DEPARTMENT OF ECONOMICS AND FINANCE

SCHOOL OF BUSINESS AND ECONOMICS

UNIVERSITY OF CANTERBURY

CHRISTCHURCH, NEW ZEALAND

Social Capital and Economic Growth: A Meta-Analysis

Xindong Xue
W. Robert Reed
Robbie C.M. van Aert

WORKING PAPER

No. 20/2022

Department of Economics and Finance
UC Business School
University of Canterbury
Private Bag 4800, Christchurch
New Zealand

WORKING PAPER No. 20/2022

Social Capital and Economic Growth: A Meta-Analysis

Xindong Xue[1]
W. Robert Reed[2†]
Robbie C.M. van Aert[3]

December 2022

Abstract: This study collects and analyses 993 estimates from 81 studies to generate an overall assessment of the empirical literature on social capital and economic growth. Using a variety of estimation procedures, we reach the following conclusions. First, there is evidence that a meaningful relationship exists between social capital and economic growth. The estimated sizes of the overall mean effect in our specifications range from somewhat larger than "small" to somewhat larger than "medium" depending on the estimation method we use. Second, our analysis does not indicate that the associated empirical literature is distorted by publication bias. Third, there is evidence to indicate that cognitive social capital (e.g., trust) has a larger effect on economic growth than other types of social capital, though the evidence is not strong. Finally, while the coefficient signs of our meta-regression analysis lined up with prior expectations, the associated effect sizes were generally small to negligible.

Keywords: Social capital, Economic growth, Cognitive social capital, Structural social capital, Meta-analysis, Meta-regression, Publication Bias

JEL Classifications: B40, O31, O40, O47, R11, Z10

Acknowledgements: This research is supported by National Social Science Fund of China (Grant. No.:21BSH122) and the Czech Science Foundation (21-09231S). We acknowledge helpful comments from Chris Doucouliagos, Tomas Havranek, Ichirou Iwasaki, Shinichi Nakagawa, and participants at the MAER-Net 2022 Colloquium and UCMeta at the University of Canterbury.

[1] School of Public Administration, Zhongnan University of Economics and Law, CHINA.

[2] Department of Economics and Finance & UCMeta, University of Canterbury, NEW ZEALAND

[2] Department of Methodology and Statistics, Tilburg University, Tilburg, THE NETHERLANDS

† Corresponding author: W. Robert Reed. Email: bob.reed@canterbury.ac.nz.

1. Introduction

The relationship between social capital and economic growth is a subject with a long history in the social sciences. Academic research dates back to the seminal work by Banfield (1958), who was the first to argue that societal trust was an important contributor to economic development. Continuing on that line, researchers such as Arrow (1972), Putnam (1993), and Fukuyama (1995) expanded the concept to include a number of other factors that collectively, and somewhat loosely, are tied together as "social capital", where social capital is generally defined as a set of norms and networks that facilitate cooperation and coordinated actions. Accordingly, a large body of empirical research has attempted to quantify the contribution of social capital to economic growth.

Social capital is commonly categorized into two types: cognitive and structural (Uphoff, 1999). At the risk of oversimplification, cognitive social capital refers to what people think and feel. Structural social capital refers to what people do (Harpham, 2008). In empirical studies, cognitive social capital is usually represented by variables measuring trust. Structural social capital is measured by membership in associations and participation in activities or organizations and the like.

Social capital is hypothesized to positively affect economic growth via numerous channels. It can facilitate the sharing of information, fostering innovation (Uzzi, 1996; Gulati, 1998). It can increase cooperative behaviour, lowering transactions costs, supporting the enforcement of contracts, and improving access to credit (Akçomak & Weel, 2009). Social capital can discourage opportunistic behaviour and increase the effectiveness of economic policies (Easterly & Levine,1997). On the other hand, social capital can sometimes work against economic growth. For example, while association membership has been argued to encourage beneficial collective action, some associations serve as special interest groups lobbying for preferential policies that impede economic growth (Olson,1982; Knack & Keefer, 1997).

Research has employed a wide variety of datasets and empirical approaches to measure the impact of social capital. While some studies report a positive effect of social capital on economic growth (e.g., Algan & Cahuc, 2010; Guiso et al., 2016), others find no effect (e.g., Gennaioli et al., 2013), or get mixed results depending on institutional contexts or the type of social capital (e.g., Knack & Keefer, 1997; Beugelsdijk & van Schaik, 2005).

Early studies generally used cross-sectional data. More recent studies have turned to panel datasets. Endogeneity is an important concern. While social capital may enhance economic growth, economic growth may support the building of social capital. Because of its nebulous nature, studies have employed a large assortment of measures, with no consensus around which one(s) are best. All of this heterogeneity makes it difficult to integrate the findings from previous research. Meta-analysis is a powerful empirical tool for handling this kind of challenge.

A search on Google Scholar for "social capital and economic growth" produces over 4,000,000 hits.[1] This is indicative of the scientific interest in this subject. Thus, it is surprising that this topic has not previously been the subject of a meta-analysis. The closest is a systematic review by Westlund & Adam (2010). Their review is qualitative. As such, it is unable to combine studies to arrive at an overall estimate of the quantitative impact of social capital on growth. Further, it is dated. The most recent study included in Westlund & Adam (2010) was published in 2008. In contrast, our meta-analysis performs a quantitative analysis of the literature. Additionally, it addresses concerns about publication bias, the implicit selection process that filters out insignificant estimates from the literature (Rothstein et al., 2005).

[1] Search conducted on November 12, 2022.

Finally, our sample of studies includes more recent research than Westlund & Adam (2010), with approximately half of the studies in our sample being published after 2008.

This study combines 993 estimates from 81 studies to address four questions: (i) Is there evidence from the empirical literature that social capital contributes to economic growth? If so, how large is the effect? (ii) Is there evidence that publication bias has distorted the estimated effects that appear in the literature? (iii) Are some types of social capital more productive for economic growth than others? (iii) Are estimated effects of social capital systematically related to characteristics of the data, studies, and empirical procedures used to produce those estimates? Our analysis provides the following answers to these questions.

We find evidence that a statistically significant relationship exists between social capital and economic growth. The size of the effect depends on the estimation procedure employed, but our best estimates indicate an effect that is approximately "medium" in size.[2] Our analysis does not indicate that the empirical literature has been distorted by publication bias. Testing for differential effects from different types of social capital produces mixed results, with weak evidence to indicate that cognitive social capital (e.g., trust) has a larger effect than other types of social capital. Finally, our exploratory analysis uncovers relatively few systematic determinants of effect heterogeneity across studies, with the only noteworthy finding being that social capital appears to have a lesser effect on economic growth in the United States (US) compared to other regions of the world.

Our study proceeds as follows. Section 2 describes the literature search we employed and the process we followed to construct our sample. Section 3 describes the data we collected from studies and why we collected the variables that we did. We also discuss the problem that arises from combining estimates that employ different measures of social capital and economic growth. Section 4 provides a statistical overview of the estimated effect sizes in our sample

[2] We explain how we define "small", "medium", and "large" below.

and discusses five estimators for estimating the effect of social capital on economic growth. Section 5 presents estimates of the overall mean effect and addresses whether publication bias causes the estimates in our sample to misrepresent the true effect of social capital on economic growth. Section 6 estimates and tests for different effects for different types of social capital. Section 7 explores for systematic determinants that can explain the observed heterogeneity in estimated effects across studies. Section 8 summarizes and concludes.

2. Literature Search and Data Construction

We conducted our literature search in accordance with the reporting guidelines for meta-analysis in economics (Havranek et al., 2020). Our literature search was begun in January 2020 using the following sources and search engines: Wiley, Elsevier, JSTOR, RePEc, SSRN, Web of Science, Google Scholar, EconLit, and EBSCO. Our search scope included published papers, working manuscripts, reports, books, doctoral dissertations, and master's theses.

To identify relevant research, we used combinations of the following keywords: "social capital", "social trust", "social networks", "social relationships", "social cohesion", "social integration", "social support", "economic growth", "economic development", and "economic performance". In the initial search, we screened titles and abstracts. We also did backwards reference searching to identify relevant articles that did not appear in our database searches. The search process was completed at the end of February 2020. It produced an initial pool of 1952 records.

To be included in our meta-dataset, a study had to meet the following criteria: (1) It needed to report the size of the sample used in the analysis and sufficient statistical information for us to construct a *t*-statistic. This eliminated theoretical studies, reviews, and non-quantitative comments. (2) The level of empirical analysis had to be a country or region. This excluded micro-level firm studies. (3) The outcome variable needed to be a measure of economic growth. This excluded related outcomes such as measures of financial development and labor market performance. (4) We excluded non-linear measures of effect such as interactions and quadratic specifications because of the difficulty of calculating reliable standard errors for the marginal effects. We also excluded path analyses and Structural Equation Models for the same reason. Our final sample consisted of 993 estimates from 81 studies.[3] A PRISMA flow diagram summarizing our literature search is given in FIGURE 1.

Once the studies were selected, we documented various data, study, and estimation characteristics associated with each estimate. Two teams of postgraduate students each worked independently to record the respective information, then met to compare their notes and resolve difficulties. When they could not come to an agreement, the case was reviewed by the first author of this study who made the final decision. Information was recorded about the measures used for economic growth and social capital, as well as various features of the data, the estimation procedure that was used, and when and where the study appeared. This information was collected to see if it these factors could explain why estimates differed across studies.

3. The Data

We introduce our data by presenting summary statistics of associated study, estimation, and data characteristics. These are presented in TABLE 1. We classified the different measures for economic growth into two categories. Approximately 62 percent of the estimates used a dependent variable consisting of some variant of the growth rate of GDP (*DV_GrowthRate*). By far the most common measure in this category was the annual growth rate of GDP per capita. Other estimates used a cumulative growth rate over a given period or something similar. Approximately 38 percent of the estimates used a measure of the level of income (*DV_GDPLevel*), with GDP per capita being the most frequent. This became our reference category in the later meta-regression analysis, indicated by the accompanying asterisk in

[3] See the Appendix for the list of studies.

TABLE 1. Other income level measures included median household income and measures of "value added".

With respect to social capital, the measures were approximately equally distributed across cognitive (*SC_Cognitive*), structural (*SC_Structural*), and other (*SC_Other*), with the last category constituting the reference group for the later meta-regression analysis. Almost all the variables used to quantify cognitive social capital were based on various flavors of trust: "inherited trust", "interpersonal trust", "generalized trust", etc. Variables used to quantify structural social capital included membership in associations and professional organizations, voter participation, and volunteer activities. The most common types of "Other" social capital (*SC_Other*) were measures that mixed together both structural and cognitive social capital. Other measures included ethnic fractionalization, social cohesion, and corruption; as well as measures of bridging and linking social capital, which come from another classification system for categorizing social capital.

The discussion above illustrates the disparate measures used to quantify economic growth and social capital. It is this heterogeneity that makes it difficult to compare estimates across studies. Clearly, a simple averaging of the estimates in our sample would be meaningless. This is a common problem when synthesizing literatures that use different variables to measure the same or similar effects.

