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The effect of financial development on economic growth: a meta-analysis

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The effect of financial development on economic growth: a meta-analysis*

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Abstract

Empirical studies on the finance-growth relationship show a wide range of estimated effects. We perform a meta-analysis on in total 551 estimates from 68 empirical studies that take private credit to GDP as a measure for financial development and distinguish between linear and logarithmic specifications. First, we find evidence of significantly positive publication bias in both the linear and log-linear specifications. This contrasts with findings in two other recent meta-studies, possibly due to a distortion introduced by their transformation procedure. Second, the logarithmic estimates give a robust significantly positive average effect of financial development on economic growth after correction for publication bias. In our preferred specification a 10 percent increase in credit to the private sector increases economic growth with 0.09 percentage points. For the linear estimates, no significant effect of credit to the private sector on economic growth is found on average. Overall, the evidence points to a positive but decreasing effect of financial development on growth.

Keywords: financial development; economic growth; credit to the private sector; meta-analysis

JEL classification: E44, G10, G21, O16, O40

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1 Introduction

The financial crisis that erupted in 2008 has renewed the interest in the effect that financial development has on the real economy. Previous to the crisis, the dominant view in the literature was that financial development had a positive effect on economic growth. Theoretically, the central argument was that more developed financial systems reduce information frictions and transaction costs and as such facilitate growth. In support of this position, Levine (2005), based on a discussion of the available empirical evidence, concludes that the overall effect of more finance on growth is positive. After the crisis, economists have grown more critical of this assessment. As summarized by Beck et al. (2014), an oversized financial sector may result in a misallocation of resources, instability, imperfect competition, rent extraction, implicit insurance due to bailouts and negative externalities from auxiliary financial services.

Despite more than twenty years of research, to date economists have not yet reached consensus on the empirical relation between financial development and economic growth. The size and even the sign of growth-effects vary between and within empirical studies. A qualitative comparison of studies suggests that the estimated effect depends on the estimation techniques, the proxy measures for financial development, the time span of the data, the countries included in the estimation, and the control variables used. For an in-depth overview of the empirical literature, we refer to review papers such as Levine (2005), Ang (2008), or Bijlsma and Dubovik (2014).

In our study, we contribute to the debate through a meta-analysis of (part of) the finance and growth literature. Specifically, we perform a meta-analysis on in total 551 estimates from 68 empirical studies that take private credit to GDP as a measure for financial development and distinguish between linear and logarithmic specifications. We focus on the following questions. First, to what extent does the empirical literature suffer from publication bias? Second, to what extent does the empirical literature provide evidence of either a constant or a declining significantly positive effect of financial development on economic growth? Finally, what is the size of the effect?

A meta-analysis has several benefits. First, it allows a more precise estimate of the effect of financial development on growth by combining multiple studies. Second, it provides insight in the sources of heterogeneity in estimates of the relation between financial development and growth. Third, it provides a way to correct for potential publication bias. Correcting for publication bias is important in order not to overestimate the effect. Also, if publication bias is present, this adds to the evidence that individual studies can not be relied upon to make inferences on the size of effects.

Three other meta-analyses have been recently published on this topic. Bumann et al. (2013) focus on the topic of the liberalization-growth nexus. More closely related are Valickova et al. (2014) and Arestis et al. (2014). We add to these studies in three ways. First, we include additional recent papers in our analysis. Second, we focus on more comparable estimation results as we only include specifications that measure financial development by credit to the private sector. This implies that we do not resort to a unit-less normalization of estimation results of the empirical studies. In section

6 we demonstrate that this normalization is not innocuous and may lead to incorrect conclusions with respect to publication bias. Indeed, simulations show that a positive significant bias can turn negative due to the transformation. An additional benefit of not using this transformation is that it allows us to give an economic interpretation of our results and identify the mean effect of more finance on growth. Third, we distinguish between papers that include credit to the private sector linearly or logarithmically. A linear specification hypothesizes that the growth effect of a one percentage point increase in private credit is independent of the prevailing financial development level, while a log-linear specification hypothesizes an effect that decreases in the level of credit to the private sector. Both types of models are used extensively in the literature, and there does not seem to be a clear preference for one over the other. In recent years scholars have started to more explicitly study the possibility of a nonlinear effect, but we also found a sizable set of recent papers using a linear specification. By distinguishing between linear and logarithmic specifications, we provide insight in what is arguably an important question: how much finance is enough?

We have the following results. First, we find consistent evidence of the presence of a publication bias in both studies with logarithmic and studies with linear specifications: studies that report a positive effect of financial development on economic growth get more easily published. Although we do not find evidence that the level of bias has decreased or increased post crisis, we do find that post crisis the range of estimates has increased in both types of studies. Second, after correcting for publication bias, we find a considerable difference between linear and logarithmic specifications. Studies using a logarithmic specification give on average a positive and significant effect of financial development on growth. In our preferred specification a 10 percent increase in credit to the private sector increases economic growth with 0.09 percentage points. In contrast, studies using linear specifications on average do not find a significant effect. Third, we find several background characteristics that can explain part of the variation in the estimation results. For logarithmic specifications the estimates are significantly related to the journal impact factor, the estimation method, whether other proxies for financial development were included, the number of countries included in the study and whether countries are developing or developed countries. The estimates from linear specifications are significantly related to the year in which the study was performed, the time span of the data used and whether other proxies for financial development were included.

The outline of the paper is as follows. Section 2 discusses the methodology used in this meta-analysis. In section 3 we discuss data sources and provide descriptives. In section 4 we present the results of our analysis and in section 5 we discuss several robustness analyses. Section 6 compares our result with other meta studies. Section 7 concludes.

2 Method

Meta-analysis treats each estimate of the finance-growth relationship as one observation. Each observation holds information on that relationship, allowing to deal with heterogeneity across studies and publication bias (e.g. Stanley (2008), Nelson and Kennedy

(2009), Kepes et al. (2012)). Heterogeneity across studies is dealt with by regressing the vector of observations (estimates) on the characteristics of the underlying studies from which the estimates are obtained.

Meta-analysis can also identify and correct for the skewed results due to publication bias. Publication bias arises if unfavorable results are suppressed in the literature. For the case of the finance-growth nexus, one could hypothesize that negative or insignificant estimates in the past were less likely to be published, because mainstream economics generally assumed a positive effect of financial development on economic growth. Since the start of the financial crisis, perspectives have changed and several studies (see for instance Arcand et al. (2015)) have appeared pointing to the possibility of “too much finance”, implying a negative relation between finance and growth under certain conditions.

In this paper, the first step in the analysis is of a qualitative nature. To analyze the potential presence of publication bias, we provide a funnel plot of all estimates in our sample. A funnel plot is a scatterplot of each study’s estimates against some measure of the precision of the estimates, usually the inverses of their standard error. Less precise studies, with a larger variation in results, therefore appear at the bottom of the funnel plot. When we move to the top of the funnel plot, estimates become more precise and less scattered. In the absence of publication bias, this decreasing variability would generate the figure of upside down funnel, symmetrically spread out around the ’true’ estimate of effect. When unfavorable results are systematically suppressed in the literature, the funnel will have an asymmetrical shape; less studies with negative (or positive) estimates of effect are published than would be expected based on a randomly increasing variability for less precise studies. In the finance-growth literature we would expect negative or insignificant estimates of the effect to get less easily published.

In the second step, we perform a formal statistical test to uncover the presence of publication bias, as well as to obtain an estimate of the true value of the parameter of interest, the coefficient linking financial development to economic growth. The test is provided by the FAT-PET method. The basis of this method is the regression:

$$EST_{ij} = \beta_0 + \beta_1 SE_{ij} + \varepsilon_{ij} \tag{1}$$

Here, EST_{ij} and SE_{ij} denote the i-th estimation of the effect in study j and its standard error, respectively. β_0 is the true effect, β_1 measures publication bias and ε_{ij} denotes an error term. Because SE_{ij} is the standard deviation of EST_{ij}, the equation is heteroskedastic. This issue is addressed by applying weighted least squares with a diagonal weight matrix with elements $1/SE_{ij}$ to correct for heteroskedasticity (see e.g. Stanley (2008)).

