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Social Capital and Economic Growth: A Meta-Analysis

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Abstract: This research provides a comprehensive, quantitative synthesis of the empirical literature on social capital and economic growth. It assesses 993 estimates from 81 studies. Utilizing a variety of estimation procedures, we draw the following conclusions: There is strong evidence to indicate that publication bias distorts the empirical literature, causing estimates of social capital's effects to be overstated. Initial, unadjusted estimates are positive, generally moderately sized, and consistently statistically significant. Correcting for publication bias reduces these estimates by half or more. Our preferred estimates indicate that the effects of social capital on economic growth, though statistically significant, are very small. This highlights that an uncritical acceptance of the empirical literature can lead to an inflated perception of the importance of social capital. Analysis of the different types of social capital (cognitive, structural, other) finds little evidence of differences in growth effects. Further investigation of moderating factors finds that most have estimated effects that are generally small to negligible, though social capital appears to have a substantially smaller effect on economic growth in the US compared to other parts of the world.

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

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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 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.

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).

A large body of empirical research has attempted to quantify the contribution of social capital to economic growth. The purpose of this study is to synthesize that literature. We analyze 993 estimates from 81 studies to address four questions: (i) Is there evidence 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? (iv) What factors may explain the wide range of estimates found in the literature? By addressing these questions, we hope to gain a better understanding of the relationship between social capital and economic growth, and the factors that influence this relationship.

Our analysis finds strong evidence that publication bias distorts the empirical literature, causing estimates of social capital's effects to be overstated. Initial, unadjusted estimates are positive, generally moderately sized, and consistently statistically significant. Correcting for publication bias reduces these estimates by half or more. Our preferred estimates indicate that the effects of social capital on economic growth, though statistically significant, are very small. Analysis of the different types of social capital (cognitive, structural, other) finds little evidence of differences in growth effects. Further investigation of moderating factors finds that most have estimated effects that are generally small to negligible, though social capital appears to have a substantially smaller effect on economic growth in the US compared to other parts of the world.

We proceed as follows. Section 2 provides a brief summary of prior research and discusses the challenge of categorizing social capital. Section 3 reports on the literature search we employed and the process we followed to construct our sample. Section 4 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 5 provides a statistical overview of the estimated effect sizes in our sample and discusses five estimators for estimating the effect of social capital on economic growth. Section 6 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 7 estimates and tests for different effects for different types of social capital. Section 8 explores for systematic determinants that can explain the observed heterogeneity in estimated effects across studies. Section 9 summarizes and concludes.

2. Overview of the Literature and the Challenge of Categorizing Social Capital

A search on Google Scholar for "social capital and economic growth" produces over 4,700,000 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 (WA; 2010). WA survey 65 studies of social capital and economic performance that range in level from firms and households, to states and regions, to countries. Most of the social capital measures in their study consist of variables related to (i) interpersonal trust and (ii) the prevalence or participation in associations. They conclude that social capital has its strongest impact at the firm level, with diminishing impact as the spatial level of analysis rises.

While WA provides useful insights, it has several shortcomings. First, it is qualitative. Numerical analysis consists of "vote counting" with results from studies categorized as "positive", "negative", or "mixed, ambivalent". As a result, they are unable to aggregate estimates to calculate an overall estimate of the quantitative impact of social capital on growth. Second, their review is dated. The most recent study included in WA was published in 2008. Much research has appeared since then. These shortcomings highlight the need for an up-to-date, quantitative synthesis of the literature.

A number of prominent studies identify trust as one of the main determinants of economic growth. Knack & Keefer (1997) employ a cross-sectional regression on 29 countries and conclude that trust is a significant causal component of growth. Zak & Knack (2001) broaden the sample to 41 countries. Their cross-sectional results indicate that a 15-percentage point increase in trust yields a 1 percentage point increase in economic growth. Beugelsdijk et al. (2004) confirm the robustness of Zak & Knack's results using the sample of 41 countries. Dearmon & Grier (2009) highlight the importance of trust in economic development by

[1] Search conducted on August 16, 2023.

investigating several previously unexplored channels. These channels include (1) fostering input accumulation, (2) increasing efficiency of other inputs, and (3) directly increasing economic growth. Algan & Cahuc (2010) argue that inherited trust had a sizeable impact on worldwide, economic growth in the twentieth century. Forte et al. (2015) focus on 85 European regions during the 1995–2008 and find that trust is positively associated with economic growth.