The common solution is to transform the variables into a partial correlation coefficient (*PCC*), where

(1.a) $$PCC_i = \frac{t_i}{\sqrt{t_i^2 + df_i}},$$

and t_i and df_i are the *t*-statistic and degrees of freedom associated with the respective estimated effect. The corresponding standard error is given by:

(1.b) $$se(PCC_i) = \frac{1 - PCC_i^2}{\sqrt{df_i}}.$$

Some readers may note that Equation (1.b) is different from a formula that is commonly found in the economics, meta-analysis literature: $se(PCC_i) = \sqrt{\frac{1-PCC_i^2}{df_i}}$ (see, for example, Stanley & Doucouliagos, 2012; Zigraiova & Havaranek, 2015; and Gunby, Jin, & Reed, 2017). However, the latter formula is a mistake that has propagated in the economics literature.[4] Accordingly, we use the correct formula in this study.

The advantage of using *PCC* is that it provides a common metric for comparing otherwise disparate estimates of the effect of social capital. The disadvantage is that it can be difficult to interpret the corresponding units. Doucouliagos (2011) is helpful in this regard. He collected 22,000 estimated effects from the economics literature and converted them to *PCCs*. He then rank-ordered them from smallest to largest. Reference points for "small", "medium" and "large" were set at the 25th, 50th, and 75th percentile values. For the full dataset, the corresponding values were 0.07, 0.17, and 0.33. For the subsample of 9,934 economic growth estimates, the corresponding values were 0.10, 0.23, and 0.39.[5] We use the latter values in interpreting the subsequent empirical work, though we are mindful that these are but rough guidelines.

Turning now to the other data characteristics, we record the year that the respective study was published (*PubYear*). Years of publication ranged from 1995 to 2019, with a median publication year of 2010. This variable is useful in investigating whether there has been a trend in the size of the estimated social capital effects over time. A common finding across many disciplines is that estimated effect sizes decline over time, perhaps because larger and more significant estimates get published sooner, something known as "time-lag bias" (Ioannidis, 1998; Koricheva et al., 2013; Pietschnig et al., 2019).

---

[4] See van Aert and Goos (2022) for more details. An example where the correct formula for $se(PCC_i)$ is used is Nakagawa et al. (2021, page 6), which comes from the ecology and evolutionary biology discipline.
[5] See Figure 3, page 13 in Doucouliagos (2011).

Approximately 42 percent of the estimates in our sample come from published journal articles (*Published*), with the remainder mostly coming from unpublished working papers and PhD and master's dissertations/theses. Some researchers argue that it is important to include unpublished studies ("grey literature") in meta-analyses, since publication bias (described below), can filter out insignificant or wrong-signed estimates from the literature (Ringquist, 2013). They suggest that a comparison between published and unpublished studies may identify this behaviour. However, if researchers ultimately want their work to be published, they may choose to only report "preferred" estimates from the beginning, in which case no systematic differences will be observed between published and unpublished work.

A number of specification issues can also affect estimated effect sizes. If a lagged dependent variable (*LaggedDV*) is included as a right-hand-side regressor, coefficients on the social capital variable will only measure immediate, short-run effects. Accordingly, one would generally expect to see smaller effect sizes when the lagged dependent variable is included in the regression. Social capital variables may also take time to exert an influence on economic growth, so that effects may only show up after a time lag (*LaggedSC*). Approximately 6 and 9 percent of the specifications used to produce the estimates in our study had a lagged dependent or lagged social capital variable, respectively. Finally, regression specifications commonly have more than one social capital variable in the regression (*NumberSCVars*). When that happens, one would expect multicollinearity to increase coefficient standard errors, decreasing *t*-statistics, and thus lowering effect sizes as measured by *PCC*. This implies a negative relationship between *PCC* and the number of social capital variables included in the regression.

Endogeneity can be expected to influence estimates of social capital effects in several ways. Simultaneity, whereby greater economic growth facilitates the development of social capital, can serve to inflate estimates of causal effects of social capital on growth. Instrumental variable estimation (*Endog_IV*) is sometimes employed to correct this bias, though good instruments are hard to find. In this case, IV estimation would be expected to reduce the estimated social capital effect. However, researchers sometimes use IV estimation to address endogeneity due to omitted variables, in which case one cannot sign the direction of the bias. Approximately 21 percent of the estimates in our sample employed IV corrections for endogeneity. Fixed effects (*Endog_FE*) is another way to address omitted variable bias when using panel data. Approximately 10 percent of the estimates used this empirical procedure. The remaining 69 percent of estimates did not address endogeneity. This latter category serves as the reference group in the subsequent meta-regression analysis. Relatedly, we also note whether the data are panel (*PanelData*) or cross-sectional. Most of the estimates in our sample are based on panel data.

We also collect data on spatial characteristics. One spatial dimension is the level of the data, whether it be city, regional, or country, with the reference category being "other". The most common type of data is country level (49 percent), with regional level data second (36 percent). We do not have any prior expectations about how the level of the data might affect social capital effects on growth, but we are interested in determining whether this data feature contributes to the heterogeneity of estimates observed in the literature.

Finally, we record what part of the world the data come from (OECD/Europe, US, Africa, Asia). The reference category is "other" for countries that fall outside these regions. Again, while we do not have prior expectations about how country origin might affect social capital effects, it seems reasonable that social capital might be more salient in some cultures/economies than others. One of the advantages of meta-analysis is that we are able to combine studies from different parts of the world to explore this.

4. Overview of *PCC* and five estimators for estimating overall mean effect

TABLE 2 summarizes the *PCC* values that are the focus of our analysis. The mean and median *PCC* values are 0.151 and 0.130. Using Doucouliagos's size categories ("small" = 0.10, “medium” = 0.23, and “large” = 0.39), these values place the unadjusted mean/median size of the effect of social capital on economic growth between “small” and “medium”, though closer to “small”.

The *PCC* values range widely, from a minimum of -0.747 to a maximum of 0.960. This is of interest for two reasons. First, meta-analysis calculates a weighted average in computing the overall mean effect, with more precise estimates receiving greater weights. As we discuss below, more precise estimates need not be values located near the mean/median. It also highlights the value of meta-analysis. The wide range of effect sizes, with both large negative and large positive values, indicates the difficulty of synthesizing this literature.

This is further illustrated in FIGURE 2, which reports the distribution of *t*-statistics (top panel) and *PCC* values (bottom panel). Given that the mean/median *PCC* values are on the smallish side, one would expect the corresponding *t*-statistics also to be relatively small. That is indeed the case. Almost half of the *t*-statistics are smaller than 2 in absolute value, indicating that a large share of the estimated social capital effects is statistically insignificant. However, when significant, the overwhelming percentage of *t*-statistics tend to be positive. Turning to the bottom panel of *PCC* values, the two, vertical dashed lines are set at ±0.10 to indicate “small” effects. While much of the distribution lies within the dashed lines, a substantial portion lies outside this range, especially on the positive side.

There are two complications in calculating an overall mean effect of social capital on economic growth. First, as indicated above, not all estimated effects should receive the same weight. In general, we want to give greater weight to those estimates that are more precise. As we discuss below, we also want our estimation procedure to best accommodate the nature of the data. The second complication is publication bias. Publication bias is a generic term to indicate that observed estimates may represent a selected sample from the population of true effects. Whether due to journal preferences for significant estimates, or researchers not submitting studies with statistically insignificant results, publication bias can distort the estimates available to the meta-analyst. We take up each of these complications in turn.

Five models to estimate the (unadjusted) overall mean effect. Three of the most common meta-analytic estimators are the (i) the Fixed Effect (FE) model (a.k.a. as the common- or equal-effect model), (ii) the Random Effects (RE) model, and (iii) the Multi-Level or 3-Level model (3L). Note that "Fixed Effect" and "Random Effects" in the context of meta-analysis models are completely different from the identically named panel data estimators.

The RE model assumes there is one estimate per study and is given by:

(2) $PCC_i = \beta_0 + \theta_i + \varepsilon_i$, $\theta_i \sim N(0, \tau^2)$, $\varepsilon_i \sim N(0, se(PCC_i)^2)$, $i = 1,\ldots,S$,

where i refers to the i^{th} study and S is the total number of studies, β_0 is the overall mean true effect size, θ_i is a normally distributed random study effect, τ^2 is the between-study variance in true effect sizes, and $cov(\theta_i, \varepsilon_i) = 0$. While $se(PCC_i)^2$ is estimated in practice, it is assumed as known in the analyses. In words, Equation (2) states that the true effect underlying the i^{th} estimated *PCC* value consists of a common value, β_0, plus a unique draw from a shared, normal distribution, θ_i. This models each *PCC* estimate as having a unique, true effect. This true effect is then estimated with sampling error, ε_i.

The RE model assumes that there is no single, true effect underlying all studies. Rather, underlying each estimated *PCC* value is a "true value" drawn from the normal distribution, $N(\beta_0, \tau^2)$, that is estimated with sampling error given by ε_i. It follows that $E(PCC_i) = \beta_0$, so that $\hat{\beta}_0$ is the estimate of the overall mean effect of social capital on economic growth. The RE model does not acknowledge the clustered nature of the *PCC* estimates, as it assumes there is only one estimate per study. However, it is commonly applied to meta-analysis datasets with multiple estimates per study. As a result, researchers often adjust the standard errors by using a robust estimator that clusters on study.

The FE model is a straightforward simplification of the RE model. It assumes $\tau^2 = 0$, In words, all social capital effects are assumed to have a single population value, with sampling error being the only reason why estimates differ across studies. As in the case of the RE model, it is common to adjust the standard errors post-estimation using a cluster robust estimator.

The use of the FE model is somewhat idiosyncratic to the economics literature. RE is the meta-analytic estimator of choice in most other disciplines (Borenstein, Hedges, & Rothstein, 2007; Dettori, Norvell, & Chapman, 2022). Almost all researchers acknowledge that the RE model is more realistic, and, indeed, the FE model is almost always statistically rejected in favor of the RE model when tested. However, there is some simulation evidence to indicate that the FE estimator produces "better" estimates in the presence of publication bias (Stanley & Doucouliagos, 2014).

The two estimators differ in the weights they assign to individual estimates. Whereas the FE model weights by the inverse of $se(PCC_i)^2$, the RE model weights by the inverse of $(se(PCC_i)^2 + \tau^2)$. Both models give greater weight to individual estimates that are estimated more precisely, but the FE model concentrates more weight on the most precise estimates. Hence, it can be insightful to use the FE model next to the RE model as a sensitivity analysis.

Caution should be exercised when the FE model places a large weight on a small number of estimates. If true effects are widely dispersed (i.e., large heterogeneity), and only a few studies receive a large proportion of the weight, that can cause the FE estimate to misrepresent the overall mean effect. That is the case illustrated by a hypothetical example in FIGURE 3, where the three most precise estimates (indicated by the grey vertical lines) lie to the right of the overall mean, β_0. On the other hand, if τ^2 is large relative to $se(PCC_i)^2$, differences in sampling error will be swamped by effect heterogeneity, and the estimate of the overall mean will give similar weights to precise and imprecise estimates.

