same regression with country dummies results in an $\bar{R}^2$ of 0.40 (not shown).

sider the specification with country dummies in column 4 as our preferred model.

The results of this preferred model lend support to hypothesis 1 that the income elasticity increases with the "broadness" of the used monetary aggregate. We find that income elasticities are significantly higher when a broader monetary aggregate – a variant of $M2$, $M3$ or $M4$ – is used. In particular, the results show that the income elasticity of $M1$ does not differ significantly from $M0$ (the base category), whereas $M4$, $M3$, $M2$ and MZM[12] are not only different from $M0$ but also from $M1$.[13] For example, the estimated coefficients imply that in studies using $M3$ income elasticities are on average 0.17 higher than if $M0$ is used. Finally, our results suggest that the use of *nominal* money as the dependent variable is associated with slightly larger income elasticities although the coefficient is not statistically significant.

Studies that include a variable for wealth have a significantly lower estimated income elasticity. This is the expected result that confirms hypothesis 2. Wealth plays a role for people's demand for financial assets (including broad money) and, since income and wealth are typically highly correlated, the omission of wealth from the money demand estimation leads to a considerable overestimation (by 0.48) of the income elasticity.

The inclusion of variables that proxy for financial innovations do not seem to influence the estimated income elasticities in a systematic manner. In column 4 the impact is negative but not statistically significant.[14] As expressed in hypothesis 3, this would mean that the proxies are related to innovations that facilitate the investment in financial assets rather than to innovations in the payment system.

12 MZM includes M1 plus institutional and retail money market funds, less small time deposits. $M2M$ is $M2$ excluding small time deposits. *Carlson* et al. (2000) argue that these deposits are responsible for the instability of $M2$. Since this paper contains a considerable number of estimations we have kept $M2M$ and MZM as separate categories.

13 Within the group of broad monetary aggregates, the income elasticity of $M4$ is significantly larger than those of $M2$ and $M3$, where the latter two concepts yield the same income elasticities, statistically. This is not surprising as the definitions of $M2$ and $M3$, depending on the country, often comprise similar assets.

14 In the models of columns 1 to 3 (without country dummies) financial innovation is significant, supposedly capturing a country effect in these specifications.

2. Extended Models and Robustness Tests

Thus far, we have focused on a set of explanatory variables for which we had clear hypotheses about the direction of their likely effect on the estimated income elasticity. Individual money demand estimations differ, however, in a number of additional dimensions for which it is less clear whether one should expect an impact on estimated income elasticities or in which direction such an impact could work. Despite these theoretical ambiguities, it is interesting to investigate whether the diversity of estimates can be explained by some of these additional variables and, furthermore, whether the results of the previous section are robust to these extensions. We focus mainly on two sets of additional explanatory variables that are contained in almost all money demand estimations and capture central aspects: the measurement of the scale variable and details of the estimation method. In column 1 of Table 5 we have amended the basic specification of Table 4, column 4 with measures for these two sets of variables.

The quantity theory of money is normally formulated with regard to total transactions rather than to total income. Since the total volume of transactions is difficult to measure most studies resort to some proxy for the scale variable, mostly GDP or national income (62% in our sample, see Table 3), but sometimes also even smaller subsets like consumption or industrial production. For empirical researchers it is of relevance to know whether the choice of a particular scale variable affects estimated income elasticities. The results in column 1 indicate that this is the case. Studies that use consumption as a scale measure seem to produce significantly higher estimates of the income elasticity than studies that use national income (our base category, measured by GNP, GDP or NNI). This finding can be rationalized if one assumes that "... consumption is more money intensive than other components of GNP, a hypothesis supported by some evidence" (Goldfeld & Sichel (1990) p. 320). Thus, if there is a shift in the composition of GNP towards more money intensive sectors, then money demand estimations that use consumption as their scale variables will find a higher income elasticity than ones that use GNP (or GDP). Under this interpretation, the positive sign of consumption indicates that such changes in the composition of GDP were in fact present in the corresponding observation periods.