Categorizing different types of social capital can be difficult. TABLE 1 reports an extensive, but not exhaustive, list of types of social capital. There is overlap between some of the categories; and different researchers can categorize given measures of social capital differently. Amongst the different categories, bonding, bridging, and linking are often grouped together, as are cognitive and structural. Trust is generally categorized as either a bonding or cognitive type of social capital.

Given the difficulty of categorizing social capital, we sought to employ a generally accepted classification system that most easily allowed us to partition our observed measures into particular types. We settled on the categories cognitive, structural, and other. These three categories seemed to most easily fit all the social capital variables used by the studies in our sample. We provide examples for each of these three categories below.

3. Literature Search and Data Construction

We conducted our literature search in accordance with the reporting guidelines for meta-analysis in economics (Havránek 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. The object of our search was all studies that estimated a version of a linear model that regressed economic growth (*G*) on a measure of social capital (*SC),* along with a set of control variables (Z_k):

(1) $G = \beta_0 + \beta_1 SC + \sum_{k=2}^{K} \beta_k Z_k + error.$

The goal was to collect estimates of the effect of social capital on economic growth, represented by β_1 in Equation (1).

To identify relevant research, we used paired 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 city, region, or country. 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.[2] 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

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

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 these factors could explain why estimates differed across studies.

4. The Data

Measures of economic growth and social capital. We introduce our data by presenting summary statistics of associated study, estimation, and data characteristics. These are presented in TABLE 2. 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 TABLE 2. 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. 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 type 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.

Partial Correlation Coefficient. 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 problem when synthesizing literatures that use different variables to measure the same or similar effects.

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

(2.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:

(2.b) $$se(PCC_i) = \frac{1 - PCC_i^2}{\sqrt{df_i}}.$$ [3]

PCC is widely used in the meta-analysis literature because it provides a common metric for comparing otherwise disparate estimates, such as is the case for the estimates in our study.

One disadvantage of *PCC* 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

[3] There is some debate about the appropriate standard error expression to use in meta-analysis. Equation (2.b) is different from a formula that is commonly found in the economics, meta-analysis literature; namely, $se(PCC_i) = \sqrt{\frac{1-PCC_i^2}{df_i}}$ (see, for example, Stanley & Doucouliagos, 2012; Zigraiova & Havaranek, 2015; and Gunby, Jin, & Reed, 2017). van Aert & Goos (2023) point out that this formula is wrong. 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. In response, Stanley & Doucouliagos (2023) note that both expressions for $se(PCC_i)$ produce biased meta-analytic estimates, with $se(PCC_i) = \sqrt{\frac{1-PCC_i^2}{df_i}}$ being less biased and preferred. We discuss this issue further below.

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.[4] We use the latter values to guide the interpretation of our subsequent estimates, though we are mindful that these are but rough guidelines.

However, there is another, more serious problem with using *PCC* in meta-analyses. Meta-analyses employ a weighting scheme whereby more precise estimates, that is, estimates with smaller estimated standard errors, receive greater weight when calculating an average of estimated effects. As can be clearly seen from Equation (2.b), as *PCC* gets larger in absolute value, $se(PCC_i)$ gets smaller. This means that larger absolute values of *PCC* receive greater weight. If estimates tend to be positive, as is the case for the literature on social capital and economic growth, weighting by precision will produce a weighted average that overestimates the population mean.

Fisher’s z. Accordingly, van Aert (2023) recommends converting *PCC* into “Fisher’s z” as follows:

(3.a) $z_i = 0.5 \times \log\left(\frac{1+PCC_i}{1-PCC_i}\right)$, and

(3.b) $se(z_i) = \frac{1}{\sqrt{df_i - 3}}$.

Van Aert (2023) identifies several advantages of Fisher’s *z* over *PCC*. Three are worth highlighting. First, unlike with *PCC*, the standard error is independent of the effect size. This eliminates the problem of dependency of weights on effect sizes noted above. A second advantage is related.