TABLE 3 reports the distribution of weights allocated by the FE and RE estimators. For the FE model, the top 3 studies -- approximately 4% of the total number of studies -- receive 62% of the weight in calculating the overall mean.[6] The top 10 studies – approximately 12% of the total number of studies – receive almost 90% of the total weight.[7] This heavy concentration on a small number of studies is concerning if these studies have heterogeneous effects as illustrated in FIGURE 3.

However, RE is also problematic. Our sample of *PCC* values is characterized by a large degree of effect heterogeneity. We can quantify this heterogeneity by using the I^2, which measures the share of the effect heterogeneity (i.e., between-study variance in true effects) as a percent of total variance. It is important to emphasize that when computing the I^2, just as for the FE and RE model, it is assumed that all effect sizes in the meta-analysis are independent. The I^2 is 97% in our meta-analysis. This is relatively, but not exceptionally, large for meta-analyses in economics. Accordingly, for the RE model, the top 3 and top 10 studies receive only 4.9% and 16.0% of the weight in calculating the overall mean. The difference between the minimum and maximum weights is slight: 0.3% versus 1.6%. As a result, the most precise estimates receive virtually the same weight as the least precise estimates.

As noted above, both the FE and RE models ignore the fact that meta-analysis datasets often have multiple estimates per study. FIGURE 4 illustrates the extent to which the studies in our sample have multiple estimates. The median number of estimates per study is 8. The mean number is 12.3, with one study reporting 74 individual estimates. One would expect that estimates from the same study would be correlated, and that is indeed the case for our sample. The intraclass correlation for the *PCC* variable is 0.325, indicating a high degree of clustering.

[6] The studies with the 3 largest weights are (in order of weights) id = 8, 57, and 67. They count for 8.9% of the total number of estimates.
[7] The studies with the 10 largest weights (in order of weights) are id = 8, 57, 67, 41, 42, 69, 37, 15, 3, and 39. They count for 35.3% of the total number of estimates.

In contrast to FE and RE, the three-level multilevel meta-analysis (3L) model explicitly incorporates within-study clustering of estimates. It is given below:

(3) $PCC_{ij} = \beta_0 + \theta_i + \varphi_{ij} + \varepsilon_{ij}, \theta_i \sim N(0, \tau_\theta^2), \varphi_{ij} \sim N(0, \tau_\varphi^2),\ \varepsilon_{ij} \sim N(0, se(PCC_{ij})^2),$
$i = 1,...,S; j = 1,..., N_i,$

where *j* is referring to the *j*[th] estimate and N_i is the total number of estimates in the *i*[th] study, φ_{ij} is a normally distributed random effect with mean zero and variance τ_φ^2, and $cov(\theta_i, \varepsilon_{ij}) = cov(\varphi_{ij}, \varepsilon_{ij}) = 0$. Equation (3) states that the true effect underlying the estimated *PCC* value consists of the same two components as the RE model, plus a third component, φ_{ij}, that indicates that the true effect of estimates within a study differ from each other.

We also include another three-level multilevel meta-analysis model (3L-VCV) where we not only take into account that the true effects from the same study may be correlated, but also that the sampling errors may be correlated.[8] We do this by assuming a within-study variance-covariance matrix for the sampling errors. Sampling errors from the same study would be expected to be correlated if, for example, the different estimates were based on the same subjects. Unfortunately, correlation between sampling errors is not something that can be separately estimated. As a result, we assume a correlation of 0.5. However, we also run our analyses with correlations of 0.3 and 0.7 as a sensitivity analysis.

Finally, as a point of comparison, we also report OLS estimates where there is no differential weighting for more precise estimates and all estimates receive identical weights. Having discussed the five estimators used in this study, we are now in a position to provide the first estimates of the overall mean effect of social capital on economic growth. Stata and R (R Core Team, 2022) are used for the analyses. The R package *metafor* (Viechtbauer, 2010) was

[8] 3L-VCV is the same model as a multivariate meta-analysis model (e.g., Gleser & Olkin, 2009; Hedges & Olkin, 1985) where the between-study covariance matrix has a compound symmetry structure and there is only one outcome in the meta-analysis.

used for fitting the multilevel meta-analysis models. All the code used to produce the estimates in this study are available at[9]:

https://osf.io/suyxz/?view_only=7979e543d9254adbbee8aa626b1bd920.I

5. RESULTS: Estimates of the overall mean effect of social capital on economic growth

TABLE 4 reports estimates of the overall mean effect of social capital on economic growth for the OLS, FE, RE, 3L, and 3L-VCV models, where the overall mean effect is given by β_0 in Equations (2) and (3).[10] Note that the OLS and RE estimates will be quite similar since I^2 is close to 100% in our sample. The estimates range from a low of 0.105 (FE) to a high of 0.187 (3L), with all five estimates being statistically significant. In terms of Doucouliagos's size classifications, these range from "small" to a little less than "medium" in effect size. While these estimates provide a synthesis of the estimates in the literature, they do not make any adjustment for publication bias. If, for example, researchers and journals tend to prefer estimates that confirm the importance of social capital, these estimates will over-estimate the true effect of social capital on economic growth. For that reason, we attempt to estimate the effect of publication bias and, if necessary, adjust these estimates accordingly.

Publication bias. A common method for detecting, and correcting, publication bias is to add the standard error of the estimated effect ($se(PCC)$) to the specifications of Equations (2) and (3). In economics, this is known as FAT-PET, for Funnel Asymmetry Test – Precision Effect Test (Stanley & Doucouliagos, 2012; Nakagawa et al., 2022). The univariate regression specification with the standard error as an explanatory variable is known as an Egger regression (Egger, et al., 1997). The coefficient on the standard error variable is interpreted as estimating the impact of publication bias on the estimated effect. Significance of this coefficient is taken

[9] Data will be added when the paper is published.

[10] The sensitivity analyses for 3L-VCV are reported in the supplemental materials. The results of the sensitivity analyses are comparable to the results reported in the paper.

as evidence of the existence of publication bias.[11,12] The idea is that as the standard error increases, there is wider scope for researchers to select estimates that are more interesting or attractive to reviewers and readers. This is the "FAT" part of FAT-PET.

Under this interpretation, by setting the value of $se(PCC)$ equal to 0, one can estimate what the overall mean value of PCC would be in the absence of publication bias. In a univariate regression with $se(PCC)$ as the only explanatory variable, this is represented by the constant term. A hypothesis test of the constant term constitutes a test whether the overall mean value of PCC is different from zero. This is the "PET" part of FAT-PET. Because it represents the estimate of the overall mean effect after adjusting for publication bias, it is sometimes referred to as "effect beyond bias".

Columns (1) to (5) of TABLE 5 report estimates of both the coefficient on $se(PCC)$ ("Bias") and the constant term ("Effect beyond bias"). The evidence on publication bias is mixed, with two of the estimates being statistically significant (OLS and RE), and three not statistically significant (FE, 3L, and 3L-VCV). However, statistical significance of the test for publication bias may also be caused by the large amount of heterogeneity in the meta-analysis. The estimates of overall mean effect, adjusted for publication bias, are also mixed. All the estimators produce adjusted estimates that are substantially smaller than the unadjusted estimates in TABLE 4. The unadjusted estimates of overall mean effect in TABLE 4 are 0.151, 0.105, 0.140, 0.187, and 0.186, respectively, with each significant at the 1 percent level. In contrast, the corresponding adjusted estimates in TABLE 5 are 0.065, 0.101, 0.053, 0.180, and 0.176, with only the OLS, 3L, and 3L-VCV estimates statistically significant at the 5-percent level. In terms of size, none of the estimates achieve Doucouliagos's threshold for "medium".

[11] Outside of economics, this is commonly known as Egger's test, or Egger's regression test (Egger et al., 1997).
[12] Although this test is commonly used to test for publication bias, it is actually testing for so-called "small-study effects". Small-study effects refer to the tendency of studies with a small sample size to go along with large effect sizes. Publication bias is only one of the possible causes of small-study effects. See Egger et al. (1997) for a list of other causes of small-study effects.

Overall, the results from Columns (1) to (5) of TABLE 5 do not provide strong evidence of an economically and statistically significant relationship between social capital and economic growth.

While the FAT-PET framework is ubiquitous in the meta-analytic literature, it is an admittedly odd specification. The use of a univariate regression to infer publication bias is unnecessarily restrictive. If $se(PCC)$ is correlated with other data, study, and estimation characteristics, and these characteristics are themselves related to the estimated effect, PCC, then what is being interpreted as publication bias may be nothing more than omitted variable bias. Just as no study would estimate the returns to education from a univariate regression of wages on education, likewise caution is called for in reading too much into a univariate regression of PCC on $se(PCC)$. And, indeed, there are grounds for being concerned about omitted variables. An OLS regression of $se(PCC)$ on the data, study, and estimation characteristic variables in our sample has an R-squared of 54.2%. Accordingly, we next attempt to strip out from $se(PCC)$ the influence of these other variables.

Columns (6) through (10) of TABLE 5 report the results of this analysis. The estimates for "Bias" and "Effect beyond bias" come from two estimation procedures. The estimate of $se(PCC)$ comes from a meta-regression in which all the data, study, and estimation characteristic variables in TABLE 1 are included with $se(PCC)$. TABLE 5 only reports the estimated coefficient for $se(PCC)$, though we will report on the other variables later.

The first thing to note from Columns (6) to (10) is that all the bias terms are statistically insignificant when testing with a 5-percent significance level. The null-hypothesis of a zero coefficient of $se(PCC)$ is rejected with 3L and 3L-VCV at the 10-percent level, but these estimates are negative, which is the opposite as what would be expected in case of publication bias. Whereas the univariate regressions in Columns (1) to (5) produced mixed results with respect to the existence of publication bias, there is no evidence of publication bias when the influence of other variables is accounted for.

To estimate the "Effect beyond bias" we take advantage of the fact that in an OLS regression, the estimated coefficients times the sample means of their respective variables equals the sample mean of the dependent variable. Thus, in an OLS regression, if we set the value of $se(PCC)$ equal to 0 and multiply all the other estimated coefficients by the sample means of their respective variables, the resulting prediction provides an estimate of the sample mean adjusted for publication bias.

This is how we calculate "Effect beyond bias" for the OLS estimate in Column (6). For the sake of consistency, we follow the same procedure for the other estimators in Columns (7) through (10) even though the relationship between coefficient estimates and sample means that we exploited for OLS does not strictly hold for weighted regressions. The result is that the estimate of "Effect beyond bias" is everywhere larger. The estimates range from 0.138 (RE) to 0.286 (FE). The OLS and RE estimates in Columns (6) and (8) are close to their original, unadjusted values in TABLE 4. The FE, 3L, and 3L-VCV values are even larger. Further, all five estimates of "Effect beyond bias" are significant at the 1 percent level.

In summary, once we account for omitted variable bias due to excluding data, study, and estimation characteristics from the univariate regressions in Columns (1) through (5), we get a very different picture of the effect of social capital on economic growth. First, we find no evidence of publication bias. That is, the empirical literature does not appear to be significantly distorted through sample selection exerted by researchers and journals. Second, the estimated effects of social capital are not insubstantial. They range from above "small" to above "medium". Given that economic growth is a complex phenomenon involving the interaction of many factors, making it hard to tease out the influence of individual elements; and given that our measures of social capital are undoubtedly crude and characterized by measurement error, we interpret these results are providing significant evidence that social capital positively contributes to economic growth.