In the next step, we analyze the second set of additional explanatory variables – the estimation methods used in the empirical analyses. This is of interest because of the fundamental change that took place in em-

Table 5

Meta-Regression – Extended Specification

	Dependent Variable: Income Elasticity					
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	BM/NM	Johansen	Post WW-II	< 23 models	Weighted
Monetary Aggregates						
M1	–0.021	–0.033	–0.037	0.012	0.016	–0.064
	(0.073)	(0.074)	(0.095)	(0.073)	(0.080)	(0.057)
M2	0.390***		0.342***	0.340***	0.340***	0.192***
	(0.077)		(0.097)	(0.078)	(0.083)	(0.059)
M2M	0.508***		0.468***	0.408***	–	0.457
	(0.115)		(0.127)	(0.118)		(0.289)
MZM	0.648***		0.594***	0.584***	–	0.601***
	(0.097)		(0.112)	(0.098)		(0.200)
M3	0.294***		0.343***	0.294***	0.296***	0.140**
	(0.082)		(0.113)	(0.082)	(0.088)	(0.071)
M4	0.521***	0.356***	0.895***	0.480***	0.484***	0.282*
	(0.148)	(0.073)	(0.215)	(0.150)	(0.160)	(0.145)
Nom. Money	0.111	0.062	0.043	0.088	0.031	0.205***
	(0.075)	(0.074)	(0.107)	(0.078)	(0.084)	(0.075)
Wealth	–0.502***	–0.480***	–	–0.492***	–0.451***	–0.617***
	(0.146)	(0.148)		(0.145)	(0.156)	(0.105)
Fin. Innov.	–0.251*	–0.252*	–0.697*	–0.234	–0.118	–0.236**
	(0.149)	(0.151)	(0.358)	(0.149)	(0.192)	(0.120)
Time	–0.013***	–0.013***	–0.017***	–0.003	–0.010***	–0.011***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
Scale Variables						
Consumption	0.193***	0.182**	0.165*	0.157**	0.132	0.140*
	(0.070)	(0.071)	(0.093)	(0.072)	(0.091)	(0.074)
Indices	0.126	0.131	0.093	0.081	0.129	0.022
	(0.082)	(0.084)	(0.106)	(0.084)	(0.162)	(0.105)
Expenditure	–0.131	–0.147*	0.094	–0.193**	–0.121	–0.264**
	(0.087)	(0.088)	(0.161)	(0.089)	(0.100)	(0.122)

Note: See continuation on next page.

Table 5

Meta-Regression – Extended Specification (continued)

	Dependent Variable: Income Elasticity					
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	BM/NM	Johansen	Post WW-II	< 23 models	Weighted
Monthly Data	–0.381***	–0.300***	–0.265***	–0.351***	–0.424***	–0.432***
	(0.072)	(0.070)	(0.084)	(0.073)	(0.148)	(0.110)
Annual Data	–0.181**	–0.192**	–0.202	–0.172**	0.168	0.053
	(0.078)	(0.079)	(0.142)	(0.079)	(0.124)	(0.111)
Dummies	0.059	0.058	0.086	0.022	0.053	0.066
	(0.044)	(0.045)	(0.068)	(0.046)	(0.048)	(0.049)
Estimation Method						
ADL	–0.082	–0.073	–	–0.088*	–0.082	–0.155***
	(0.051)	(0.051)		(0.051)	(0.057)	(0.050)
EG	–0.034	–0.029	–	–0.034	–0.144	–0.090
	(0.076)	(0.077)		(0.076)	(0.102)	(0.064)
DOLS	–0.057	–0.050	–	–0.076	–0.052	–0.052
	(0.057)	(0.057)		(0.061)	(0.070)	(0.066)
FMOLS	–0.005	–0.008	–	–0.025	0.046	–0.013
	(0.061)	(0.063)		(0.063)	(0.070)	(0.072)
CP	–0.317**	–0.285**	–	–0.320**	–	–0.428***
	(0.135)	(0.138)		(0.135)		(0.087)
Random Coeff.	–0.591***	–0.610***	–	–	–0.793***	–0.869***
	(0.126)	(0.128)			(0.149)	(0.212)
Spectral	–0.253*	–0.261*	–	–0.219	–	–0.606
	(0.152)	(0.155)		(0.152)		(0.479)
Const.	25.646***	25.580***	33.430***	6.180	19.889***	22.775***
	(4.357)	(4.262)	(6.307)	(8.057)	(6.331)	(5.693)
R^2	0.57	0.55	0.55	0.56	0.56	0.74
$\bar{R}^2$	0.51	0.49	0.47	0.49	0.48	0.71
Obs.	491	491	268	467	319	491