Significance of β_1 in regression (1) indicates the presence of publication bias. This is called the Funnel Asymmetry Test (FAT), or Egger test. In the finance-growth case, we would expect β_1 to be positive if publication bias is present, as insignificant and negative estimates would be underrepresented in the sample. Additionally, the Precision Estimate Test (PET) is a test for the presence of a significant ’true’ effect and tests the significance of β_0.

When there is heterogeneity in the estimates, the FAT-PET regression can give false significant results and the funnel plot can show asymmetry even when an actual publication bias is absent (see e.g. Stanley (2008) and Terrin et al. (2003)). For example, if studies using instrumental variables give smaller estimates with higher standard errors than studies using simple OLS, it might seem in the funnel plot that large estimates with high standard errors, and therefore low precision, are missing. Also, in this case there is a negative correlation between estimates and standard errors that is not driven by publication bias. We can control for this by including the estimation technique and other real factors that might affect the estimates as explanatory variables. To correct for possible sources of heterogeneity, we modify the model in the following way:

$$EST_{ij} = \beta_0 + \beta_1 SE_{ij} + \gamma X_{ij} + \varepsilon_{ij} \tag{2}$$

Here, X_{ij} is a vector of characteristics of the estimates. Equation (2) is the main specification in our analysis, and is referred to as the meta regression analysis or mra.

Instead of including SE_{ij} in equations (1) and (2) to control for publication bias, it is also possible to use the variance VAR_{ij} of each estimate. Recent research has shown that when using the standard error the estimated 'true' effect β_0 is biased towards zero (Stanley and Doucouliagos (2014)) and that this bias is smaller when the variance is used instead. On the other hand, most meta studies, including the two benchmark meta studies on finance-growth Valickova et al. (2014) and Arestis et al. (2014), use the standard error SE_{ij} in the analysis. We will follow their approach, but provide results for VAR_{ij} as a robustness check.

One study usually presents several estimation results. In our meta-analysis sample, the number of estimates per study varies between 1 and 51. To avoid distortion of the meta-analysis by studies that contain many estimates, we weigh each estimate with the inverse of the number of estimates in its study.

3 Data collection and description

The literature studying the relation between finance and growth is vast and heterogeneous. Researchers have adopted various methodologies to address the issue of causality: does economic growth induce demand for financial services or does financial development spur growth? Studies also differ in their preferred measure of financial development. Doing a meta-analysis on such a vast and heterogeneous literature requires several choices, which are guided by the aim of getting a large set of comparable studies.

First, because it is the largest group of relatively comparable studies, our meta-analysis focuses on cross-country studies only. This choice rules out papers relying on time series techniques, such as studies using single country co-integration analysis and studies using micro data trying to construct control and treatment groups to address causality issues. The latter are often unique in their methodology and focus on specific outcome variables.

Second, within the set of cross-country studies there is still a lot of heterogeneity in methodology. We include cross-country studies using basic OLS, fixed or random effects panel models, lagged explanatory variables, instrumental variables, or dynamic panel techniques. However, we exclude vector error correction-models and multivariate time series analyses. These are unsuited for a meta-analysis because they have multiple relevant coefficients measuring the impact of financial development rather than one relevant coefficient.

Third, researchers use different measures of financial development. Ideally, an indicator for financial development captures the capacity of the sector to efficiently provide financial services. Constructing such a measure is challenging. Indeed, Levine et al. (2000) argue that researchers cannot construct accurate and comparable measures of these financial services for a large number of countries over a long time span. A large part of the empirical cross-country studies use domestic credit to the (non-financial) private sector relative to GDP as a measure of financial development. In this, they follow the seminal paper by King and Levine (1993), who find that this measure of financial development is a good predictor of economic growth. A key advantage of this measure is also that it is available for a large cross-section of countries and over a long time period, as the data go back to 1960 for many countries. Because we want our set of studies to be as large as possible while at the same time as comparable as possible, we include those specifications that use as their measure credit to the private sector relative to GDP. This implies we do not include studies that use other measures such as the size or turn-over of stock markets or the amount of central bank credit to total credit.

Fourth, we focus on studies that use the growth of real GDP per capita as dependent variable. This is the large majority of available studies. Some studies analyze the effect of financial development on other macro-economic development indicators, such as the growth of human capital or the growth of physical capital. As these different dependent variables have different units of measurement, regression results from those dependent variables are not readily comparable. Including multiple measures of macro-economic development would require a normalization of the estimates. We demonstrate in section 6 that such a normalization can lead to incorrect conclusions on the publication bias.

Finally, researchers have to choose a particular functional form. Part of the literature uses a linear functional form of the finance growth relationship, suggesting a monotonic link between the two. Another part of the literature implements a logarithmic specification, implying decreasing returns to financial development. Finally, a very small fraction of the literature uses a quadratic specification, allowing for a point where financial development hurts growth. In our view, the issue of non-linearity is important. A linear model assumes that returns to financial development remain constant, regardless of the level of development of the financial sector. A non-linear model loosens this restriction and allows for diminishing as well as increasing returns of financial development. We explicitly distinguish studies on the basis of their assumption of either a linear or log-linear relation between financial development and growth by performing two separate meta-analyses. In a separate section, we will compare our results for the two groups with the results in Valickova et al. (2014) and Arestis et al. (2014). Both of these combine the two groups in a joint analysis.

We do not include the quadratic specifications in our study, as each quadratic form is characterized by two joint parameter estimates. This does not easily fit in the setup of a meta-analysis where each estimate is a dependent variable in a multivariate regression. As mentioned earlier, the number of studies using quadratic specifications is still rather limited.

Summarizing, we searched for studies that meet the following criteria:

1. The study regresses growth of real GDP per capita on two or more variables including a proxy for financial development;
2. The study uses credit to the private sector relative to GDP as proxy for financial development;
3. The study uses a cross country-dataset;
4. The estimate is not based on a vector error-correction model or multivariate time series analysis;
5. The estimated equation is linear or logarithmic in the financial development proxy;
6. The study reports sufficient statistical information on the regression (coefficient and standard error, t-statistic or p-value);
7. The study is written in English.

In the end, we found 68 studies, with 551 estimates, that meet all of the aforementioned criteria. We include all the estimates presented in a study and do not differentiate between main regressions and regressions that are presented for robustness purposes. In total 249 estimates, from 27 studies, are based on an equation that is logarithmic in the financial development proxy. The remaining 302 estimates, from 42 studies, are based on a linear specification.[1] In all studies real GDP per capita growth serves as the dependent variable, though the exact measurement sometimes slightly differs.[2] We rescale each estimate to a specification where both the dependent variable and the main independent variable - the ratio of private credit to GDP - are measured in rates, to allow for a joint analysis and interpretation.

Tables 1 and 2 present some descriptives statistics of the included studies.[3] We report the number of estimates from each study, the mean of the estimates from each study, the standard deviation of the reported estimates and the average of the reported standard errors.[4]

For the logarithmic specifications, the number of estimates per study varies quite strongly, from 1 estimate to 51 estimates from a single study. As expected, most studies

[1] Arcand et al. (2015) estimates both linear and logarithmic specifications.

[2] Some use GDP growth in percentages, others the GDP growth rate (defined as a percentage divided by 100), other again the log of 1 + the GDP growth rate.

[3] Our final dataset is available at http://www.cpb.nl/en/publication/the-effect-of-financial-development-on-economic-growth-a-meta-analysis

[4] Suppose a study reports n estimates $x_1, x_2, \ldots, x_n$ with standard errors $s_1, s_2, \ldots, s_n$. The standard deviation of the reported estimates is calculated as the root of $\frac{1}{n-1}\sum_i (x_i - \bar{x})^2$ while the average of the reported standard errors is calculated as $\frac{1}{n}\sum_i s_i$.

report positive estimates. It is clear from the mean estimates that the estimates from Hassan et al. (2011a) strongly differ from the other studies. The (unweighted) mean of the estimates excluding the estimates from Hassan et al. (2011a) is 0.014. This would imply that a 10 percent increase in the ratio of private credit to GDP leads to a 0.13 percentage point increase in annual GDP growth.