As we discuss below, a common approach to correct for publication bias is to include the standard error variable as an explanatory variable when estimating the overall mean effect.

[4] See Figure 3, page 13 in Doucouliagos (2011).

However, the mathematical relationship between $se(PCC_i)$ and PCC will generate a relationship between these two variables even in the absence of publication bias, biasing estimation and tests for publication bias. Once again, the independence of Fisher's z and its standard error eliminates this problem.

A third advantage is that Fisher's z more closely follows a normal distribution than the *PCC*, especially if the true *PCC* is different from zero. Hence, meta-analyzing Fisher's z is more in line with the assumptions of the common meta-analysis models that assume that the sampling distribution of each study's effect size is normal. Accordingly, our subsequent analysis employs Fisher's z as its measure of the effect of social capital on economic growth.[5]

With respect to interpreting the size of Fisher's z, one can transform estimated values of Fisher's z back to *PCC* using the formula $PCC(Fz) = (e^{2Fz} - 1)/(e^{2Fz} + 1)$, where *Fz* is the meta-analytic estimate based on the Fisher's z transformed *PCCs.* From a practical perspective, Fisher's z values are approximately equal to *PCC* for everything but the largest values. For example, the "small", "medium", and "large" *PCC* values of 0.10, 0.23, and 0.39 convert to Fisher's z values of 0.10, 0.23, and 0.41.

Other data characteristics. 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

[5] An earlier version of this paper used *PCC* as its measure of effect before we learned of the problems with this measure (Stanley & Doucouliagos, 2023; Hong & Reed, 2023). Some of the results changed (see Xue, Reed, & van Aert, 2022). Using Fisher's z rather than *PCC* resulted in smaller estimates and stronger evidence for publication bias when using Egger's regression test. This is precisely what one would expect given the mathematical relationship between *PCC* and $se(PCC)$ (see Equations 1a and 1b). The negative relationship between these two variables means that larger *PCC* will be associated with smaller estimated standard errors. This will give large *PCC* values disproportionately greater weight, inflating the estimate of the overall mean; and generate a negative bias for the estimated coefficient for $se(PCC)$. The latter bias will counteract any evidence of real publication bias.

larger and more significant estimates get published sooner, something known as "time-lag bias" (Ioannidis, 1998; Koricheva et al., 2013; Pietschnig et al., 2019).

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/z*. This implies a negative relationship between z 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. We note that Westlund & Adam (2010) found that the effects of social capital on growth diminished as one increased the spatial level of the data.

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.

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

TABLE 3 summarizes the z values that are the focus of our analysis. The mean and median z values are 0.163 and 0.131. Using Doucouliagos' size categories ("small" = 0.10, "medium" = 0.23, and "large" = 0.41), 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". As can be seen from the table, z values and *PCC* values are closely matched across a broad range of values. The z values vary widely, from a minimum of -0.967 to a maximum of 1.943. 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 z values (bottom panel). Given that the mean/median z 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 z 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 (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:

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

where i refers to the ith 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 we assume $cov(\theta_i, \varepsilon_i) = 0$. In words, Equation (4) states that the true effect underlying the i^{th} estimated z value consists of a common value, β_0, plus a unique draw from a shared, normal distribution, θ_i. This models each z estimate as having a unique, true effect. This true effect is then estimated with sampling error, ε_i.

Fundamental to the RE model is the assumption that there is no single, true effect underlying all studies. Rather, underlying each estimated z 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 $E(z_i) = \beta_0$, 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 z 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, typically using one of two cluster robust standard errors, CR1 and CR2 (Pustejovsky, 2016).