Note: All models include country dummies. Standard errors in parentheses. *** (**) [*] indicate significance at a 1% (5%) [10%] level. The models in column (1)–(5) are estimated by OLS, the model in column (6) is estimated by weighted LS. The weight is the inverse of the number of observations per country. See Table 1 for a definition of variables.

pirical money demand estimations: while a decade ago most estimations involved partial adjustment or buffer stock models, a majority of the papers today employs the Johansen method to estimate long-run money demand functions (Table 3 provides an overview about the use of the different estimation methods).[15] In principle, the method used for estimation should not have any systematic influence on the results asymptotically if the econometric model is correctly specified. In practice, however, taking small sample properties into account, the estimated income elasticities are likely to vary across different methods.

Accordingly, several dummy variables capture the specificities of the econometric method in column 1 of Table 5. The results indicate that the estimation method does not seem to matter for those methods that are most frequently employed (ADL, Johansen, EG, DOLS and FMOLS). Two other methods, in particular the random coefficient method and to a lesser extent the Cooley-Prescott method, generate lower point estimates than the other methods. However, since only a small number of studies in our sample use these two methods, the corresponding negative coefficients might also capture some other (omitted) characteristic(s) from these studies.

The insignificant effect of the most frequently used econometric techniques, however, indicates only the absence of any *systematic* relationship (from a meta-analytic perspective) between the methods and the income elasticity estimates. This does not imply that parameter estimates do not vary with different methods in individual studies. To the contrary, some papers which apply different methods, e.g. Ball (2001) and Wolters et al. (1998), provide evidence that the estimation method influences point estimates of income elasticities.[16] Thus we think that our results as well as a reading of the literature suggest that it is highly advisable not to rely too much on a single method but to apply several methods. Interestingly, this "robustness check" is done in only 30% of all papers in our sample.[17]

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[15] In *Fase* (1994), the majority of surveyed empirical papers employs partial adjustment models and only 1.5% of all studies use cointegration techniques. In our sample of papers, the partial adjustment models have almost disappeared.

[16] *Ball* (2001) compares the income and interest rate elasticities obtained from various methods for two samples of U.S. data. For the first sample ranging from 1946 to 1987, he finds point estimates for the income and interest rate elasticity which vary widely across estimators. However, when the sample is extended to 1996, the point estimates are much more clustered. *Wolters* et al. (1998) compare various methods using German data and obtain income elasticities ranging from 0.94 to 1.44.

Since estimated income elasticities may also reflect peculiarities of the sample and not differences in the estimators, we have also controlled for sample effects. In particular, we include a number of additional variables that capture the observation time, the data frequency and the potential inclusion of dummies in the underlying regressions.[18] The results for these variables indicate that the use of monthly and of annual data results in lower estimates for the income elasticity than studies that employ quarterly data (the base category). We have no good explanation why this might be the case and can only speculate that probably the frequency of the data determines the degree to which the results on long-run money demand are disturbed by short-run influences. Also, we find a significantly negative coefficient for the time period over which money demand was estimated *(Time)* – the earlier a sample starts, the higher the income elasticity. This effect is likely to reflect the steady increase in financial innovations over time. Finally, there is also some evidence that the inclusion of dummy variables in money demand specifications increases the estimated income elasticity.