For most studies, the standard deviation of the reported estimates is in the same order of magnitude as the average of the reported standard errors. This indicates that within a study, the estimates do not diverge more than expected. If the standard deviation of the reported estimates would be much larger than the average of the reported standard errors, this would indicate that there is a great amount of within-study variation caused by the different specifications and methods that the study uses. Apparently, the studies that use a logarithmic specification present results that are fairly robust to different specifications and estimation methods, or the specifications and methods used are not very different within a study.

Between studies, the variation in estimates is mainly caused by the estimates from Hassan et al. (2011a). The standard deviation of all reported estimates is 0.23, but excluding Hassan et al. (2011a) it is 0.02. As expected, the standard deviation excluding the diverging estimates is higher than most within-study standard deviations, but the difference is not extreme. Also, the standard deviation of the reported estimates excluding the diverging estimates is in the same order of magnitude as the average of the reported standard errors. Most of the heterogeneity in estimates therefore seems to come from the nine observations originating from Hassan et al. (2011a).

For the linear specifications, the number of estimates per study varies between 1 and 36. There is quite some variation between the mean estimates; several studies report a negative effect. The studies by Hassan et al. (2011b) and Saci et al. (2009) stand out as they report extremely high estimates and standard errors. In the next section we will treat two estimates from Hassan et al. (2011b) and all four estimates from Saci et al. (2009) with caution. The (unweighted) mean of the estimates, excluding the six diverging estimates, is 0.013. The interpretation is slightly different from the logarithmic specifications; the coefficient of 0.013 implies that an increase of 10 percentage points in the ratio of private credit to GDP increases the percentage growth of GDP with 0.13 percentage points.

When comparing linear and log-linear results for the growth effect of financial development, we need to take into account the starting level of financial development. For example, starting from a credit to GDP ratio of 70% of GDP, the linear models on average predict that an increase to 77% increases GDP growth by 0.09 percentage points, while the logarithmic models on average predict an increase in GDP growth of 0.13 percentage points. For most relevant ratios of private credit to GDP, linear models imply a smaller effect than logarithmic models.

For most of the linear studies the standard deviation of the reported estimates is in line with the average of the reported standard errors, indicating that the estimates within a study do not differ more from each other than expected given their standard errors. As before, the between-study variation is quite sizable, but this is mainly caused by the six estimates from Hassan et al. (2011b) and Saci et al. (2009). When those observations are removed, the standard deviation of the remaining estimates is 0.08, which is not extremely larger than the within-study standard deviations. The standard deviation of all estimates excluding the diverging estimates is a factor 4 larger than the average reported standard errors, which is sizable but again not extremely so. Note that, compared to the logarithmic studies, the linear studies show a higher standard deviation, both within and between studies. The analysis in the next section will confirm this feature of the data.

Table 1: Descriptives logarithmic specifications

Study	**Number of estimates**	**Mean estimate**	**Standard deviation estimates**	**Mean standard error**
Allen and Ndikumana (2000)	2	.0735	.0714	.0498
Andersen and Tarp (2003)	4	.0235	.0275	.0358
Arcand et al. (2015)	9	.0075	.0044	.0037
Beck and Levine (2004)	27	.0097	.0092	.0069
Beck et al. (2000)	4	.0232	.0073	.0078
Beck et al. (2014)	51	.0014	.0032	.0036
Benhabib and Spiegel (2000)	4	.0215	.0119	.0148
Capelle-Blancard and Labonne (2016)	2	-.0023	.0154	.0196
Cojocaru et al. (2011)	9	.0270	.0167	.0134
Estrada et al. (2015)	14	.0176	.0021	.0081
Favara (2009)	23	.0059	.0031	.0055
Gantman and Dabós (2012)	15	.0024	.0017	.0049
Giedeman and Compton (2009)	2	.0219	.0039	.0105
Hassan et al. (2011a)	9	-.3222	1.2540	.6156
Huang and Lin (2009)	3	.0302	.0044	.0107
Huang et al. (2010)	2	.0252	.0005	.0094
Jalilian and Kirkpatrick (2005)	2	.2050	.0495	.0946
Ketteni et al. (2007)	2	.0155	.0008	.0014
Law et al. (2013)	1	.0158	*	.0050
Levine et al. (2000)	13	.0274	.0125	.0090
Loayza and Ranciere (2006)	4	.0097	.0004	.0008
McCaig and Stengos (2005)	6	.0232	.0082	.0073
Rioja and Valev (2004b)	8	.0134	.0072	.0041
Seetanah et al. (2009)	1	.0700	*	.0347
Tang (2006)	3	.0277	.0130	.0343
Valev and Tasic (2008)	3	.0226	.0023	.0110
Yay and Oktayer (2009)	26	.0117	.0063	.0086
Total	249	.0015	.2349	.0306
Excluding Hassan et al. (2011a)	240	.0137	.0228	.0123

* Standard deviation cannot be calculated as the number of estimates is 1

Table 2: Descriptives linear specifications

Study	Number of estimates	Mean estimate	Standard deviation estimates	Mean standard error
Andersen (2003)	5	.0328	.0141	.0131
Andini (2011)	21	.0264	.0076	.0134
Andrés et al. (2004)	12	-.0211	.0420	.0482
Apergis et al. (2007)	6	.0385	.0462	.0074
Arcand et al. (2015)	6	.0226	.0207	.0116
Bandyopadhyay (2005)	2	.0411	.0215	.0116
Bangake and Eggoh (2011)	4	.2228	.1003	.0143
Beck et al. (2012)	1	.0080	*	.0033
Caporale et al. (2015)	4	.0303	.0239	.0320
De Gregorio and Guidotti (1995)	17	.0059	.0624	.0254
Dudian et al. (2013)	2	-.0660	.0000	.0249
Estrada et al. (2010)	4	.0181	.0011	.0064
Fink et al. (2009)	12	-.0036	.0279	.0189
Gaffeo and Mazzocchi (2014)	8	-.0519	.0074	.0185
Garretsen et al. (2004)	3	.0437	.0346	.0227
Georgantopoulos et al. (2015)	3	-.1913	.1649	.0691
Grassa and Gazdar (2014)	12	.0241	.0433	.0330
Gründler (2015)	14	-.0059	.0056	.0028
Haiss and Kichler (2009)	3	.0208	.0097	.0157
Haslag and Koo (1999)	3	.0308	.0030	.0097
Hassan et al. (2011b)	4	1.1025	.8290	.4675
Hodges and Knabb (2010)	36	.0176	.0221	.0082
Kemal et al. (2007)	1	-.0121	*	.0043
King and Levine (1993)	2	.0345	.0035	.0105
Kjosevski (2013)	2	-.0587	.0180	.0279
Levine (1998)	6	.0448	.0140	.0140
Levine (1999)	6	.0672	.0406	.0210
Levine and Zervos (1998)	13	.0124	.0026	.0069
Manning (2003)	4	.0075	.0042	.0061
Mhadhbi (2014)	9	-.0554	.0127	.0398
Minier (2003)	3	.0050	.0174	.0073
Musamali et al. (2014)	8	.2450	.1433	.0471
Naceur and Ghazouani (2007)	6	-.0510	.0450	.1320
Narayan and Narayan (2013)	7	-.0494	.1107	.0380
Oluitan (2012)	2	.0152	.0160	.0044
Petkovski and Kjosevski (2014)	1	-.4150	*	.1318
Rioja and Valev (2004a)	1	.0370	*	.0112
Rousseau and Wachtel (2011)	18	.0110	.0143	.0111
Saci et al. (2009)	4	-1.3908	.4792	.8553
Sassi and Goaied (2013)	8	-.0264	.0207	.0137
Shen and Lee (2006)	18	-.0261	.0128	.0051
Yu et al. (2012)	1	.0809	*	.0376
Total	302	.0059	.2378	.0375
Excluding Saci et al. (2009) and two estimates from Hassan et al. (2011b)	296	.0126	.0810	.0207