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 $se(z_i)^2$, the RE model weights by the inverse of $(se(z_i)^2 + \tau^2)$. 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 $se(z_i)^2$, 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 4 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 66% of the weight in calculating the overall mean.[6] The top 10 studies – approximately 12% of the total number of studies – receive 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 *z* values is characterized by a large degree of effect heterogeneity. We can quantify this heterogeneity by using the I^2 statistic, 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 I^2, like the FE and RE estimators, assumes that all estimated effects are independent. The I^2 is 97.6% in our meta-analysis. This is relatively, but not extraordinarily, large for meta-analyses in economics. Accordingly, for the RE model, the top 3 and top 10 studies receive only 5% and 18% of the weight in calculating the overall mean. The difference between the minimum and maximum weights is slight: 0.3% versus 1.9%. 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

[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 (in order of weights). They count for 35.3% of the total number of estimates.

estimates from the same study would be correlated, and that is indeed the case for our sample. The intraclass correlation for the z variable is 0.321, indicating a high degree of clustering.

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

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

where j is referring to the jth estimate and N_i is the total number of estimates in the ith study, φ_{ij} is a normally distributed random effect with mean zero and variance τ_φ^2, and we assume $cov(\theta_i, \varepsilon_{ij}) = cov(\varphi_{ij}, \varepsilon_{ij}) = 0$. Equation (5) states that the true effect underlying the estimated z value consists of the same two components as the RE model, plus a third component, φ_{ij}, that indicates that the true effects 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 sample. 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. The 3L and 3L-VCV models are alternatively known as hierarchical effects meta-analysis and correlated and hierarchical effects meta-analysis, respectively.

[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.

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. Our main results are obtained using the programming language R (R Core Team, 2022). Most estimates come from the R package *metafor* (Viechtbauer, 2010). All the code used to produce the estimates in this study are available at:[9]

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

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

TABLE 5 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 (4) and (5).[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 0.061 (FE) to a high of 0.187 (3L), with all five estimates being statistically significant at the 5-percent level. In terms of Doucouliagos' size classifications, these range approximately from "small" to "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(z)) to the specifications of Equations (4) and (5). In economics, this is known as FAT-PET, for Funnel Asymmetry Test – Precision

[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.

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. Statistical significance of this coefficient is taken 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 $se(z)$ equal to 0, one can estimate what the overall mean value of z would be in the absence of publication bias. In a univariate regression with $se(z)$ 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 z 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 6 report estimates of both the coefficient on $se(z)$ ("Bias") and the constant term ("Effect beyond bias"). Evidence of the existence of publication bias is strong and consistent. Across all five estimation procedures, we obtain positive and statistically significant estimates for the coefficient of $se(z)$**.** The positive sign indicates that effects that are estimated less precisely tend to be larger in size.

The constant term in Columns (1) to (5) represents the predicted value of the overall mean effect in the absence of publication bias, so that $se(z) = 0$. The corresponding estimates of "Effect beyond bias" are 0.032, 0.038, 0.025, 0.025, and 0.020 -- well below Doucouliagos'

[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.

(2011) “small” threshold of 0.10. These compare with the unadjusted estimates in TABLE 5 of 0.163, 0.061, 0.138, 0.187, and 0.166. The substantial difference between the two sets of estimates shows how publication bias can cause the literature to distort the true effects of economic factors.

While the FAT-PET framework is ubiquitous in the meta-analytic literature, it is an odd specification. The use of a univariate regression to infer publication bias is unnecessarily restrictive. If $se(z)$ is correlated with other data, study, and estimation characteristics, and these characteristics are themselves related to the estimated effect, z, 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 z on $se(z)$.

Indeed, there are grounds for being concerned about omitted variables. An OLS regression of $se(z)$ on the data, study, and estimation characteristic variables in our sample has an R-squared of 53.8%. Accordingly, we next attempt to strip out from $se(z)$ the influence of these other variables.

Columns (6) through (10) of TABLE 6 report the results of this analysis. The estimates for “Bias” and “Effect beyond bias” come from two separate estimation procedures. The estimated coefficient for $se(z)$ comes from a meta-regression in which all the data, study, and estimation characteristics in TABLE 2 are added to the regression along with $se(z)$. TABLE 6 only reports the estimated coefficient for $se(z)$, though we will report the estimates for the other variables later.

The inclusion of the additional variables does not affect our conclusion concerning the existence of publication bias. The coefficients for the bias terms continue to be positive and strongly significant in each of the models in Columns (6) to (10). However, they are somewhat smaller. This is important because it has follow-on effects for the estimates of "Effect beyond bias".