To check for the robustness of our results, we also estimate the above specification with several different subsamples: In column 2 of Table 5 we use a "coarser" classification of the monetary aggregates that consists of only three groups: currency ($M0$, the base category), narrow money ($M1$) and broad money ($M2$, $M2M$, MZM, $M3$, $M4$).[19] In column 3, we take only models that are estimated with the Johansen cointegration technique. Arguably, this yields a more homogeneous and comparable sample. In column 4, we exclude estimations that cover pre-World War II observations since money demand is likely to have changed fundamentally since these early days. The next robustness test deals with the potential problem that papers, which contain a large number of estimations, could dominate the meta-regressions. In fact, three of our 79 papers – each containing more than 23 individual estimations – cover 30% of our total sample.[20] In column 5 these papers are excluded. An

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17 Out of these 30%, two thirds apply two and one third more than two methods.

18 We want to note, that it might also matter whether money demand is estimated in per capita or in aggregate terms if the "true" income elasticities are smaller than 1.0 (as, e.g., in the individualist inventory approaches). In this case, the impact of income growth on money demand might depend on whether the former is primarily due to intensive (per capita) or extensive (population) growth. Since a considerable number of papers does not include clear information on this matter we are, however, not able to further pursue this issue.

19 In column 2 the category "broad money" is denoted as $M4$.

alternative approach towards this issue is provided in column 6, where individual money demand estimations are weighted according to the inverse of the number of observations for a particular country.

Altogether, the results of the robustness tests support the main findings of the benchmark regression in the first column of Table 5. Income elasticities are significantly higher for broader monetary aggregates and accounting for wealth leads to significantly lower estimates. The inclusion of variables controlling for financial innovations also causes lower estimates, although this effect is not always statistically significant. Some part of the influence of financial innovations might, however, be captured by the variable *Time* which is significantly negative in most of the regressions (with the exception of column 4).[21] Independent of the subsample, the use of monthly data results in lower point estimates while for annual data the results are more ambiguous. The effect of the various estimation methods differs across subsamples and only the use of random coefficients and of the Cooley-Prescott method seems to be correlated with lower estimates (although, as previously mentioned, the small number of studies using these methods raises some doubts about this result). As far as the scale variables are concerned, we can also uphold our conclusion that the use of consumption is associated with higher estimates of the income elasticity. This is of relevance because consumption (being a proxy variable for permanent income) could be a superior scale variable than national income (cf. Laidler (1993) p. 167).

3. How Much of the Variation in Point Estimates Can Be Explained?

Although the previous analyses revealed some systematic relationships between the specification of individual studies and estimated income elasticities, the question remains how much of the variation in individual point estimates can be explained. Table 6 provides a comparison between different estimation models.

For the total sample, the standard deviation of point estimates is 0.4. This standard deviation is reduced to 0.34 by the small specification in

[20] These papers are *Ball* (2001), *Carlson* et al. (2000) and *Arrau* et al. (1995).

[21] The fact that *Time* is not significant in the specification using only post-World War II data is compatible with the interpretation that this variable might implicitly control for the effects of financial innovations that took place over long periods of time.

Table 6

Model Comparison

		Total Sample (491 obs.) Std. Dev. Residuals	$\bar{R}^2$
(1)	No Explanatory Variables	0.40	–
(2)	Small Set of Explanatory Variables	0.34	0.22
(3)	Only Country Dummies	0.32	0.29
(4)	(2) + Country Dummies	0.29	0.40
(5)	(2) + Country Dummies + Scale + Econometric	0.26	0.51

Note: The table summarizes the standard deviations of the residuals and the adjusted $\bar{R}^2$ for various estimated models.

column 1 of Table 4. Alternatively, adding only country dummies without further explanatory variables results in a standard deviation of 0.32 ($\bar{R}^2 = 0.29$). A model including country dummies and a small set of explanatory variables, is able to reduce the standard deviation to 0.29 ($\bar{R}^2 = 0.4$). This shows, that both explanatory variables and country dummies play an important role in explaining the variety of results. Extending this model by controlling for scale variables and econometric methods, reduces the standard deviation to 0.26. Thus, about one third of the variation in the dependent variable can be explained by variations in our independent variables.