* Standard deviation cannot be calculated as the number of estimates is 1

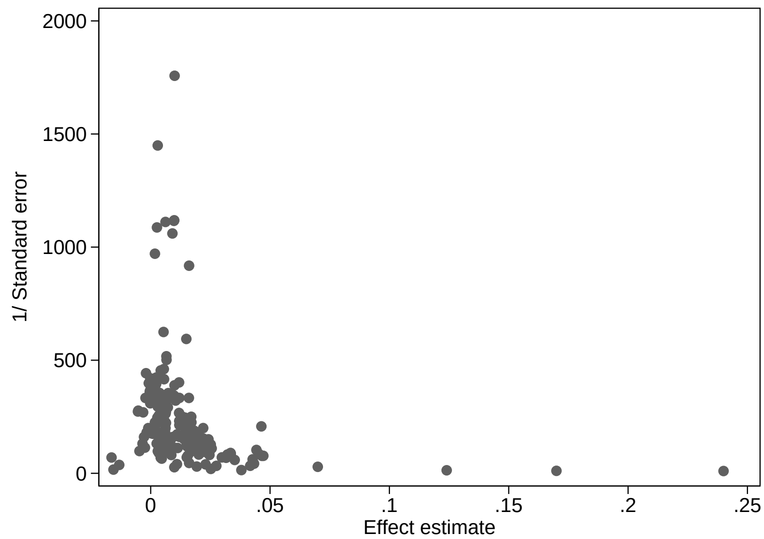
4 MRA: results

4.1 Preliminary analysis

Before estimating a full meta regression model, we present some descriptives and simple analyses. We choose to base the analysis of the logarithmic specifications in this section, including the regression in subsection 4.2, on the sample excluding all nine estimates from Hassan et al. (2011a), to prevent them from having a dominant effect on our estimation results in the meta regressions analysis. Those estimates have a disproportional size and standard error. Six of them are more than two standard deviations away from the mean estimate. Moreover, the standard errors of these nine estimates range between 0.27 and 1.37, while the other estimates have standard errors in the range between 0.0006 and 0.098. Section 5 presents a robustness check, including the Hassan et al. (2011a) estimates.

Figure 1 presents the funnel plot for the logarithmic specifications.[5] Most estimates from the logarithmic specifications are fairly small, between -0.01 and 0.03. As expected, the larger estimates have a lower precision. The data seems asymmetrical as the estimates with a low precision almost exclusively are positive. This is a sign of publication bias where (strong) negative estimates are suppressed.

Figure 1: Funnel plot of log models (excluding disproportionate estimates)



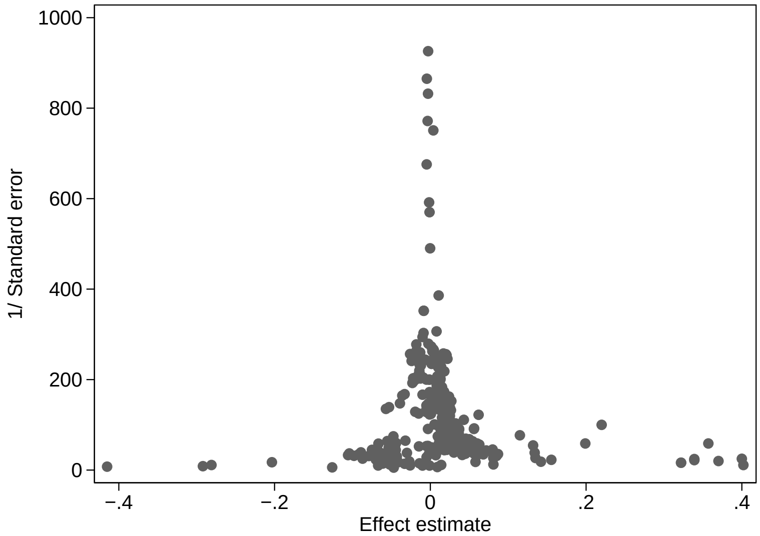
We choose to base our main analysis of the linear specifications in this section on the sample excluding the four estimates from Saci et al. (2009) and two estimates from Hassan et al. (2011b), as those estimates have a very large size and standard error. Each

[5]Figure A.1 in Appendix A presents a funnel plot of the full sample, including the nine estimates from Hassan et al. (2011a).

of those estimates is more than three standard deviations away from the mean estimate, while the estimates that are included in our sample all depart less than 2 standard deviations from the mean. Moreover, the standard errors of the six excluded estimates range between 0.65 and 1.10, while the other estimates have standard errors between 0.001 and 0.18. We present a robustness check including the six estimates in section 5.

Figure 2 presents a funnel plot of the estimates from linear specifications and the inverse of their standard errors.[6] The estimates from linear specifications are quite diverse, the majority ranging between -0.2 and 0.2. There is no immediately obvious asymmetry in the funnel plot, although it does seem that negative estimates are slightly underrepresented, especially for intermediate precisions.

Figure 2: Funnel plot of linear models (excluding disproportionate estimates)



4.2 Meta regression analysis

In the meta regression analysis (mra), we regress the estimates on a set of explanatory variables in addition to the standard error. We also test whether the publication bias effect has changed since the financial crisis. We expect that the crisis may have led to more open mindedness to nonsignificant or negative results, implying a lower publication bias. We define estimates as 'before crisis' if they have been published before or in 2009. This way, we allow for a time lag between acceptance of the manuscript and publication in print. Section 5 presents the results based on 2008 or 2010 as cutoff point as a robustness check.

Table 3 defines the variables we included in the mra. Appendix B contains some descriptive statistics of the explanatory variables. We normalized most continuous vari-

[6]Figure A.2 in Appendix A plots the full set of estimates.

ables, rescaling the minimum value observed in the dataset to 0 and the maximum observed value to 1. For the variables 'only developing' and 'only developed' we followed the classification that the authors of the underlying studies use. This classification can slightly differ between studies.[7]

Table 4 presents the mra results for the estimates from logarithmic specifications. Column I gives the results of a specification with a constant and the standard error as explanatory variables, also known as the FAT-PET regression or Egger test. The constant in this regression can be interpreted as the average effect of an increase in bank credit to the private sector over GDP, corrected for publication bias. Column II in the table gives the results of a specification with a constant publication bias effect and multiple explanatory variables. Column III gives an mra where the publication bias is allowed to vary dependent on whether or not the study has been published before the financial crisis. Note that the constants in regressions II and III do not have an economic interpretation as the added explanatory variables have a nonzero average. The three specifications will be used throughout the paper.

In columns I and II the coefficient for the standard error is positive and significant, confirming the presence of a bias towards publishing positive estimates. The results in column III show that this bias is present both in pre-crisis and post-crisis studies. The coefficients of the standard deviation before and after 2009 are quite similar. A Wald test fails to reject the hypothesis that the coefficients are equal to each other. The coefficient of the post-crisis standard deviation however has a larger standard error of the coefficient. Given that the estimates are more or less equally divided in pre- and post-crisis estimates, the higher standard error suggests that the range of published estimates has increased in the post-crisis literature.

The constant in regression I is positive and significant. This indicates that after correction for publication bias there is a 'true' positive average effect. As expected, the effect of 0.009 is smaller than the unweighted mean estimate (excluding disproportionate estimates) of 0.014. The effect of 0.009 implies that a 10 percent increase in credit to the private sector increases economic growth with 0.09 percentage points.

The level of the estimates does not significantly differ over time, as evidenced by the insignificant value of Year. Most of the other explanatory variables have the expected effect. Studies published in journals with higher impact scores on average report smaller estimates, which suggests that those journals might be more critical on the methodology used and robustness of the results. Similarly, specifications using the panel structure of the data, that is, incorporating both the country and time dimension, give smaller estimates. Using the time dimension allows for more precise estimates and better correction for endogeneity. Surprisingly, specifications that explicitly try to correct for endogeneity, by using instrumental variables or GMM with lagged instruments, give larger estimates. We tested the robustness of this result by incorporating separate dummies for IV correction and GMM correction, GMM has a positive and significant effect of similar size,

[7] For example, some countries joined the OECD fairly recently. Older papers classify those countries as 'developing', while more recent papers classify those countries as 'developed'.