To estimate "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, setting the value of $se(z)$ equal to 0 and multiplying all the other estimated coefficients by the sample means of their respective variables provides a prediction of the overall mean effect when the effect of publication bias has been eliminated.

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. Following this procedure produces "Effect beyond bias" estimates that are approximately twice the size of the estimates Columns (1) to (5), ranging from 0.052 to 0.077. Even so, these all fall short of Doucouliagos' "small" threshold. While economically very small in size, the estimates are consistently statistically significant.[13]

We prefer the estimates of Columns (6) to (10) because they correct for omitted variable bias in the estimation of $se(z)$. Among these, we prefer the 3L and 3L-VCV estimates because they incorporate the effect of clustering in the estimation of coefficients. Even so, there is not much difference across the respective models. They all lead to the same conclusion: that the effect of social capital on economic growth is statistically significant but very "small".

[13] Unfortunately, the available statistical packages do not allow one to calculate CR2 standard errors for the "Effect beyond bias" predictions in Columns (6) through (10). Accordingly, we use the CR1 estimator for clustered standard errors (Pustejovsky, 2016). These are smaller than the CR2 standard errors in Columns (1) through (5). However, this does not appear to explain their statistical significance, because the estimates in (1) through (5) remain statistically insignificant even when the CR1 estimator is used.

7. 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 7 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.[14]

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 $H_0: \beta_{Cognitive} = \beta_{Structural} = 0$. 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 differ from other types of social capital. We investigate this latter question by testing $H_0: \beta_{Cognitive} = \beta_{Structural}$. The results of testing the two hypotheses are reported in separate rows at the bottom of TABLE 7.

[14] An earlier version of this paper also reported LASSO estimates in TABLE 7 (StataCorp. 2021). We omit LASSO from this version because the model selection algorithm only selected 3 control variables, and none were found to be correlated with the dependent variable, so we deemed the model unreliable.

The results are easily summarized. Across the board, for all 10 models, we fail to reject the two null hypotheses at the 5 percent level. Despite much literature that teases out various facets of the different types of social capital, at least when it comes to economic growth, we find no evidence to indicate that different types of social capital have different effects, nor that there is a difference in the growth effects of cognitive versus structural social capital. Across the empirical literature on economic growth, “trust”, which is effectively equivalent to cognitive social capital in our study, is widely seen as an important determinant of economic growth (Banfield, 1958; Knack and Keefer, 1997; Zak and Knack, 2001; Beugelsdijk et al., 2004; Dearmon and Grier, 2009). Our analysis does not find anything unique about trust relative to other types of social capital when it comes to economic growth.

8. 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 estimates that we see in the literature. The problem is that we have a large number of variables. There is a total of 2^{20} different models one can specify given the 20 data, study, and estimation variables in our study. We do not know which ones to select to get the “best” estimate of the moderating effects of these variables, yet we know from the economic growth literature that different model specifications can produce different findings (Sala-i-Martin, ,1997; Brock & Durlauf, 2001; Fernandez, Ley, & Steel, 2001; Hoover & Perez, 2004). Our approach is to use Bayesian Model Averaging, BMA (Hoeting et al., 1999; Zeugner & Feldkircher, 2015).

It is impossible to estimate 2^{20} different 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.[15]

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.[16,17]

Columns (1) through (3) in TABLE 8 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 the estimated probability that the respective variable belongs in the "true model". Each specification receives a posterior probability of being 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.

[15] Personal correspondence with Zeugner on October 15, 2015.
[16] We note that this approach implicitly assumes that the estimates are independently distributed. Unfortunately, this assumption is violated in any meta-analysis dataset that has multiple estimates per study where clustering is likely to exist. Unfortunately, limitations in the available statistical packages do not allow us to assume a more general prior distribution for the coefficients.
[17] Our BMA analysis sets the model prior = "random", which assumes a "Binomial-beta" distribution over model size. This is the approach taken by Ley & Steel (2009). For Zellner's g, we select the option "g = "hyper = UIP", also recommended by Zeugner.