These numbers imply, that country differences and a small set of theoretically informed variables contribute most to the explanation of the observed diversity of estimation results. At the same time, however, substantial variation remains that cannot be reduced to country differences or to other explanatory variables.

V. Precision of Estimation

In this section, we therefore investigate the possibility that the observed diversity of income elasticity estimates is a reflection of the imprecision of the underlying estimations. In order to illustrate this argument, we can again look at the variability of the point estimates of the

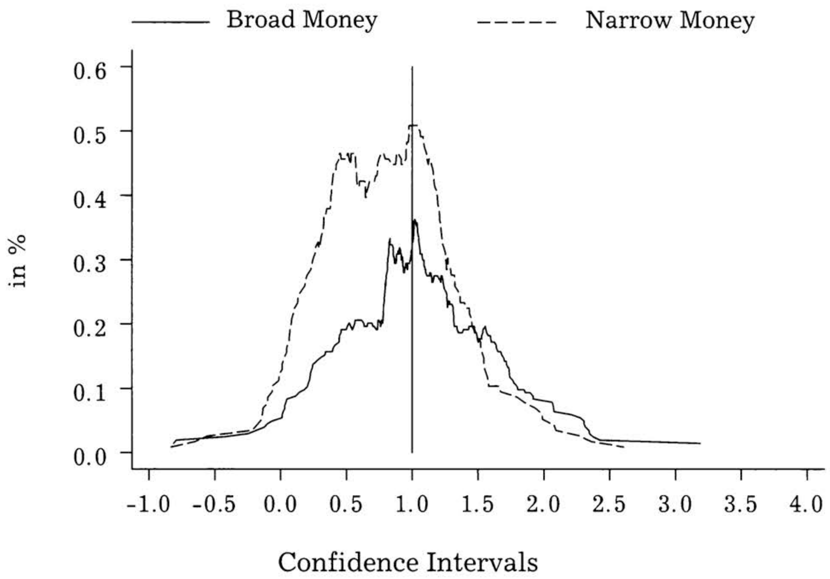

Figure 2: Frequency Plot of Confidence Intervals

income elasticities visible in the "smoothed histograms" in Figure 1. Interestingly, it is rarely asked in money demand surveys whether this variation in point estimates is due to imprecise estimation or whether it is "genuine", i.e. reflecting differences in the underlying economic structure. This can be analyzed only if the stochastic distribution of the point estimates will be also taken into account. For example, a peak at 0.5 does not a priori imply that a unitary income elasticity is rejected by the data, since the value of 1.0 could still be included in most confidence intervals of the respective point estimates. To account for this possibility, we have constructed frequency plots of confidence intervals (shown in Figure 2) for which we have used the information of all studies that report some measure for the precision of estimation (standard errors, t-statistics or p-values).[22]

The height of the curve indicates the sample frequency with which a certain income elasticity is contained in the respective 95% confidence interval of 323 individual point estimates. Quite surprisingly, this analy-

22 Unfortunately, this is not the case for all studies and thus the number of observations decreases in this case to 323.

sis shows that for broad money the value 1.0 is included in only 32% of these confidence intervals implying that for a majority of empirical money demand estimations the prediction of the quantity theory is clearly rejected.[23] In contrast, the value of 0.5 is contained in only 18% of all confidence intervals for broad money. For narrow money, the values of 0.5 and 1.0 are included in 44% and 50% of all confidence intervals, respectively.

Although these frequency plots of the confidence intervals do not control for the study characteristics (as was done in the regressions), we still regard the results as sufficiently strong to conclude that imprecision alone is not able to explain the wide diversity of point estimates.

VI. Conclusion

When summarizing the results from the huge literature on empirical money demand estimations, one typically encounters coefficient values that vary substantially. In this paper, we have analyzed whether and how this wide diversity of results can be explained.