Table 3: Explanatory variables in the mra

Pre crisis	Dummy indicating whether the study has been published before or in 2009.
Post crisis	Dummy variable indicating whether the study has been published after 2009.
Standard error pre crisis	Interaction of standard error with the pre crisis dummy.
Standard error post crisis	Interaction of standard error with the post crisis dummy.
Year	The publication year of the article or discussion paper, normalized between zero and one.
Impact factor	The impact factor of the journal or discussion paper series, normalized between zero and one.
Panel model	Dummy indicating whether the estimate is based on a model with a time dimension.[a]
Endogeneity corrected	Dummy indicating whether the estimate is based on a model that corrects for endogeneity.[b]
Extended model	Dummy indicating whether the estimate is from a model that includes an extensive set of additional explanatory variables.[c]
Additional proxy	Dummy indicating whether the estimate is from a model that includes one or more other proxies for financial development (e.g. stock market development).
Data after 2000	Dummy indicating whether the data includes one or more years after 2000.
Countries	The number of countries the estimate is based on, normalized between zero and one.
Only developing	Dummy indicating whether the model includes only developing countries.
Only developed	Dummy indicating whether the model includes only developed countries.

[a] Each estimate in our set is based on panel data, with both a time and country dimension, but in some models the data is first averaged over time such that the resulting data and model has only a country dimension. We categorize those averaged models as non-panel.

[b] That is, an instrumental variables model or a gmm model with internal (lagged) instruments.

[c] An extended model includes initial schooling and/or log initial GDP, and the model includes at least three variables out of government consumption, inflation, black market premium and trade openness.

Table 4: mra on estimates from logarithmic specifications

	I	II	III
	b/se	b/se	b/se
Standard error	0.987***	0.985***	
	(0.180)	(0.165)	
Pre crisis		0.002	0.002
		(0.002)	(0.002)
Year		0.000	0.000
		(0.004)	(0.004)
Impact factor		-0.007***	-0.007***
		(0.003)	(0.002)
Panel model		-0.005***	-0.005***
		(0.002)	(0.002)
Endogeneity corrected		0.004***	0.004***
		(0.001)	(0.001)
Extended model		-0.002	-0.002
		(0.002)	(0.002)
Additional proxy		-0.007***	-0.007***
		(0.002)	(0.002)
Data after 2000		-0.004**	-0.003*
		(0.002)	(0.002)
Countries		-0.025***	-0.024***
		(0.009)	(0.009)
Only developing		-0.003	-0.003
		(0.002)	(0.002)
Only developed		-0.009***	-0.009***
		(0.003)	(0.003)
Standard error pre crisis			0.954***
			(0.166)
Standard error post crisis			1.090***
			(0.375)
Constant	0.009***	0.024***	0.023***
	(0.001)	(0.007)	(0.007)
N	240	240	240
Adjusted R^2	0.148	0.636	0.634

Robust standard errors in parentheses. *: p<.1, **: p<.05 and ***: p<.01.

while IV has a positive, smaller, and insignificant effect. Also, we found no indication for multicollinearity.

Estimates that are based on an extended specification and/or on a specification that includes additional proxies for financial development are on average smaller. This is in line with standard econometric theory. Estimates that are based on data that includes one or more years after 2000 are also smaller than average. The negative effect of the number of countries can have at least two causes. First, adding more countries to the data allows more precise estimates of the effect. Second, our dataset includes several studies that focus on a specific set of countries, e.g. Tang (2006) considers APEC countries and Allen and Ndikumana (2000) consider countries in southern Africa. These specific data sets might show different effects than worldwide data. Finally, estimates based only on developed countries are significantly smaller than estimates based on a mixed data set. This suggests that the effect of financial development on economic growth is smaller in developed countries, which is in line with the theory of diminishing returns to financial development. The results would then suggest that the logarithmic specification (which already features diminishing returns), then apparently only partly corrects for this effect. Another explanation could be that credit to the private sector is a poor measure of financial development, that does not capture all relevant aspects.

Table 5: mra on estimates from linear specification

	I b/se	II b/se	III b/se
Standard error	1.420*** (0.423)	1.176* (0.603)	
Pre crisis		-0.027*** (0.006)	-0.029*** (0.006)
Year		-0.049*** (0.010)	-0.047*** (0.011)
Impact factor		0.003 (0.009)	0.003 (0.008)
Panel model		0.005 (0.003)	0.005 (0.003)
Endogeneity corrected		-0.006 (0.006)	-0.007 (0.005)
Extended model		0.001 (0.003)	0.001 (0.003)
Additional proxy		-0.011*** (0.004)	-0.010** (0.004)
Data after 2000		-0.012*** (0.003)	-0.012*** (0.003)
Countries		0.003 (0.010)	0.003 (0.010)
Only developing		0.011 (0.031)	0.012 (0.031)
Only developed		-0.001 (0.006)	-0.001 (0.006)
Standard error pre crisis			1.512*** (0.430)
Standard error post crisis			1.049 (0.780)
Constant	-0.001 (0.002)	0.054*** (0.009)	0.052*** (0.008)
N	296	296	296
Adjusted R^2	0.073	0.184	0.182

Robust standard errors in parentheses. *: p<.1, **: p<.05 and ***: p<.01.

The regression analysis of the linear models is reported in table 5. Also here, we find evidence for publication bias as the coefficients in columns I and II on the standard error are significant, although in column II only at the 10% level. Both coefficients are positive, indicating a tendency to suppress negative results. The bias seems to be mostly driven by pre-crisis studies, as the coefficient on the pre-crisis standard error is significant, while the coefficient on the post-crisis standard error is not. However, a Wald-test on specification III shows that the difference between the pre- and post-crisis standard error is non-significant. This suggests that, as in the logarithmic case, the range of estimates has increased in the post-crisis era.

The 'true' average effect as measured by the constant in specification I is insignificant and much lower than the unweighted average. Given that the publication bias correction is significant and relatively sizable, the drop in the effect is caused by correcting for publication bias.

Only a few of the additional explanatory variables are significant. This is also reflected in the (adjusted) R-squared, which is relatively low. The diversity that is visible in the funnel plot of the linear estimates apparently cannot be explained well by the variables we included in the mra.

Of the significant variables, the variables 'Additional proxy' and 'Data after 2000' have a negative effect. This is similar to the logarithmic specifications and in line with our expectations. In contrast to the logarithmic specifications, the variables 'Year' and 'Pre-crisis' have a negative significant effect. The negative effect of year of publication is quite common in meta-regressions and is explained by the development of better methodology, allowing for a more precise estimate. The downward trend has been observed in the literature before, see Rousseau and Wachtel (2011). The negative effect of the pre-crisis dummy is more puzzling as one would expect that journals prefer smaller and less optimistic estimates after the crisis.

5 Robustness checks

In this section, we present a number of robustness checks. First, we consider whether the use of the variance instead of the standard error as an indicator of publication bias influences the results. A recent contribution by Stanley and Doucouliagos (2014) argues that when using the standard error the estimated 'true' effect β_0 is biased towards zero and that this bias is smaller when the variance is used instead. Nevertheless, all meta-studies we are aware of use the standard error as an indicator and in the previous section we conformed to that standard. Second, instead of excluding the disproportionate estimates from our analysis, we do our analysis including all studies, to assess the effect of excluding those estimates. Third, we consider what happens to our findings when we include only published studies, and exclude working papers. Fourth, we analyse how robust our findings are when varying the year that distinguishes pre-crisis and post-crisis studies. We took this year to be 2009. This seemed like a reasonable choice given a publication lag of one year. We study what happens if we change this year to 2008 or to 2010. Fifth, some literature (see Nelson and Kennedy (2009)) suggests to correct for the number of estimates per study by using cluster-robust error terms, clustering at study-level. We use this method as a robustness check. Finally, we consider what happens if we estimate either study fixed effects or random effects models, where the panel dimension is the number of estimates in a particular study. Note that in case of fixed effects, the constant and several study-level variables are not identified, and studies that report only one estimate cannot be included in the analysis.