6. RESULTS: Estimating the effects of different kinds of social capital

Are some types of social capital more effective at contributing to economic growth than others? Up to now we have pooled estimates of social capital on economic growth without attempting to differentiate the effects of different kinds of social capital. In this section, we identify estimates by type of social capital: cognitive, structural, or other. As discussed above, cognitive social capital can be thought of as referring to what people think and feel (e.g., perceptions of trust), while structural social capital references what people do (e.g., membership in associations and participation in activities or organizations).

TABLE 6 distinguishes the estimated effects of cognitive and structural social capital, with "other" social capital serving as the reference category. The first five columns report the results of a multiple regression analysis consisting of two dummy variables to indicate whether the respective estimated effect is associated with cognitive or structural social capital. The next five columns report the results of a full regression with all data, study, and estimation variables included. The last column reports the result of a LASSO regression, which we discuss separately below.

We are interested in two questions. First, is there any evidence that different kinds of social capital have different effects on economic growth? To get at this question, we test $H_0\colon \beta_{Cognitive} = \beta_{Structural} = 0$. Rejection of this hypothesis is evidence that there are differing social capital effects. Second, do cognitive and social capital have different effects on economic growth? Note that this differs from the first question in that cognitive and structural social capital could have the same effect on economic growth, but still different from other types of social capital. We investigate this latter question by testing $H_0\colon \beta_{Cognitive} =$

$\beta_{Structural}$. The results of testing the two hypotheses are reported in separate rows at the bottom of TABLE 6.

A test of the first hypothesis that different kinds of social capital have different effects on economic growth (H_0: $\beta_{Cognitive} = \beta_{Structural} = 0$) finds no support in Columns (1) – (10). All the respective p-values are larger than 0.10. With respect to the second hypothesis, there is slight evidence that cognitive and structural social capital have differing effects (H_0: $\beta_{Cognitive} = \beta_{Structural}$) but only for the OLS and RE estimators, and only in the simple, two-variable regressions of Columns (1) and (3). These estimates suggest that cognitive social capital has a larger impact on economic growth than either structural or other types of social capital. The difference in effect size equates to "small" according to Doucouliagos's size classifications. However, the respective tests fail to achieve significance when the full specification of data, study, and estimation variables are included (cf. Columns 6 and 8). The loss of significance does not appear to be due to multicollinearity: Variance Inflation Factors (VIFs; Kutner et al., 2005, p. 408) for the cognitive and structural social capital variables equal 1.90 and 1.76, respectively.

To explore the difference in estimates for the OLS specifications in Columns (1) and (6) we turn to LASSO. It is common in meta-regression in economics to choose a final model for frequentist estimation based on a prior model selection algorithm such as stepwise regression or Bayesian Model Averaging (BMA).[13] However, this approach is invalid because it ignores model selection uncertainty. In contrast, LASSO provides a way of testing hypotheses about a subset of variables that accounts for model selection uncertainty. Automated procedures allow one to include a large number of nonlinear effects from control variables in order to estimate and draw inference on the selected subset of variables. In our

[13] For BMA, it is common to select variables whose Posterior Inclusion Probability (PIP) is larger than some threshold such as 0.5.

analysis, we allowed for all possible interaction and quadratic effects. The results are reported in Column (11) of TABLE 6.

While the estimated effect sizes for the respective social capital dummy variables are very small, the estimates are considerably more precise, allowing sharper inference. Cognitive social capital is now significantly different from “Other” social capital. Further, the hypotheses of (i) no difference in effects for different types of social capital, and (ii) no difference between cognitive and structural social capital are also rejected.

In summary, combined with our previous analysis, we conclude that there is strong evidence to indicate that social capital is positively associated with economic growth, and mixed evidence to indicate that of the various types of social capital, cognitive (i.e., trust) has the largest impact.

7. RESULTS: Investigating systematic determinants of effect heterogeneity

Section 3 discussed the variables that we collected and presented possible reasons why these might be systematically related to the sizes of effects reported in the literature. In this section we explore whether one or more of these data, study, and estimation characteristics can help explain the heterogeneity of estimated effects that we see in the literature.

Our previous regression analysis focused on just two variables -- the two social capital variables. Acknowledging the differences between the “No control variables” models and the “Full set of control variables” models in TABLE 6, we turned to LASSO for reliable inference results that incorporated model uncertainty. LASSO allows us to do that for a small subset of variables, but not for all variables (StataCorp, 2021). No estimation procedure will do that. However, if our interest lies primarily in the range of estimates that arise under different model specifications, and not so much in inference, model averaging approaches can be insightful. One such approach is Bayesian Model Averaging (BMA).

There are a total of 2^{20} different models one can specify given the 20 data, study, and estimation variables in our study. It is impossible to estimate each and every one of those models, so BMA uses a sampling procedure (Markov Chain Monte Carlo sampling, or MCMC) to efficiently select the variable combinations that provide the greatest explanatory power.

The "B" in BMA refers to the fact that the researcher needs to identify prior beliefs over two distributions. The first prior that the researcher needs to specify is to assign a distribution of probabilities over the model space. One possibility is to give each model an equal initial probability of $\frac{1}{2^{20}}$. However, this has the effect of giving mid-sized models more weight than models with a few or many variables. An alternative approach is to specify probabilities over the number of variables the researcher believes to be in the "true model". This is the approach that Zeugner and Feldkircher (2015) recommend and the approach that we adopt in our analysis.[14]

The second prior the researcher needs to specify is a distribution of probabilities over the coefficient space. This is commonly done by positing a normal distribution with given mean and variance. The mean is generally set equal to zero. The variance is set proportional to the variance from the corresponding model's estimated OLS variance-covariance matrix, where the factor of proportionality is given by Zellner's g (Zeugner & Feldkircher, 2015). That is the approach that we adopt.[15]

Columns (1) through (3) in TABLE 7 present the results. Recall that BMA assumes a prior distribution of coefficient values that are normally distributed. The post-BMA distribution of coefficient values is also normal. Their posterior means and standard deviations are given in Columns (1) and (2). Column (3) reports the "Posterior Inclusion Probability" (PIP). This is

[14] Personal correspondence with Zeugner on October 15, 2015.
[15] Our BMA analysis sets the model prior = "random", which assumes a "Binomial-beta" distribution over model size. This is the approach taken by Ley and Steel (2009). For Zellner's g, we select the option "g = "hyper = UIP", also recommended by Zeugner.

the estimated probability that the respective variable belongs in the “true model”. Each specification receives a posterior probability of being in the “true model” such that the sum of the posterior probabilities equals 1. PIP is the sum of the model probabilities for those models that include the respective variable.

We also report the results from an OLS regression with all variables included in Columns (4) and (5). We previously reported the OLS estimates for the two social capital variables in Column (5) of TABLE 6. We now report all the estimates from that regression. We include the OLS estimates in TABLE 7 for several reasons. First, they provide a useful comparison to see how much multicollinearity in the fully specified, single model causes estimates to differ from the more sophisticated BMA approach. But they also are a reminder that BMA, for all its sophistication, is based on OLS regression. A comparison of Columns (1) and (3) confirms the association between BMA and OLS.

In interpreting the estimates in TABLE 7, it is useful to note that other than *PubYear, NumberSCVars,* and *sepcc,* all variables are dummy variables. Thus, the coefficients can be interpreted as the change in the overall mean value when the respective dummy variable changes value from 0 to 1. Applying Doucouliagos’s size classifications, we see that the only data, study, and estimation variables to achieve the threshold value of “small” (= 0.10) are *Endog_FE* and *Reg_US.*

The BMA mean value of -0.126 for *Endog_FE* indicates that panel studies that included group fixed effects had smaller *PCC* values than other studies. However, since the *PCC* is based on *t*-statistics, and since we expect within-variation for social capital variables to be relatively small, so that the corresponding standard errors will be large and *t*-values small, caution should be exercised before interpreting this as the effect of controlling for unobserved, time-constant omitted variables. Supporting this caution is the fact that estimates based on IV estimation were only negligibly different from those that did not correct for endogeneity.

With respect to *Reg_US,* the BMA estimate for studies estimating the effect of social capital on US economic growth indicates that US social capital effects are lower than those estimated for other parts of the world. That may reflect the fact that there exist institutions that to some extent can serve as substitutes for social capital.

A number of other effects have the expected sign, however, are of negligible size. We would expect short-run effects of social capital to be smaller than long-run effects, and that is consistent with the sign of *LaggedDV*. Compatible with our finding of little evidence for publication bias, which includes "time-lag bias", we find a trivial effect associated with *PubYear*. We also find a miniscule difference between estimates that appear in published and unpublished sources. When multiple social capital variables are included in the same regression, multicollinearity can inflate standard errors and reduce *t*-statistics, and hence lower *PCC* values. This is consistent with the negative sign for *NumberSCVars.*

8. Summary and Conclusion

In this paper we conduct the first meta-analysis of the literature examining the effect of social capital on economic growth. We collect and analyse 993 estimates from 81 studies in order to synthesize the empirical research on social capital and economic growth. Because different studies use different measures of both economic growth and social capital, we transform estimates into partial correlation coefficients (*PCCs*) and assess the resulting values using Doucouliagos's (2012) effect size classifications. Using a variety of estimation procedures, we reach the following conclusions.

First, there is evidence of the existence of a meaningful relationship between social capital and economic growth. The size of the overall mean effect ranges from somewhat larger than "small" to somewhat larger than "medium" depending on the estimation method we use (cf. TABLE 4 and Columns 6-10 in TABLE 5). Second, our analysis does not indicate that the empirical literature is distorted by publication bias. This conclusion was supported by corresponding evidence from the meta-regression analysis. Third, there is some evidence to indicate that cognitive social capital (e.g., trust) has a larger effect on economic growth than other types of social capital, though the evidence is not strong. Finally, while the coefficient signs of our meta-regression analysis lined up with prior expectations, the associated effect sizes were generally small to negligible. The most noteworthy finding is that social capital is estimated to have a smaller effect on economic growth in the US compared to other parts of the world.

REFERENCES

Akçomak, S. & ter Weel, B. (2009). Social capital, innovation and growth: Evidence from Europe. *European Economic Review*, 53(5), 544-567.

Algan, Y., Cahuc, P. (2010). Inherited trust and growth. *American Economic Review*, 100(5), 2060–2092.

Aloe, A. M. & Thompson, C. G. (2013). The synthesis of partial effect sizes. *Journal of the Society for Social Work and Research*, 4(4), 390-405.

Arrow, K. J. (1972). Gifts and Exchanges. *Philosophy Public Affairs*, 1(4), 343-362.

Banfield, A. W. F., & Tener,J.S. (1958). A Preliminary Study of the Ungava Caribou. *Journal of Mammalogy*, 39(4), 560-573.

Beugelsdijk, S., van Schaik, T. (2005). Social capital and growth in European regions: An empirical test. *European Journal of Political Economy*, 21(2), 301–324.