We also report the results from an OLS regression with all variables included in Columns (4) and (5). We had already reported the OLS estimates for the two social capital variables in Column (6) of TABLE 7. We now report all the estimates from that regression. We include the OLS estimates in TABLE 8 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 8, it is useful to note that other than *PubYear, NumberSCVars,* and *sez,* all variables are dummy variables. Thus, the coefficients can be interpreted as the change in the overall mean effect of social capital on economic growth when the respective dummy variable changes value from 0 to 1. Applying Doucouliagos' size classifications, we see most of the moderating effects fail to achieve Doucouliagos' threshold value of "small" (= 0.10). The exceptions are *Endog_FE* and *Reg_US.*

The BMA mean value of -0.132 for *Endog_FE* indicates that panel studies that included group fixed effects had smaller estimated social capital effects than other studies. However, one must be careful not to misinterpret this finding. Fisher's *z* is based on *PCC* and *PCC* is based on *t*-statistics. We expect within-variation for social capital variables to be relatively small compared to between-variation because social norms change slowly over time. A consequence of larger standard errors and smaller *t*-values will thus be smaller social capital effects.

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. We conjecture that this may reflect that there exist institutions in the US that can serve as substitutes for social capital, at least to some extent. This may be a fruitful topic for future research to explore.

9. 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 then convert them further into Fisher z values, assessing the resulting values using Doucouliagos' (2011) effect size classifications. Using a variety of estimation procedures, we reach the following conclusions.

We find consistent evidence of publication bias in the empirical literature. The sign of the respective estimates indicate that publicly available estimates overstate the true impact of social capital on economic growth. While these estimates are not large to begin with, they become substantially smaller after correcting for publication bias. The associated estimates fail to achieve Doucouliagos' (2011) threshold value of "small", though they are statistically significant. Our results highlight the value of meta-analysis. Based purely on the available empirical literature, one might come to the conclusion that social capital is a substantial contributor to economic development. Our publication bias-adjusted estimates indicate that this is not the case.

We also do not find any evidence to indicate that trust plays a more important role in economic development than other kinds of social capital. This is a noteworthy finding given the importance role many researchers have attributed to this factor (Banfield, 1958; Knack & Keefer, 1997; Zak & Knack, 2001; Beugelsdijk et al., 2004; Dearmon & Grier, 2009). Finally, while most of the moderating factors we investigate are found to have little effect, we do find that studies based on US data find substantially lower social capital effects on growth than those using data from other parts of the world. This is a potential topic for future research to explore.

REFERENCES

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

Adler, P. S., & Kwon, S. W. (2002). Social capital: Prospects for a new concept. *Academy of Management Review*, 27(1), 17-40.

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

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

Banfield, E. G. (1958). *The moral basis of a backward society*. New York: Free Press.

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

Brock, W. A., & Durlauf, S. N. (2001). What have we learned from a decade of empirical research on growth? Growth empirics and reality. *The World Bank Economic Review*, 15(2), 229-272.

Coleman, J. S. (1990). *Foundations of Social Theory*. Cambridge, MA: Harvard University Press.

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

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

Fernandez, C., Ley, E., & Steel, M. F. (2001). Model uncertainty in cross-country growth regressions. *Journal of Applied Econometrics*, 16(5), 563-576.

Forte, A., Peiró-Palomino, J., & Tortosa-Ausina, E. (2015). Does social capital matter for European regional growth? *European Economic Review*, 77, 47–64.

Fukuyama, F. (1995). Social capital and the global economy. *Foreign Affairs,* 74(5), 89-103.

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.

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.

Havránek, T., Stanley, T. D., Doucouliagos, H., Bom, P., Geyer-Klingeberg, J., Iwasaki, I., ... & van Aert, R. C. (2020). Reporting guidelines for meta-analysis in economics. *Journal of Economic Surveys*, 34(3), 469-475.

Hedges, L. V., & Olkin, I. (1985). *Statistical Methods for Meta-Analysis*. San Diego, CA: Academic Press.

Hoeting, J. A., Madigan, D., Raftery, A. E., & Volinsky, C. T. (1999). Bayesian model averaging: a tutorial (with comments by M. Clyde, David Draper and EI George, and a rejoinder by the authors. *Statistical Science*, 14(4), 382-417.