We also performed some unreported robustness checks with respect to disproportionate large or small estimates and weights. Moreover, we estimated several specifications that included the years of the primary studies' data sets in more detail than the 'Data after 2000' dummy. In addition we estimated specifications that included the number of estimates in the primary studies and the number of explanatory variables in the underlying regressions. The results of those robustness checks are available on request, and are very similar to our main results.

5.1 logarithmic models

Tables 6 and 7 summarize the results of the robustness checks for the logarithmic specifications with respect to the most important coefficients. In panel (a) of table 6 we report the results for specification I with the standard error (or variance) as single explanatory variable. Panel (b) contains the results for specification II which includes additional control variables. Table 7 shows the results for specification III. Compared to specification II, here we distinguish in the pre- and post-crisis effect of the standard error.

We start our discussion with panel (a) of table 6. The first column with results ('base') repeats the coefficients of our baseline regression. Since the estimated coefficient on the standard error is positive and significant, publication bias cannot be rejected. Moreover, the 'true' effect of financial development on economic growth, captured by the constant, is found to be significantly positive. The second column ('var') shows that indeed the estimated constant increases when the variance is used to correct for publication bias, though the increase is modest. Also, the coefficient for the variance is positive and highly significant.

In the subsequent columns, we include the disproportionate estimates ('all') and use only published studies ('pub'), respectively. The results remain virtually the same as in the baseline specification. Note that the disproportionate observations all have a high standard error and thus get a low weight in the regression. When we vary the year that separates pre-crisis and post-crisis studies (columns '2008' and '2010' respectively), the results are exactly identical to the baseline results as specification I does not include crisis-dependent variables.

Using cluster-robust standard errors (column 'clustered') strongly increases the standard errors of the coefficients. This is a common feature of cluster-robust standard errors, which makes it difficult to compare the levels of the estimated coefficients. Due to the high standard errors, no significant publication bias is found. There is still evidence of a significantly positive 'true' effect, though. The coefficients of the fixed effects and random effects models (columns 'fixed' and 'random') in general follow the baseline specification in terms of sign and significance, but the size of the coefficients differs from the baseline.

All in all, in the case of specification I for the logarithmic model, we conclude that our findings are robust to all the alternative specifications mentioned above. We find strong support for significant publication bias as well as a small but significantly positive effect of financial development on economic growth.

Panel (b) of table 6 has the same format as panel (a) and shows the results for the extended specification II. The sign, size and significance of the publication bias is robust to the different checks and very similar to the effect found in panel (a). The estimated constant is significantly positive in most cases and more than double the size from that in panel (a). Due to the non-zero mean character of the control variables, no direct conclusions can be drawn with respect to the size of the 'true' effect. Overall, the results from the extended specification support those from the simple specification in panel (a).

In table 7 we report the robustness results for specification III, where separate coefficients are estimated for the pre- and post-crisis standard error (variance) to investigate the possible decrease in publication bias in the later period. Without discussing every column in detail, we summarize the results as follows. First, the estimated pre-crisis coefficient for the standard error (variance) is significantly positive and similar in magnitude to the results in table 6. The estimated coefficient for the post-crisis standard error fluctuates quite strongly across the different robustness tests, but given the high standard error of the estimate this is not surprising. The estimated coefficient for the post-crisis variance (column 'var') is not significant. Although the size of the effect is similar to the effect of the pre-crisis variance, the estimated standard deviation is much higher. Finally, the estimated constant is similar in size and significance to that in panel (b) of table 6.

Overall, the results in table 7 confirm the robustness of our baseline results.

Table 6: Logarithmic specifications; robustness checks on specifications I and II

(a) Summary table robustness checks specification I

	base b/se	var b/se	all b/se	pub b/se	2008 b/se	2010 b/se	clustered b/se	fixed b/se	random b/se
Standard error	0.987***		0.911***	0.999***	0.987***	0.987***	0.670	0.607***	0.617***
	(0.180)		(0.174)	(0.197)	(0.180)	(0.180)	(0.503)	(0.161)	(0.153)
Variance		23.493***							
		(3.164)							
Constant	0.009***	0.010***	0.009***	0.009***	0.009***	0.009***	0.006**		0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)		(0.002)
N	240	240	249	191	240	240	240	238	240
Adjusted R^2	0.148	0.093	0.130	0.137	0.148	0.148	0.052	-0.048	

(b) Summary table robustness checks specification II

	base b/se	var b/se	all b/se	pub b/se	2008 b/se	2010 b/se	clustered b/se	fixed b/se	random b/se
Standard error	0.985***		0.869***	0.941***	1.146***	0.975***	0.929**	0.558***	0.571***
	(0.165)		(0.164)	(0.215)	(0.169)	(0.164)	(0.334)	(0.146)	(0.142)
Variance		18.538***							
		(3.133)							
Constant	0.024***	0.032***	0.025***	0.023***	0.016***	0.025***	0.017**		0.021
	(0.007)	(0.006)	(0.006)	(0.008)	(0.005)	(0.007)	(0.007)		(0.018)
N	240	240	249	191	240	240	240	238	240
Adjusted R^2	0.636	0.596	0.606	0.731	0.680	0.635	0.588	0.152	

Robust standard errors in parentheses. *: $p<.1$, **: $p<.05$ and ***: $p<.01$.

Table 7: Logarithmic specifications; robustness checks on specification III

	base	var	all	pub	2008	2010	clustered	fixed	random
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
S.e. pre crisis	0.954***		0.935***	1.076***			0.639*	0.685***	0.691***
	(0.166)		(0.168)	(0.200)			(0.342)	(0.169)	(0.164)
S.e. post crisis	1.090***		0.711**	0.175			1.555***	0.199	0.228
	(0.375)		(0.310)	(0.420)			(0.551)	(0.284)	(0.276)
Var. pre crisis		18.411***							
		(2.977)							
Var. post crisis		22.457							
		(32.626)							
S.e. pre crisis (2008)					1.163***				
					(0.196)				
S.e. post crisis (2008)					1.120***				
					(0.254)				
S.e. pre crisis (2010)						0.933***			
						(0.166)			
S.e. post crisis (2010)						1.140***			
						(0.406)			
Constant	0.023***	0.032***	0.026***	0.027***	0.016***	0.024***	0.016**		0.021
	(0.007)	(0.007)	(0.007)	(0.009)	(0.005)	(0.008)	(0.006)		(0.018)
N	240	240	249	191	240	240	240	238	240
Adjusted R^2	0.634	0.594	0.606	0.742	0.679	0.634	0.605	0.157	

Robust standard errors in parentheses. *: p<.1, **: p<.05 and ***: p<.01.

5.2 linear models

The results of the robustness checks for the linear models are in tables 8 and 9. The lay-out is the same as in tables 6 and 7.

The baseline result in panel (a) of table 8 shows a significantly positive publication bias and an insignificant 'true' effect (the constant). Across all robustness checks that use the standard error as explanatory variable, this baseline result is confirmed. The only exception occurs when the variance is used to correct for publication bias. Then, we find insignificant publication bias and a positive and significant constant. A possible explanation for the insignificant publication bias is that our baseline findings may be driven by observations with relatively small standard errors. Due to the compression of these small numbers when squaring them, the size of the estimate decreases, while the standard error in the estimate increases due to the non-linearity of the transformation, resulting in an insignificant estimate of the variance coefficient.

In panel (b), we extend the specification by including control variables. In the baseline specification, we find significantly positive publication bias - though a bit smaller than in panel (a) - and a significantly positive constant. As before, the latter cannot be taken to reflect a 'true' effect, due to the non-zero mean of the control variables. Inspection of the results of the different robustness checks for specification II shows that they are very close to the baseline result. For the case where the variance is included, we find that, similar to the results in panel (a), the publication bias is insignificant.