Borenstein, M., Hedges, L., & Rothstein, H. (2007). Meta-analysis: Fixed effect vs. random effects. *Meta-analysis.com*. https://www.meta-analysis.com/downloads/M-a_f_e_v_r_e_sv.pdf

Dettori, J. R., Norvell, D. C., & Chapman, J. R. (2022). Fixed-effect vs random-effects models for meta-analysis: 3 points to consider. *Global Spine Journal*, 12(7), 1624-1626.

Doucouliagos, C. (2011). How large is large? Preliminary and relative guidelines for interpreting partial correlations in economics. Deakin University, Department of Economics. https://www.deakin.edu.au/__data/assets/pdf_file/0003/408576/2011_5.pdf

Easterly, W. & Levine, R. (1997). Africa's growth tragedy: policies and ethnic divisions. *Quarterly Journal of Economics*, 112(4), 1203-1250.

Egger, M., Smith, G. D., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *British Medical Journal*, 315, 629–634. https://doi.org/10.1136/bmj.315.7109.629

Fukuyama, F. (1995). Social Capital and the Global Economy. *Foreign Affairs,* 74(5), 89-103.

Gennaioli, N., La Porta, R., Lopez-de-Silanes, F. & Shleifer, A. (2013). Human Capital and Regional Development. *Quarterly Journal of Economics*, 128(1), 105-164.

Gleser, L. J., & Olkin, I. (2009). Stochastically dependent effect sizes. In H. Cooper, L. V. Hedges, & J. C. Valentine (Eds.), *The Handbook of Research Synthesis and Meta-Analysis* (pp. 357–376). Russell Sage Foundation.

Gnambs, T. (2022). A brief note on the standard error of the Pearson correlation. Working paper, Leibniz Institute for Educational Trajectories. https://psyarxiv.com/uts98/

Guiso, L., Sapienza, P. & Zingales, L. (2016). Long-Term Persistence. *Journal of the European Economic Association*, 14(6), 1401–1436.

Gulati, R. (1998). Alliances and Networks. *Strategic Management Journal*, 19(4), 293-317.

Gunby, P., Jin, Y., & Reed, W. R. (2017). Did FDI really cause Chinese economic growth? A meta-analysis. *World Development*, 90, 242-255.

Harpham T. (2008). The measurement of community social capital through surveys. In: Kawachi I, Subramanian SV, Kim D, (eds.). *Social capital and health*. New York: Springer, 51–62.

Hedges, L. V., & Olkin, I. (1985). *Statistical methods for meta-analysis*. Academic Press.

Ioannidis, J. P. (1998). Effect of the statistical significance of results on the time to completion and publication of randomized efficacy trials. *JAMA*, 279(4), 281-286.

Knack, S. & Keefer, P. (1997). Does Social Capital Have an Economic Payoff? A Cross-Country Investigation. *Quarterly Journal of Economics*, 112(4), 1251-1288.

Koricheva, J., Jennions, M. D., & Lau, J. (2013). Temporal trends in effect sizes: Causes, detection and implications. In J. Koricheva, J. Gurevitch, & K. Mengersen (Eds.), *The handbook of meta-analysis in ecology and evolution* (pp. 237–254). Princeton University Press.

Kutner, M. H., Nachtsheim, C., Neter, J., & Li, W. (2005). Applied linear statistical models (5th ed.). McGraw-Hill Irwin.

Ley, E. & Steel, M.F.J. (2012). Mixtures of g-priors for Bayesian Model Averaging with economic applications." *Journal of Econometrics*, 171(2), 251-266.

Nakagawa, S., Lagisz, M., Jennions, M. D., Koricheva, J., Noble, D. W., Parker, T. H., ... & O'Dea, R. E. (2022). Methods for testing publication bias in ecological and evolutionary meta-analyses. *Methods in Ecology and Evolution*, 13(1), 4-21.

Olson, M. (1982). *The rise and decline of nations: Economic growth, stagflation, and social rigidities*. New Haven: Yale University Press.

Pietschnig, J., Siegel, M., Eder, J. S. N., & Gittler, G. (2019). Effect declines are systematic, strong, and ubiquitous: A meta-meta-analysis of the decline effect in intelligence research. *Frontiers in Psychology*, 10, 2874.

Putnam, R. (1993). The Prosperous Community: Social Capital and Public Life. *The American Prospect*, 4, 35-42.

R Core Team. (2022). *R: A language and environment for statistical computing*.

Ringquist, E. (2013). *Meta-analysis for public management and policy*. John Wiley & Sons.

Rothstein, H. R., Sutton, A. J., & Borenstein, M. (2005). Publication bias in meta-analysis. In H. R. Rothstein, A. J. Sutton, & M. Borenstein (Eds.), *Publication bias in meta-analysis: Prevention, assessment and adjustments*. Wiley.

Stanley, T. D. & Doucouliagos, H. (2012). *Meta-regression analysis in economics and business*. Routledge.

Stanley, T. D., & Doucouliagos, H. (2014). Better than random: Weighted least squares meta-regression analysis. Economics Series, SWP 2013/2 (updated July 2014). https://www.deakin.edu.au/__data/assets/pdf_file/0010/897355/2013_2.pdf

StataCorp. 2021. Stata: Release 17. Statistical Software. Lasso: Lasso inference intro. College Station, TX: StataCorp LP. https://www.stata.com/manuals/lassolassoinferenceintro.pdf

Uphoff, N.(1999). *Understanding social capital: Learning from the analysis and experience of participation*. The World Bank, Washington, DC.

Uzzi ,B. (1996). The sources and consequences of embeddedness for the economic performance of organizations: The network effect. *American Sociological Review*, 61(4), 674-698.

Van Aert, R.C.M. & Goos, C. (2022). A critical reflection on computing the sampling variance of the partial correlation coefficient. Working paper, Department of Methodology and Statistics, Tilburg University, Tilburg, the Netherlands.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, 36(3), 1–48. https://doi.org/10.18637/jss.v036.i03

Westlund, H. & Adam, F. (2010). Social capital and economic performance: A meta-analysis of 65 studies. *European Planning Studies*, 18(6), 893-919.

Zeugner, S., & Feldkircher, M. (2015). Bayesian model averaging employing fixed and flexible priors: The BMS package for R. *Journal of Statistical Software*, 68, 1-37.

Zigraiova, D. & Havranek, T. (2016). Bank competition and financial stability: much ado about nothing? *Journal of Economic Surveys*, 30(5), 944-981.

TABLE 1
Description of Variables

Variable	*Description*	*Mean*	*Min*	*Max*
	ECONOMIC GROWTH VARIABLE			
1) DV_GrowthRate	=1, if dep. variable is GDP growth rate	0.623	0	1
*-- DV_GDPLevel**	=1, if dep. variable is level of income (GDP)	0.377	0	1
	SOCIAL CAPITAL VARIABLES			
3) SC_Cognitive	=1, if social capital is cognitive	0.343	0	1
4) SC_Structural	=1, if social capital is structural	0.314	0	1
*--SC_Other**	=1, if social capital is other type	0.342	0	1
	STUDY CHARACTERISTICS			
5) PubYear	Year study was published	2009.8	1995	2019
6) Published	=1, if study is a published journal article	0.424	0	1
	SPECIFICATION			
7) LaggedDV	=1, if lagged DV included in equation	0.063	0	1
8) LaggedSC	=1, if lagged SC variable(s) included in equation	0.095	0	1
9) NumberSCVars	Number of SC variables included in equation	2.33	1	12
	ENDOGENEITY			
10) Endog_IV	=1, if instrumental variable estimator used	0.208	0	1
11) Endog_FE	=1, if fixed effects included in equation	0.105	0	1
*-- NoEndogeneity**	=1, if estimation did not address endogeneity	0.687	0	1
12) PanelData	=1, if data are panel data	0.728	0	1
	DATA CHARACTERISTICS			
13) CityLevel	=1, if data are city level	0.035	0	1
14) RegionLevel	=1, if data are regional level	0.360	0	1
15) CountryLevel	=1, if data are country level	0.492	0	1
*-- OtherLevel**	=1, if data are other level	0.113	0	1
	COUNTRIES			
16) Reg_OECDEurope	=1, if countries are in OECD or Europe	0.374	0	1
17) Reg_US	=1, if countries are in US	0.097	0	1
18) Reg_Africa	=1, if countries are in Africa	0.024	0	1
19) Reg_Asia	=1, if countries are in OECD or Europe	0.070	0	1
*-- Reg_Other**	=1, if countries outside the above regions	0.435	0	1

NOTE*:* When the grouped variables include all possible categories, the categories omitted in the subsequent analysis (the benchmark categories) are indicated by an asterisk.

TABLE 2
Descriptive Statistics for Effect Size Variables

	t-Statistics	*df*	*PCC Values*
Mean	1.95	922	0.151
Median	1.86	112	0.130
Minimum	-13.51	6	-0.747
Maximum	57.41	10,795	0.960
Std. Dev.	3.87	2319	0.229
1%	-3.66	11	-0.454
5%	-2.34	21	-0.227
10%	-1.38	28	-0.087
90%	4.00	1,658	0.460
95%	5.91	9,727	0.526
99%	17.70	10,143	0.712
Obs	993	993	993

TABLE 3
Study Weights

	Fixed Effects	*Random Effects*
Mean	1.2%	1.2%
Median	0.1%	1.3%
5%	0.0%	0.5%
10%	0.0%	0.7%
90%	1.7%	1.7%
95%	5.0%	1.8%
Minimum	0.0%	0.3%
Maximum	36.1%	1.8%
Top 3[a]	62.0%	5.5%
Top 10[b]	89.3%	17.8%
I-squared	----	97.5%
Studies	81	81

[a] The studies with the 3 largest weights are id = 8, 57, and 67. See the Appendix to match id's with studies.

[b] The studies with the 10 largest weights are id = 8, 57, 67, 41, 42, 69, 37, 15, 3, and 39 (in descending order of weights). See the Appendix to match id's with studies.

TABLE 4
Estimate of (Unadjusted) Overall Mean Effect

Variable	*OLS (1)*	*FE (2)*	*RE (3)*	*3L (4)*	*3L-VCV (5)*
Constant	0.151*** (0.022)	0.105*** (0.037)	0.140*** (0.022)	0.187*** (0.019)	0.186*** (0.020)
Observations	993	993	993	993	993
Studies	81	81	81	81	81

NOTE: Standard errors are in parentheses. All of the estimation procedures calculate cluster robust standard errors. *, **, and *** indicate statistical significance at the 10-, 5-, and 1-percent level, respectively.

TABLE 5
Estimate of the Adjusted Overall Mean Effect

Variable	*OLS* (1)	*FE* (2)	*RE* (3)	*3L* (4)	*3L-VCV* (5)	*OLS*[a] (6)	*FE*[a] (7)	*RE*[a] (8)	*3L*[a] (9)	*3L-VCV*[a] (10)
Constant (Effect beyond bias)	0.065** (0.029)	0.101* (0.053)	0.053* (0.029)	0.180*** (0.036)	0.176*** (0.038)	0.143*** (0.028)	0.286*** (0.076)	0.138*** (0.029)	0.253*** (0.052)	0.272*** (0.057)
$se(PCC)$ ***(Bias)***	0.935*** (0.297)	0.183 (0.905)	1.086*** (0.317)	0.073 (0.264)	0.103 (0.294)	0.088 (0.323)	-1.958 (1.331)	0.145 (0.337)	-0.821* (0.458)	-1.015* (0.514)
Observations	993	993	993	993	993	993	993	993	993	993
Studies	81	81	81	81	81	81	81	81	81	81

NOTE: Standard errors are in parentheses. All of the estimation procedures calculate cluster robust standard errors. *, **, and *** indicate statistical significance at the 10-, 5-, and 1-percent level, respectively.