Hong, S. & Reed, W. R. (2023). Meta-analysis and partial correlation coefficients: A matter of weights. Working Papers in Economics, University of Canterbury, Department of Economics and Finance.
https://EconPapers.repec.org/RePEc:cbt:econwp:23/07

Hoover, K. D., & Perez, S. J. (2004). Truth and robustness in cross-country growth regressions. *Oxford Bulletin of Economics and Statistics*, 66(5), 765-798.

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. (2009). Comments on 'Jointness of growth determinants'. *Journal of Applied Econometrics*, 24(2), 248-251.

Lin, N. (2001). Social capital: A theory of social structure and action. Cambridge University Press.

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.

Portes, A. (1998). Social capital: Its origins and applications in modern sociology. *Annual Review of Sociology*, 24, 1-24.

Pustejovsky, J. E. (2016, January 10). Clustered standard errors and hypothesis tests in fixed effects models. https://www.jepusto.com/clubsandwich-for-crve-fe/

Putnam, R. (1993). The prosperous community: Social capital and public life. *The American Prospect*, 4, 35-42.

Putnam, R. D. (2000). *Bowling Alone: The Collapse and Revival of American Community.* Simon and Schuster.

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.

Sala-i-Martin, X. (1997). I just ran two million regressions. *American Economic Review*, 87(2), 178-183.

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

Stanley, T. D., & Doucouliagos, H. (2023). Correct standard errors can bias meta-analysis. *Research Synthesis Methods*, 14(3), 515-519.

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

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. (2023). Meta-analyzing partial correlation coefficients using Fisher's *z* transformation. Preprint, Tilburg University.
https://files.de-.osf.io/v1/resources/cbyr6/providers/osfstorage/6495a55e67aff807b8edf86b?action=download&direct&version=1

van Aert, R.C.M. & Goos, C. (2023). A critical reflection on computing the sampling variance of the partial correlation coefficient. *Research Synthesis Methods*. https://onlinelibrary.wiley.com/doi/10.1002/jrsm.1632

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.

Woolcock. M. (1998) Social capital and economic development: Toward a theoretical synthesis and policy framework. *Theory and Society,* 27(2), 151-208.

Xue, X., Reed, W. R., & van Aert, R. C.M. (2022). Social capital and economic growth: A meta-analysis. Working Papers in Economics, University of Canterbury, Department of Economics and Finance.
https://EconPapers.repec.org/RePEc:cbt:econwp:22/20.

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
Types of Social Capital

Type of Social Capital	Description	Reference
Bonding	Refers to strong ties and relationships between individuals within a similar social group or community, such as family, friends, or members of a religious or cultural group. Bonding social capital is important for building trust and social cohesion within communities.	Putnam (2000)
Bridging	Refers to connections and relationships between individuals or groups from different social backgrounds or communities. Bridging social capital is important for promoting diversity and creating opportunities for collaboration and exchange between different groups.	Portes (1998)
Cognitive	Refers to shared values, beliefs, and norms that shape social interactions and relationships. Cognitive social capital is important for building trust and social cohesion, and for facilitating cooperation and collective action.	Coleman (1990)
Experiential	Refers to the knowledge and skills that individuals gain through social interactions and relationships. Experiential social capital can enhance individuals' social and economic opportunities.	Lin (2001)
Linking	Refers to connections between individuals or groups of different social status or power, such as between individuals and institutions or between local and national organizations. Linking social capital is important for creating pathways to resources, knowledge, and opportunities that may be otherwise inaccessible.	Woolcock (1998)

Type of Social Capital	**Description**	**Reference**
Normative	Refers to the social norms and values that influence social interactions and relationships. Normative social capital can promote social cohesion and trust within a community.	Fukuyama (1995)
Relational	Refers to the quality and strength of individual relationships within a social network. Relational social capital can facilitate information sharing, resource exchange, and collective action.	Adler & Kwon (2002)
Structural	Refers to the formal and informal networks and institutions that facilitate social interactions and relationships, such as schools, clubs, and community organizations. Structural social capital is important for creating opportunities for social engagement and building community resilience.	Lin (2001)