Finally, table 9 contains the results for specification III with separate coefficients pre- and post-crisis. The baseline result shows a positive and significant estimate for the pre-crisis standard error, suggesting a publication bias, as well as a positive and significant constant. The magnitude of the estimates is similar to that in panel (b) of table 8. The estimate for the post-crisis standard error is positive but insignificantly different from zero. However, its magnitude is similar to that of the pre-crisis estimate and statistically insignificantly different. Variation in the included observations (columns 'all' and 'pub') as well as in the year that separates pre- and post-crisis periods (columns '2008' and '2010') leave the baseline results virtually unchanged. When different estimation techniques are used ('clustered', 'fixed', 'random') the result show more variation. In particular, the pre-crisis estimate turns insignificant while the post-crisis coefficient becomes positive and in some cases significant. However, standard deviations typically are so large that equality of pre- and post-crisis estimates remains hard to reject. When the variance is included neither the pre-crisis estimate nor the post-crisis estimate become significant.

Overall, the robustness results for the linear specification in tables 8 and 9 confirm our baseline results.

Table 8: Linear specifications; robustness checks on specifications I and II

(a) Summary table robustness checks specification I

	base b/se	var b/se	all b/se	pub b/se	2008 b/se	2010 b/se	clustered b/se	fixed b/se	random b/se
Standard error	1.420***		1.307***	1.307***	1.420***	1.420***	1.365**	0.789***	0.793***
	(0.423)		(0.399)	(0.479)	(0.423)	(0.423)	(0.519)	(0.251)	(0.234)
Variance		2.176							
		(8.402)							
Constant	-0.001	0.004***	-0.001	0.000	-0.001	-0.001	-0.004*		0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		(0.014)
N	296	296	302	259	296	296	296	291	296
Adjusted R^2	0.073	-0.003	0.065	0.055	0.073	0.073	0.080	-0.103	

(b) Summary table robustness checks specification II

	base b/se	var b/se	all b/se	pub b/se	2008 b/se	2010 b/se	clustered b/se	fixed b/se	random b/se
Standard error	1.176*		1.041*	1.200*	1.142*	1.303**	1.107*	0.820***	0.823***
	(0.603)		(0.556)	(0.725)	(0.610)	(0.638)	(0.656)	(0.263)	(0.250)
Variance		-0.587							
		(8.139)							
Constant	0.054***	0.068***	0.055***	0.041***	0.038***	0.038***	0.042***		0.040
	(0.009)	(0.010)	(0.009)	(0.010)	(0.011)	(0.008)	(0.014)		(0.126)
N	296	296	302	259	296	296	296	291	296
Adjusted R^2	0.184	0.147	0.177	0.148	0.151	0.157	0.262	-0.080	

Robust standard errors in parentheses. *: p<.1, **: p<.05 and ***: p<.01.

Table 9: Linear specifications; robustness checks on specification III

	base	var	all	pub	2008	2010	clustered	fixed	random
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
S.e. pre crisis	1.512***		0.944**	1.426***			0.712	0.201	0.199
	(0.430)		(0.425)	(0.542)			(0.561)	(0.427)	(0.406)
S.e. post crisis	1.049		1.083	1.116			1.293	1.213***	1.218***
	(0.780)		(0.750)	(0.909)			(0.874)	(0.338)	(0.321)
Var. pre crisis		3.374							
		(2.868)							
Var. post crisis		-3.181							
		(12.202)							
S.e. pre crisis (2008)					1.498***				
					(0.497)				
S.e. post crisis (2008)					1.043				
					(0.730)				
S.e. pre crisis (2010)						1.823***			
						(0.463)			
S.e. post crisis (2010)						1.097			
						(0.819)			
Constant	0.052***	0.068***	0.056***	0.040***	0.037***	0.036***	0.043***		0.040
	(0.008)	(0.010)	(0.009)	(0.011)	(0.010)	(0.008)	(0.015)		(0.120)
N	296	296	302	259	296	296	296	291	296
Adjusted R^2	0.182	0.145	0.175	0.145	0.149	0.157	0.262	-0.071	

Robust standard errors in parentheses. *: p<.1, **: p<.05 and ***: p<.01.

6 Comparison to previous meta studies

This section compares our study with two previous meta-studies. Both studies differ from our study in at least two important aspects. First, both studies pool the estimates from logarithmic and linear specifications in one meta regression analysis. Second, both studies include all estimates of the effect of financial development on growth, no matter how financial development is measured. In order to make the estimates comparable, both studies transform the estimates using the so-called partial correlation coefficient.

Valickova et al. (2014) analyze 1334 estimates from 67 studies. They find a positive and statistically significant effect of finance on growth. Because of the transformation of the estimates, the result does not allow an interpretation in terms of economic size of the effect. In addition, in their FAT-PET analysis they do not find evidence of publication bias. In the full mra the standard error however has a negative and significant effect. This is counterintuitive, as it would imply that studies with larger standard errors would be more likely to present lower estimates, that is, a bias against significant large results.

Arestis et al. (2014) have 1151 observations from 69 published papers. They also find a positive and significant effect of more finance on growth, but in contrast to Valickova et al. (2014), they do find a positive publication bias in their FAT-PET analysis. In a number of specifications in the full mra, however, they find a negative and significant bias.

To compare our results to these papers, we performed the following analysis. First, we estimated one model for linear and logarithmic specifications together, see table 10. In this pooled regression, we find evidence for publication bias. Intuitively, we get roughly the average of the logarithmic and linear estimates presented previously. If we use the PCC transformed outcome variable, however, we find a negative bias, see table 11, while the overall constant remains positive and significant. This is rather counterintuitive, as this corresponds to a lower probability of papers with larger effect to be published. We conjecture that this is driven by the PCC transformation.

To gain some intuition as to the effect that the transformation might have on the analysis, we resort to numerical simulation. In each simulation, we generate 300 uniformly distributed standard errors $\sigma \in [0.01, 0.051]$. For each standard error σ we then draw the coefficient β from a normal distribution with mean 0.05 and standard error σ. In some of our simulations we generate publication bias by dropping negative β's with a probability of 60%. In addition, as the PCC transformation uses the degrees of freedom of the regression, we introduce a random variable corresponding to the degrees of freedom $df \in [10, 80]$. This variable is correlated with the standard error with correlation ρ. We consider various levels of correlation. Next, we estimate the FAT-PET regression with both the transformed and untransformed variable. We repeat this 1.000 times.

For the untransformed variable the results are as expected and do not depend on the correlation parameter ρ. When there is no publication bias, and when we use a 5% significance level, the FAT-PET regression finds a significant effect of the standard error in approximately 5% of the cases. In about half of these cases the coefficient of the standard error is negative. When we introduce publication bias, the FAT-PET regression reports a positive and significant effect of the standard error in about 99.6% of the cases. In the remaining cases the coefficient of the standard error is not significant.

The PCC transformation gives quite different results. For $\rho = 0$ and no publication bias, the FAT-PET regression finds bias in 4.1% of the cases. But when we introduce publication bias, this percentage only increases to 16%. Hence, when $\rho = 0$ the PCC specification seems to be unable to find bias while it does exist.

For $\rho = -0.4$ and no publication bias, the PCC transformation does find bias in 46.2% of the cases. Interestingly, all those cases find a negative coefficient of the standard error. When we introduce publication bias, the PCC transformation again seems to be unable to find the bias, as only 16.6% of the cases report a significant coefficient of the standard error. Again, this coefficient tends to be negative (16.2% of the cases).

When we set $\rho = -0.8$ this pattern becomes even stronger. When there is no publication bias, the PCC transformation does find bias in 95.7% of the cases. All significant coefficients are negative. When there is bias, the coefficient of the standard error is significant in 70.1% of the cases, and again all significant coefficients are negative.

Concluding, when $\rho < 0$, the PCC transformation seems to underreport bias when it does exist, and overreport bias when it does not exist. Moreover, if the PCC transformed FAT-PET regression reports bias, in the majority of cases this is a negative bias, even though we simulated a positive bias.