We have extended the existing literature in various dimensions. First, we have performed a meta-analysis of almost 500 empirical money demand studies to investigate whether different study characteristics play a role for the variation. In particular, it has been shown that the estimations for the income elasticity of money demand are systematically and significantly higher, if broader definitions for the monetary aggregate are used. Also, the inclusion of wealth tends to be associated with lower estimates. By contrast, the results for the use of proxies for financial innovation, the use of different econometric methods and various additional empirical specification details are less clear-cut. Furthermore, we have found that country-specific effects play an important role for the determinination of the size of income elasticities. These country differences are not only present between more heterogeneous groups (e.g. between OECD and Non-OECD countries) but also within the more homogeneous group of OECD countries itself. It is noteworthy, that some of these results are similar to observations made in previous surveys – despite the fact that we use a completely different sample of papers and despite the fact that in our sample most studies use modern cointegra-

23 The peak of the curve is reached at an income elasticity of 1.02 which is contained in 36% of all studies.

tion techniques while older surveys (e.g. Fase (1994); Laidler (1993)) were dominated by partial adjustment models, etc.

The meta-analyses have revealed that, while specific features of the individual studies help to explain a substantial part of the differences in the empirical results, the unexplained variation still remains large. Therefore, we have also dealt with the argument that the large variability of estimates over studies could be related to uncertainty of estimation – e.g. wide confidence intervals for individual point estimates. We have demonstrated, however, that this issue does not seem to be at the root of the problem since point estimates are in general rather precise.

Our overall conclusion is, that a substantial part of the variation in point estimates cannot be explained by differences in study characteristics or by imprecision of estimation. We interpret this fact as an indication that the frequently encountered practice of estimating a *"standard"* money demand model with only a few common variables might be problematic. On the other hand, our findings do not necessarily imply that money demand estimations are genuinely non-robust and unreliable. In fact, we think that the evidence presented in this paper highlights the necessity for a careful empirical specification. If the influence of financial innovations, structural breaks and other country-specific circumstances are taken into account, it is likely that money demand estimations are able to reveal a consistent and stable relation.

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Summary

How Robust are Money Demand Estimations? A Meta-Analytic Summary of Findings about Income Elasticities

In this paper we conduct a meta-analysis of empirical money demand studies involving almost 500 individual money demand estimations. We analyze whether the wide variety of results can be explained by characteristics of the studies or the imprecision of individual estimates. We find that estimates for the income elasticity of money are systematically related to various study characteristics (e.g., broadness of the monetary aggregate, inclusion of financial innovation and wealth). Nevertheless, a substantial part of the variability remains unexplained. (JEL E41, E52)

Zusammenfassung

Wie robust sind Geldnachfrageschätzungen? Eine meta-analytische Zusammenfassung von Ergebnissen bezüglich der Einkommenselastizität

In diesem Artikel führen wir eine Meta-Analyse empirischer Geldnachfragestudien durch, die auf fast 500 einzelnen Schätzungen beruht. Wir untersuchen, ob die große Bandbreite der Ergebnisse durch verschiedene Charakteristika der einzelnen Spezifikationen bzw. durch die Schätzgenauigkeit erklärt werden kann. Es zeigt sich, dass die Schätzungen der Einkommenselastizität in systematischer Weise von bestimmten Spezifikationsmerkmalen abhängen (z.B. vom Typ des verwendeten Geldmengenaggregats und von der Einbeziehung von Variablen für Finanzinnovationen bzw. für Vermögen). Dennoch kann aber ein maßgeblicher Teil der beobachtbaren Variation durch diese Variablen alleine nicht erklärt werden.

Résumé

A quel point les estimations de demande monétaire sont-elles robustes? Un résumé méta-analytique de résultats concernant l'élasticité des revenus

Les auteurs font ici une méta-analyse d'études empiriques sur la demande monétaire qui se base sur 500 estimations individuelles. Ils analysent si la large variété des résultats peut s'expliquer par les différentes caractéristiques des études ou par l'imprécision des estimations individuelles. Ils constatent que les estimations de l'élasticité des revenus dépendent de manière systématique de certaines caractéristiques des études (par exemple du type de l'aggrégat monétaire utilisé et de l'inclusion de variables telles que l'innovation financière et la richesse). Néanmoins, une partie substantielle de la variabilité reste inexpliquée.