[a] An OLS regression of *SE* on the full set of data, study, and estimation characteristics has an R-squared of 54.2%.

TABLE 6
Meta-Regression Analysis - Social Capital Variables

	No control variables					*Full set of control variables*					*LASSO*
Variable	***OLS (1)***	***FE (2)***	***RE (3)***	***3L (4)***	***3L-VCV (5)***	***OLS (6)***	***FE (7)***	***RE (8)***	***3L (9)***	***3L-VCV (10)***	***OLS (11)***
SC_Cognitive	0.094* (0.049)	0.056 (0.068)	0.100** (0.049)	0.013 (0.061)	0.025 (0.062)	0.056 (0.044)	0.049 (0.054)	0.053 (0.042)	-0.006 (0.076)	0.000 (0.080)	0.056*** (0.021)
SC_Structural	-0.012 (0.038)	0.069 (0.068)	-0.007 (0.036)	-0.001 (0.048)	0.005 (0.049)	0.005 (0.038)	0.083 (0.087)	0.017 (0.036)	0.028 (0.047)	0.034 (0.048)	0.003 (0.018)
Constant	0.122*** (0.029)	0.062* (0.033)	0.111*** (0.027)	0.182*** (0.036)	0.173*** (0.037)	----	----	----	----	----	----
$H_0: \beta_{Cognitive} = \beta_{Structural} = 0$	*F = 2.20 (p=0.117)*	*F = 0.81 (p=0.450)*	*F = 2.36 (p=0.101)*	*F = 0.02 (p=0.974)*	*F = 0.08 (p=0.923)*	*F = 0.89 (p=0.415)*	*F = 1.18 (p=0.313)*	*F = 0.81 (p=0.450)*	*F = 0.21 (p=0.814)*	*F = 0.28 (p=0.759)*	χ^2 *= 7.84 (p=0.020)*
$H_0: \beta_{Cognitive} = \beta_{Structural}$	*t = 2.00 (p=0.049)*	*t = -0.14 (p=0.893)*	*t = 2.00 (p=0.048)*	*t = 0.21 (p=0.833)*	*t = 0.289 (p=0.774)*	*t = 1.11 (p=0.269)*	*t = -0.30 (p=0.768)*	*t = 0.79 (p=0.433)*	*t = -0.43 (p=0.668)*	*t = -0.43 (p=0.672)*	*z = 2.30 (p=0.021)*
Observations	993	993	993	993	993	993	993	993	993	993	993
Studies	81	81	81	81	81	81	81	81	81	81	81

NOTE: All estimation procedures calculate cluster robust standard errors. *, **, and *** indicate statistical significance at the 10-, 5-, and 1-percent level, respectively.

TABLE 7
Meta-Regression Analysis – All Variables

	BMA			*OLS*	
	Post Mean *(1)*	***Post SD*** *(2)*	***PIP*** *(3)*	***Coeff*** *(4)*	***SE*** *(5)*
DV_GrowthRate	-0.034	0.017	0.933	-0.041	0.035
Cognitive	0.054	0.018	0.993	0.056	0.044
Structural	0.004	0.014	0.621	0.005	0.038
PubYear	-0.004	0.002	0.986	-0.005*	0.003
Published	0.042	0.017	0.980	0.044	0.035
LaggedDV	-0.074	0.031	0.970	-0.082	0.051
LaggedSC	-0.089	0.027	0.998	-0.091**	0.037
NumberSCVars	-0.013	0.003	1.000	-0.014**	0.006
Endog_IV	-0.043	0.020	0.958	-0.049	0.034
Endog_FE	-0.129	0.024	1.000	-0.140**	0.060
PanelData	-0.052	0.019	0.989	-0.057	0.067
CityLevel	0.032	0.056	0.675	0.068	0.105
RegionLevel	0.039	0.039	0.773	0.067	0.064
CountryLevel	0.043	0.047	0.775	0.066	0.080
Reg_OECDEurope	-0.034	0.029	0.832	-0.045	0.048
Reg_US	-0.156	0.045	0.998	-0.159**	0.075
Reg_Africa	-0.054	0.052	0.787	-0.073	0.068
Reg_Asia	0.004	0.035	0.651	0.003	0.068
sepcc	0.068	0.143	0.661	0.088	0.323

NOTE: The column headings *Post Mean, Post SD* and *PIP* stand for Posterior Mean, Posterior Standard Deviation, and Posterior Inclusion Probability, Posterior Mean, These are described in Section 7 in the text. The Bayesian Model Averaging (BMA) analysis was done using the R package BMS, described in Zeugner & Feldkircher (2015).

FIGURE 1
PRISMA Flow Diagram

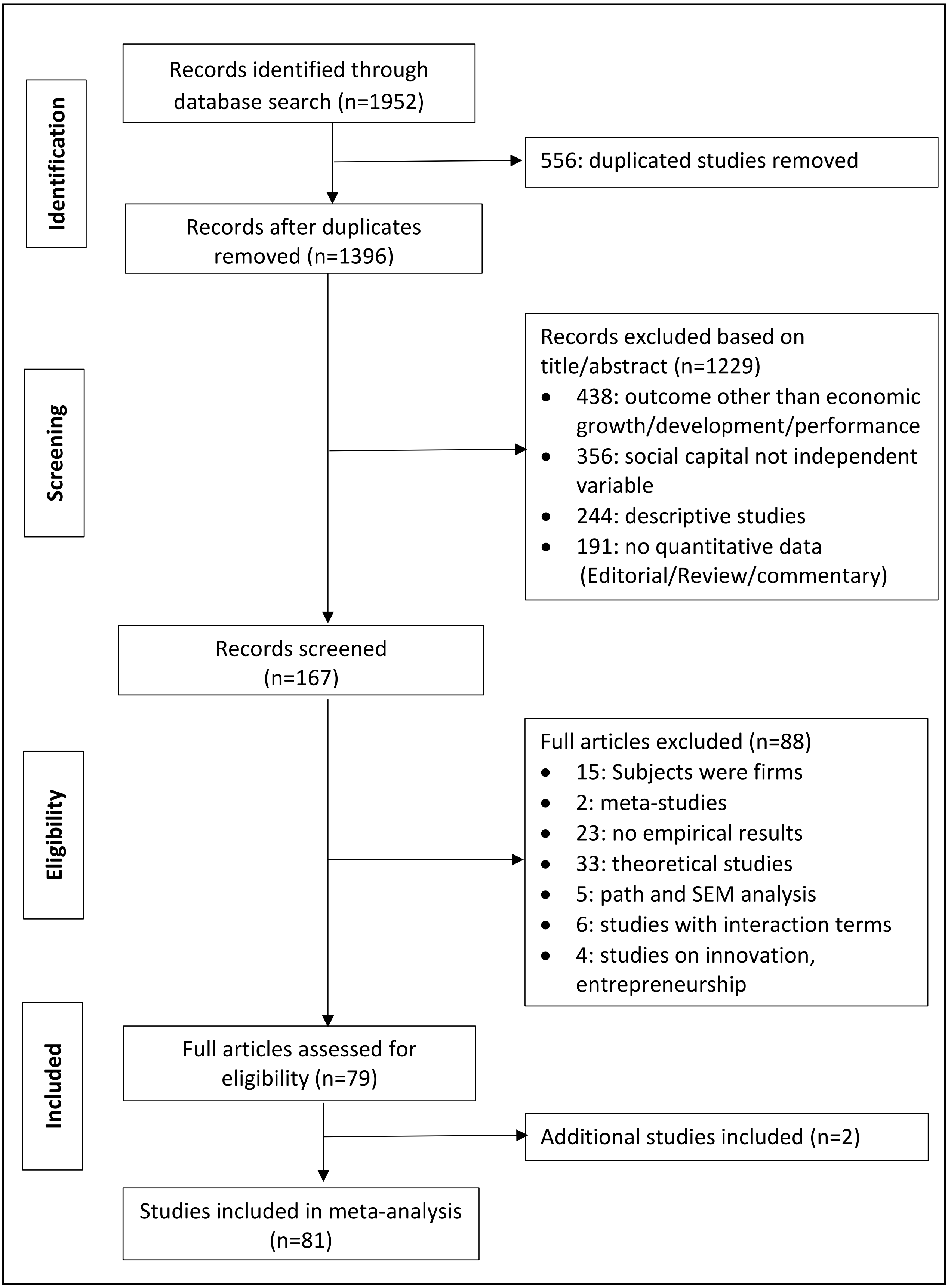
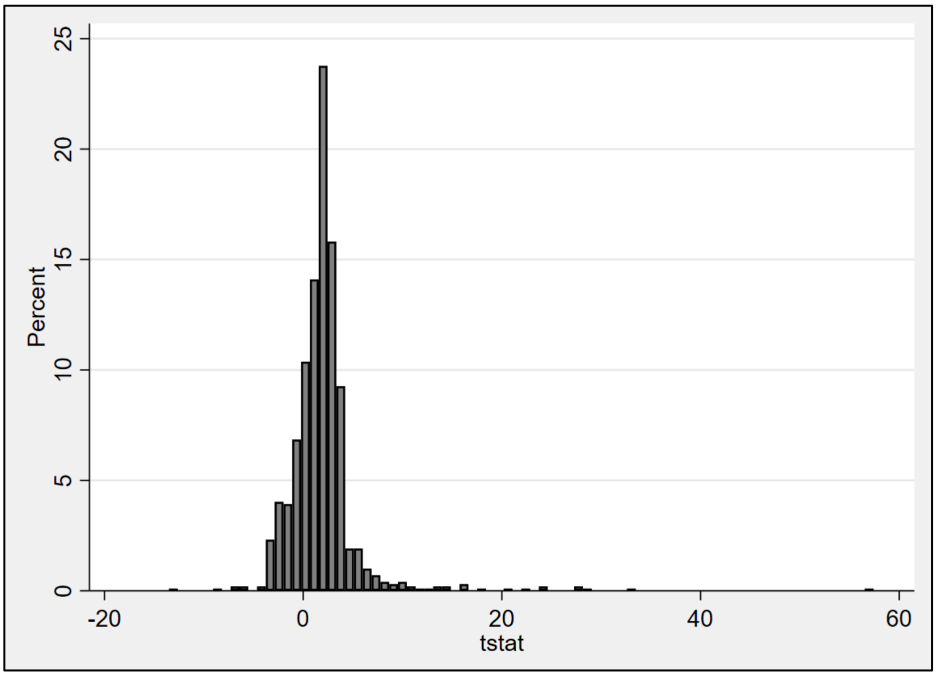