Table 10: mra on pooled data (i.e. logarithmic and linear specifications combined)

	I	II	III
	b/se	b/se	b/se
Standard error	0.849***	1.137***	
	(0.284)	(0.307)	
Pre crisis		-0.009***	-0.009***
		(0.003)	(0.003)
Year		-0.021***	-0.021***
		(0.006)	(0.007)
Impact factor		-0.013***	-0.013***
		(0.004)	(0.004)
Panel model		-0.002	-0.002
		(0.002)	(0.002)
Endogeneity corrected		-0.000	-0.000
		(0.002)	(0.002)
Extended model		-0.002	-0.002
		(0.002)	(0.002)
Additional proxy		-0.006***	-0.006***
		(0.002)	(0.002)
Data after 2000		-0.010***	-0.010***
		(0.002)	(0.002)
Countries		-0.007	-0.007
		(0.005)	(0.005)
Only developing		0.001	0.001
		(0.005)	(0.005)
Only developed		-0.007**	-0.007**
		(0.003)	(0.003)
Logarithmic specification		0.007***	0.007***
		(0.001)	(0.001)
Standard error pre crisis			1.134***
			(0.180)
Standard error post crisis			1.140*
			(0.608)
Constant	0.007***	0.034***	0.034***
	(0.001)	(0.005)	(0.005)
N	536	536	536
Adjusted R^2	0.039	0.256	0.254

Robust standard errors in parentheses. *: p<.1, **: p<.05 and ***: p<.01.

Table 11: mra on pooled data with PCC transformed estimates

	I	II	III
	b/se	b/se	b/se
Standard error	-0.820	-2.746***	
	(0.850)	(0.869)	
Pre crisis		0.010	0.124
		(0.060)	(0.082)
Year		-0.051	-0.157
		(0.137)	(0.127)
Impact factor		-0.200	-0.240**
		(0.123)	(0.117)
Panel model		-0.360***	-0.314***
		(0.068)	(0.053)
Endogeneity corrected		0.086***	0.092***
		(0.033)	(0.034)
Extended model		0.079*	0.055*
		(0.041)	(0.032)
Additional proxy		-0.027	-0.028
		(0.039)	(0.036)
Data after 2000		-0.199***	-0.175***
		(0.058)	(0.054)
Countries		-0.609***	-0.508***
		(0.115)	(0.094)
Only developing		-0.034	-0.019
		(0.070)	(0.066)
Only developed		-0.184***	-0.179***
		(0.059)	(0.057)
Logarithmic specification		0.184***	0.167***
		(0.025)	(0.024)
Standard error pre crisis			-2.930***
			(0.787)
Standard error post crisis			-1.088
			(0.868)
Constant	0.369***	0.929***	0.835***
	(0.100)	(0.143)	(0.132)
N	536	536	536
Adjusted R^2	0.013	0.720	0.732

Robust standard errors in parentheses. *: p<.1, **: p<.05 and ***: p<.01.

7 Conclusion

In this paper, we perform a meta-analysis on in total 551 estimates from 68 empirical studies that take private credit to GDP as a measure for financial development. We distinguish between linear (302 estimates) and logarithmic (249 estimates) specifications.

First, we find evidence of significantly positive publication bias in both the linear and log-linear specifications. This contrasts with findings in two other recent meta-studies. We conjecture that the difference is caused by the PCC transformation used in these other studies to make estimates with different dependent variables comparable. Obviously, this has the benefit of increasing the size of the sample of the meta-analysis. However, using a simple simulation experiment, we show that the PCC transformation can cause a distortion of the estimated publication bias.

Second, the logarithmic estimates give a robust significantly positive average effect of financial development on economic growth after correction for publication bias. In our preferred specification a 10 percent increase in credit to the private sector increases economic growth with 0.09 percentage points. For the linear estimates, no significant effect of credit to the private sector on economic growth is found on average.

Overall, the evidence points to a positive but decreasing effect of financial development on growth. Note that the effect that we find is substantially smaller than suggested by much-cited studies such as Levine (2005). In that sense, our analysis supports recent research that argues that pre-crisis estimates of the sizeable positive effect of more developed financial markets on economic growth were overly optimistic.

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Appendices

A Funnel plots of the full sample

Figure A.1: Funnel plot of log models (including all estimates)

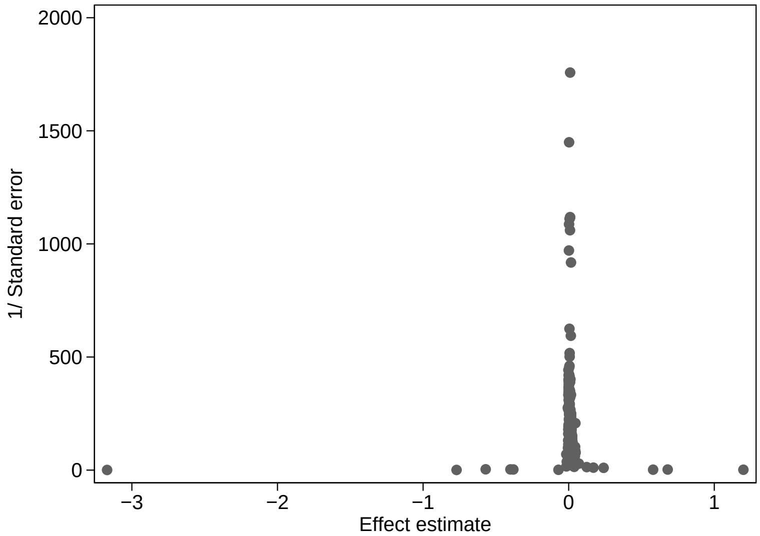
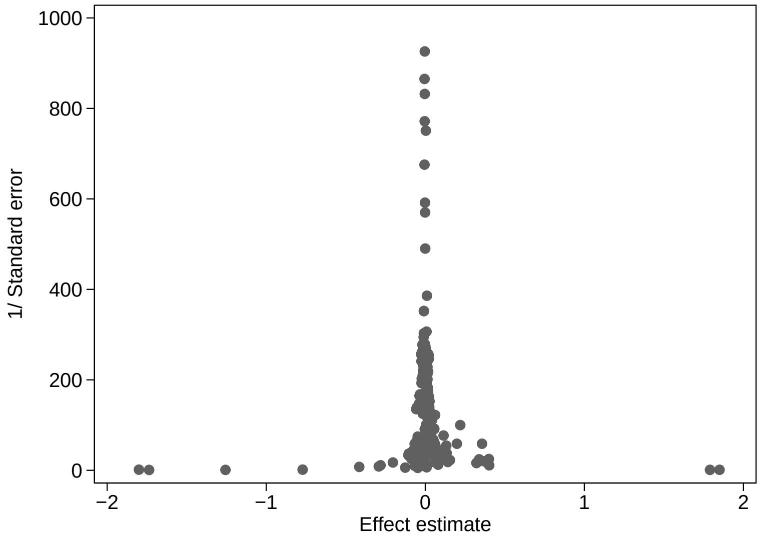


Figure A.2: Funnel plot of linear models (including all estimates)



B Descriptive statistics explanatory variables

The table below presents some descriptive statistics of the explanatory variables, excluding the disproportionate estimates. For the dummy variables we report the mean of the variable. For the normalized variables we report both the mean and standard error.

Table B.1: Descriptives explanatory variables, excluding disproportionate estimates

	logarithmic specification		**linear specification**	
	mean	**standard error**	**mean**	**standard error**
Pre crisis	0.57		0.42	
Post crisis	0.43		0.58	
Variance pre crisis	2.03×10^{-4}	9.90×10^{-4}	6.33×10^{-4}	3.13×10^{-3}
Variance post crisis	0.21×10^{-4}	0.67×10^{-4}	4.73×10^{-4}	1.66×10^{-3}
Year	0.57	0.30	0.69	0.27
Impact factor	0.18	0.24	0.10	0.16
Panel model	0.76		0.58	
Endogeneity corrected	0.60		0.51	
Extended model	0.43		0.52	
Additional proxy	0.48		0.25	
Data after 2000	0.53		0.43	
Countries	0.32	0.18	0.29	0.22
Only developing	0.10		0.05	
Only developed	0.19		0.20	

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