FIGURE 2
Distribution of *t*-and *PCC* Values

A. *t*-Statistics



Distribution of t-statistics	*Percent*
t < -2.00	7.2
-2.00 ≤ t ≤ 2.00	48.3
t > 2.00	44.5

B. *PCC* Values

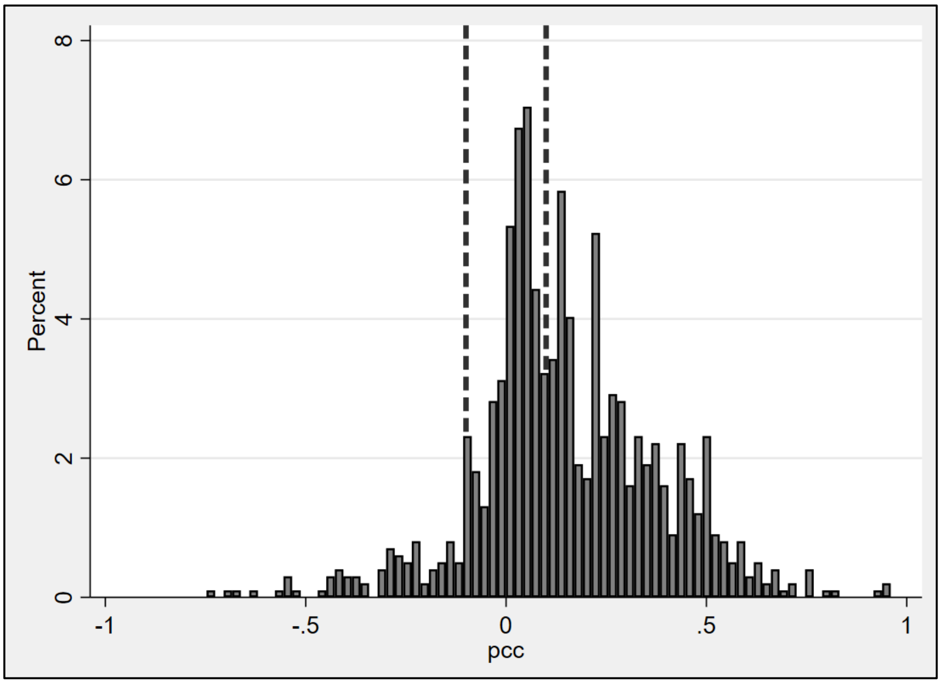


FIGURE 3
Weights and the FE Model

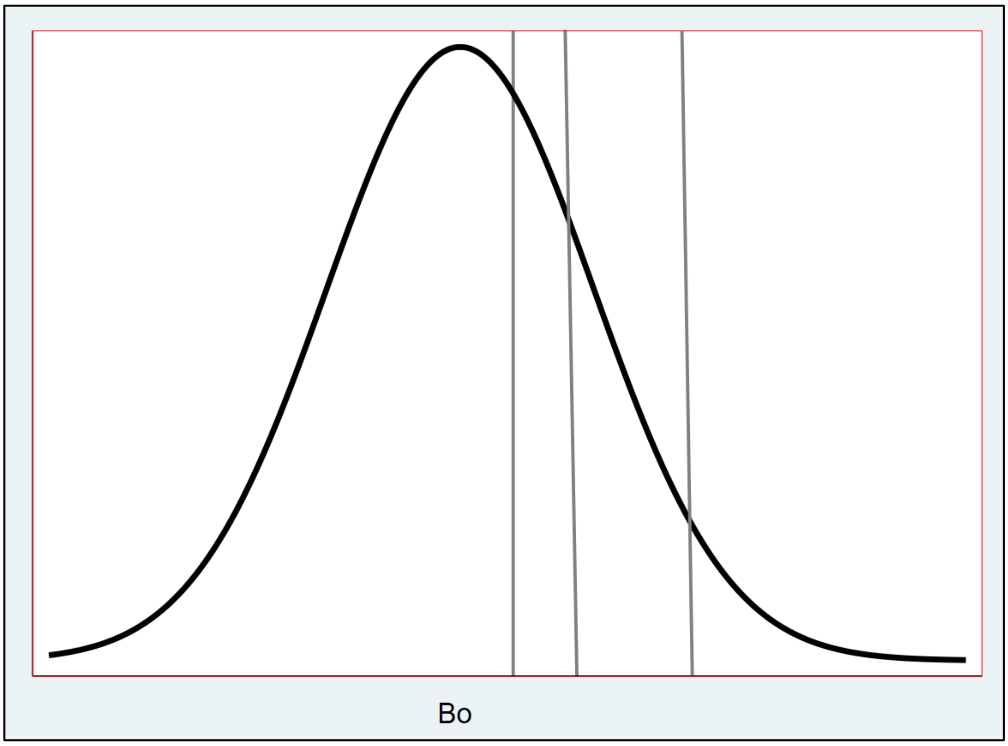
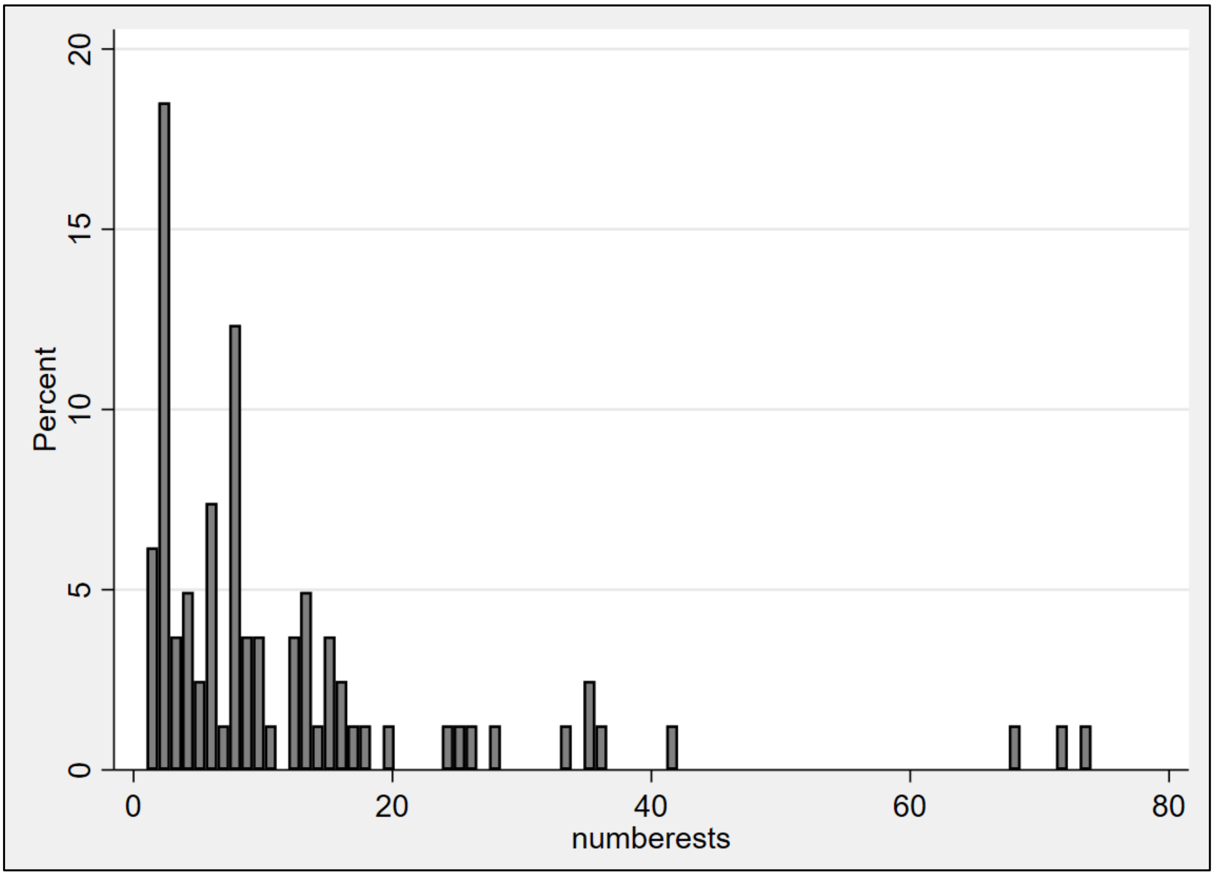


FIGURE 4
Number of Estimates per Study

A. Histogram



B. Distribution

Minimum	*Median*	*Mean*	*Maximum*
1	8	12.3	74

APPENDIX:
Studies included in this meta-analysis

[1] Aguilera, J. C. (2016). Social capital and Economic growth. Master thesis in Lund University, Lund.

[2] Ahlerup, P., Olsson, O., & Yanagizawa, D. (2009). Social capital vs institutions in the growth process. *European Journal of Political Economy*, 25(1), 1–14.

[3] Ahmad, M., & Hall, S. G. (2017). Trust-based social capital, economic growth and property rights: Explaining the relationship. *International Journal of Social Economics*, 44(1), 21–52.

[4] Akcomak, İ. S., & ter Weel, B. (2009). Social capital, innovation and growth: Evidence from Europe. *European Economic Review*, 53(5), 544–567.

[5] Algan, Y., & Cahuc, P. (2010). Inherited Trust and Growth. *American Economic Review*, 100(5), 2060–2092.

[6] Algan, Y., & Cahuc, P. (2014). Trust, Growth, and Well-Being: New Evidence and Policy Implications. In *Handbook of Economic Growth*,2,49–120.

[7] Ali, M., Egbetokun, A., & Memon, M. (2018). Human Capital, Social Capabilities and Economic Growth. *Economies*, 6(1), 2.

[8] Andini, C., & Andini, M. (2019). Social capital and growth: Causal evidence from Italian municipalities. *Journal of Economic Geography*, 19(3), 619–653.

[9] Schneider, G., Plümper, T., & Baumann, S. (2000). Bringing Putnam to the European regions: on the relevance of social capital for economic growth. *European Urban and Regional Studies*, 7(4), 307-317.

[10] Berggren, N., Elinder, M., & Jordahl, H. (2008). Trust and growth: A shaky relationship. *Empirical Economics*, 35(2), 251–274.

[11] Beugelsdijk, S., & Schaik, T. V. (2001). Social capital and regional economic growth. Discussion Paper #102.

[12] Beugelsdijk, S., & van Schaik, T. (2005). Social capital and growth in European regions: An empirical test. European Journal of Political Economy, 21(2), 301–324.

[13] Beugelsduk, S., & Smolders, S. (2003). Bridging and bonding social capital: which type is good for economic growth?. In *The cultural diversity of European unity*.147-184.

[14] Beugelsdijk, S., & Smulders, S. (2009). Bonding and Bridging Social Capital and Economic Growth. *SSRN Electronic Journal*, 27.

[15] Borja, K. (2014). Social Capital, Remittances and Growth. *The European Journal of Development Research*, 26(5), 574–596.

[16] Dearmon, J., & Grier, K. (2009). Trust and development. *Journal of Economic Behavior & Organization*, 71(2), 210–220.

[17] Del R. (2005). The Social Capital Effect on Economic Growth. Doctor thesis in The Ohio State University, Ohio.

[18] Dincer, O. C., & Uslaner, E. M. (2010). Trust and growth. Public Choice, 142(1), 59-67.

[19] Dinda, S. (2007). Social capital in the creation of human capital and economic growth: A productive consumption approach. *The Journal of Socio-Economics*, 37(5), 2020–2033.

[20] Działek, J. (2014). Is social capital useful for explaining economic development in polish regions?. Geografiska Annaler: Series B, *Human Geography*, 96(2), 177-193.

[21] Dzialek, J. (2009). Social capital and economic growth in Polish regions. MPRA Paper No. 18287.

[22] Fafchamps, M., & Minten, B. (2002). Returns to social network capital among traders. *Oxford Economic Papers*, 54(2), 173-206.

[23] Pan, F., & He, C. (2010). Regional difference in social capital and its impact on regional economic growth in China. *Chinese Geographical Science*, 20(5), 442–449.

[24] Forte, A., Peiró Palomino, J., & Tortosa Ausina, E. (2015). Does social capital matter for European regional growth? *European Economic Review*, 77, 47–64.
[25] Guiso, Luigi, Paola Sapienza & Luigi Zingales. (2011). Civic Capital as the Missing Link. *Social Economics Handbook*, 1,417-480.
[26] Gupta, R. N. R. (2015). Economic Development: Is Social Capital Persistent? CES Working Papers, Available at halshs-01157891.
[27] Hall, S. G., & Ahmad, M. (2013). Can Trust Explain Social Capital Effect on Property Rights and Growth? *Procedia Economics and Finance*, 7, 55–64.
[28] Helliwell, J. F., Putnam, D.(1995):, R. D. P. R. (1995). Economic Growth and Social Capital in Italy. *Eastern Economic Journal*, 21(3), 295–307.
[29] Hoyman, M., McCall, J., Paarlberg, L., & Brennan, J. (2016). Considering the Role of Social Capital for Economic Development Outcomes in U.S. Counties. *Economic Development Quarterly*, 30(4), 342–357.
[30] James, H. S. (2015). Generalized Morality, Institutions and Economic Growth, and the Intermediating Role of Generalized Trust: Generalized Morality, Institutions and Economic Growth. *Kyklos*, 68(2), 165–196.
[31] Kaldaru, H., & Parts, E. (2005). The Effect of Macro-level Social Capital on Sustainable Economic Development. *SSRN Electronic Journal*.
[32] Kapan, L. (2019). Economic growth-A matter of trust?: The impact of social capital on economic growth. Doctor thesis in Jönköping University, Jönköping.
[33] Knack, S., & Keefer, P. (1997). Does Social Capital Have an Economic Payoff? A Cross-Country Investigation. *The Quarterly Journal of Economics*, 112(4), 1251–1288.
[34] Li, Y., Wang, X., Westlund, H., & Liu, Y. (2015). Physical Capital, Human Capital, and Social Capital: The Changing Roles in China's Economic Growth: Physical Capital, Human Capital, and Social Capital. *Growth and Change*, 46(1), 133–149.
[35] Baliamoune-Lutz, M., & Mavrotas, G. (2009). Aid effectiveness: looking at the aid–social capital–growth nexus. *Review of Development Economics*, 13(3), 510-525.
[36] Baliamoune-Lutz, M. (2005). Institutions, social capital, and economic development in Africa: an empirical study. International Centre for economic research working paper series, 18.
[37] Lyon, T. P. (2005). Making Capitalism Work: Social Capital and Economic Growth in Italy, 1970-1995. Available at SSRN 726201.
[38] Doh, S., & McNeely, C. L. (2012). A multi-dimensional perspective on social capital and economic development: An exploratory analysis. *The Annals of Regional Science*, 49(3), 821–843.
[39] Miguel, E., Gertler, P., & Levine, D. I. (2005). Does Social Capital Promote Industrialization? Evidence from a Rapid Industrializer. *Review of Economics and Statistics*, 87(4), 754–762.
[40] Montolio, D., & Tur-Prats, A. (2018). Long-Lasting Social Capital and its Impact on Economic Development: The Legacy of the Commons. XREAP2018-08.
[41] Neira, I., Vázquez, E., & Portela, M. (2009). An Empirical Analysis of Social Capital and Economic Growth in Europe (1980-2000). *Social Indicators Research*, 92(1), 111–129.
[42] Otto, D. M., Tirmizi, S. N., & Ryan, V. (2001). Role of social capital in economic and community development. Available at American Agricultural Economics Association Annual Meeting, No.374-2016-19775.
[43] Peiró-Palomino, J. (2016). Social capital and economic growth in Europe: Nonlinear trends and heterogeneous regional effects. *Oxford Bulletin of Economics and Statistics*, 78(5), 717-751.
[44] Peiró Palomino, J., & Tortosa-Ausina, E. (2012). Social Capital, Investment and Economic Growth. Evidence for Spanish Provinces. *SSRN Electronic Journal*,14

[45] Pérez, F., Fernandez de Guevara, J., Serrano, L., & Montesinos, V. (2006). Measurement of social capital and growth: An economic methodology. *Fundación BBVA*, 4.
[46] Pervaiz, Z., & Chaudhary, A. R. (2015). Social Cohesion and Economic Growth: An Empirical Investigation: Social Cohesion and Economic Growth. *Australian Economic Review*, 48(4), 369–381.
[47] Roth, F. (2022). Social Capital, Trust, and Economic Growth. In: Intangible Capital and Growth. *Contributions to Economics*. Springer, Cham.
[48] Rupasingha, A., Goetz, S. J., & Freshwater, D. (2002). Social and institutional factors as determinants of economic growth: Evidence from the United States counties. *Papers in Regional Science*, 81(2), 139–155.
[49] Schneider, G., Plümper, T., & Baumann, S. (2000). Bringing Putnam to the European Regions: On the Relevance of Social Capital for Economic Growth. *European Urban and Regional Studies*, 7(4), 307–317.
[50] Temple, J. (1998). Initial conditions, social capital and growth in Africa. *Journal of African Economies*, 7(3), 309-347.
[51] Algan, Y., & Cahuc, P. (2013). Trust and Growth. *Annual Review of Economics*, 5(1), 521–549.
[52] Roth, F. (2007). Social Capital, Trust, and Economic Growth—A cross-sectional and panel analysis. Doctor thesis in Universität Göttingen, Göttingen.
[53] Wan, J., & Wan, H. (2015). Can Social Capital Drive Economic Growth and Environmental Protection — Evidence from China. In 2015 International Conference on Mechanical Science and Engineering, 113-126.
[54] Press.Westlund, H. (2013). *Social capital and rural development in the knowledge society*. Edward Elgar Publishing.
[55] Whiteley, P. F. (2000). Economic Growth and Social Capital. *Political Studies*, 48(3), 443–466.
[56] Zak, P. J., & Knack, S. (2001). Trust and growth. *The Economic Journal*, 111(470), 295-321.
[57] Beugelsdijk, S., & Smulders, S. (2009). Bonding and bridging social capital and economic growth. CentER Discussion Paper, 2009-27.
[58] Brito, J. A. (2015). Social Cohesion and Economic Growth: Small States vs Large States. MPRA Paper, No.66118
[59] Chen, F.W., Fu, L.W., Wang, K., Tsai, S.B., & Su, C.H. (2018). The Influence of Entrepreneurship and Social Networks on Economic Growth—From a Sustainable Innovation Perspective. *Sustainability*, 10(7), 2510.
[60] Schmidt, K. (2003). Is trust important for economic development and growth?. *Berlin Disponível Science and Politics*, 28, 664-83.
[61] Granato, J., Inglehart, R., & Leblang, D. (1996). Cultural values, stable democracy, and economic development: a reply. *American Journal of Political Science*, 40(3), 680-696.
[62] James Jr, H. S. (2013). An Empirical Investigation of the Relationship Among Generalized Morality, Institutions, Generalized Trust and Economic Growth. Institutions, Generalized Trust and Economic Growth. Available at SSRN 2331483.
[63] Heller, L. (2009). Social Cohesion and Its Relationship to Endogenous Institutional Formation and Economic Growth. *Journal of Private Enterprise*, 25(1).
[64] Holthe, I. C. (2009). Tracking trust-Investigating how social capital influences economic development in Latin America. Master thesis in University of Bergen, Bergen.
[65] Jackman, R. W., & Miller, R. A. (1996). A Renaissance of Political Culture? *American Journal of Political Science*, 40(3), 632.

[66] Komándi-Jánosi, K. (2016). How does trust affect economic growth through spurring innovation?. Analysis of nuts regions. Doctor thesis in Central European University, Budapest.
[67] Kanas, A. (2011). The economic performance of immigrants: The role of human and social capital. Ph.D. thesis in Utrecht University, The Netherlands.
[68] Knack, S. (2001). Trust, associational life, and economic performance. MRPA Paper No.27247.
[69] Laughlin, T. W. (2012). The effects of social capital on local government performance and economic development. Ph.D. thesis in Auburn University, Alabama.
[70] Liou, F., & Ding, C. G. (2007). Trust and economic growth in a democratic power shift: An empirical study of Taiwan. *International Journal of Development Issues*, 6(1), 63–78.
[71] Manyasa, E. O. (2009). Social capital and rural economic development in western province of Kenya : An empirical analysis. Doctor thesis in Kenyatta University, Nairobi.
[72] Moesen, W., Puyenbroeck,T. & Cherchye, L. (2000). Trust as societal capital: economic growth in European regions, Public Economics Working Paper Series,1.
[73] Pervaiz, Z., & Chaudhary, A. R. (2018). Does trust matter for economic growth and human development? Empirical evidence from a panel of countries. *Pakistan Journal of Commerce and Social Sciences*, 9(3), 916-927.
[74] Schneider, G., Plümper, T., & Baumann, S. (2000). Bringing Putnam to the European Regions: On the Relevance of Social Capital for Economic Growth. *European Urban and Regional Studies*, 7(4), 307–317.
[75] Sibt-e- Ali, M., Chaudhary, I. S., & Farooq, F. (2018). Impact of Human and Social Capital on Economic Development in Pakistan: Empirical Evidence from Primary Data Analysis. *Journal of Accounting and Finance in Emerging Economies*, 4(1), 39–46.
[76] Yokoyama, S., & Sakurai, T. (2006). Potential of social capital for community development. Available from APO's web site.
[77] Tabellini, G. (2010). Culture and Institutions: Economic Development in the Regions of Europe. *Journal of the European Economic Association*, 8(4), 677–716.
[78] Alcántar-Toledo, J., & Venieris, Y. P. (2014). Social capital, sociopolitical instability, and economic development: A general equilibrium model. *The Economics of Peace and Security Journal*, 9(1).
[79] Vizitei, C. C. (2012). Can trust substitute for quality institutions to promote economic growth?. Master thesis in University of Missouri-Columbia, Columbia.
[80] Volland, B. (2010). Trust, confidence and economic growth: An evaluation of the Beugelsdijk Hypothesis. *Jena Economic Research Papers*, 80.
[81] Xia, M. (2009). Social Capital in Rural China: Its Impact on Economic Development, Grassroots Governance, and Democratic Participation. Ph.D. thesis in Old Dominion University, Virginia.