TABLE 2
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 3
Descriptive Statistics for Effect Size Variables

	t-Statistics	*df*	*PCC Values*	*z Values*
Mean	1.95	922	0.151	0.163
Median	1.86	112	0.130	0.131
Minimum	-13.51	6	-0.747	-0.967
Maximum	57.41	10,795	0.960	1.943
Std. Dev.	3.87	2319	0.229	0.266
1%	-3.66	11	-0.454	-0.490
5%	-2.34	21	-0.227	-0.231
10%	-1.38	28	-0.087	-0.087
90%	4.00	1,658	0.460	0.497
95%	5.91	9,727	0.526	0.584
99%	17.70	10,143	0.712	0.890
Obs	993	993	993	993

TABLE 4
Study Weights

	Fixed Effects	*Random Effects*
Mean	1.2%	1.2%
Median	0.1%	1.3%
5%	0.0%	0.4%
10%	0.0%	0.5%
90%	1.6%	1.7%
95%	4.9%	1.8%
Minimum	0.0%	0.3%
Maximum	38.0%	1.9%
Top 3[a]	65.9%	5.5%
Top 10[b]	90.1%	17.9%
I-squared	----	97.6%
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 5
Estimate of (Unadjusted) Overall Mean Effect

Variable	***OLS (1)***	***FE (2)***	***RE (3)***	***3L (4)***	***3L-VCV (5)***
Constant	0.163*** (0.024)	0.061** (0.017)	0.138*** (0.023)	0.187*** (0.019)	0.166*** (0.020)
Observations	993	993	993	993	993
Studies	81	81	81	81	81

NOTE: The dependent variable is Fisher's z. Standard errors are estimated using the "CR2" cluster robust standard error estimator (Pustejovsky, 2016) and are reported 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 6
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)***	0.032 (0.026)	0.038 (0.030)	0.025 (0.028)	0.025 (0.028)	0.020 (0.026)	0.055** (0.024)[b]	0.071*** (0.012)[b]	0.052** (0.025)[b]	0.068** (0.031)[b]	0.077** (0.034)[b]
$se(z)$ ***(Bias)***	1.215*** (0.248)	1.076** (0.471)	1.286*** (0.288)	1.425** (0.238)	1.483*** (0.250)	1.005*** (0.221)	0.856** (0.303)	1.022*** (0.270)	1.046*** (0.266)	1.002*** (0.338)
Observations	993	993	993	993	993	993	993	993	993	993
Studies	81	81	81	81	81	81	81	81	81	81

NOTE: The dependent variable is Fisher's z. Unless otherwise indicated, standard errors are estimated using the "CR2" cluster robust standard error estimator (Pustejovsky, 2016) and are reported in parentheses. *, **, and *** indicate statistical significance at the 10-, 5-, and 1-percent level, respectively.

[a] An OLS regression of $se(z)$ on the full set of data, study, and estimation characteristics has an R-squared of 53.8%.

[b] These standard errors are estimated using the "CR1" cluster robust standard error estimator (Pustejovsky, 2016). Note that CR1 standard error estimates tend to be smaller than CR2 estimates, which may inflate significance.

TABLE 7
Meta-Regression Analysis - Social Capital Variables

	No control variables					*Full set of control variables*				
Variable	***OLS (1)***	***FE (2)***	***RE (3)***	***3L (4)***	***3L-VCV (5)***	***OLS (6)***	***FE (7)***	***RE (8)***	***3L (9)***	***3L-VCV (10)***
SC_Cognitive	0.106* (0.056)	0.030 (0.055)	0.094* (0.054)	-0.006 (0.069)	0.012 (0.069)	0.029 (0.046)	-0.003 (0.027)	0.010 (0.044)	-0.038 (0.068)	-0.024 (0.074)
SC_Structural	-0.013 (0.044)	0.035 (0.023)	-0.008 (0.041)	-0.007 (0.061)	0.000 (0.059)	-0.012 (0.045)	-0.007 (0.023)	-0.002 (0.043)	0.016 (0.046)	0.022 (0.048)
Constant	0.131*** (0.033)	0.040* (0.016)	0.112*** (0.030)	0.192*** (0.041)	0.161*** (0.040)	----	----	----	----	----
$H_0: \beta_{Cognitive} = \beta_{Structural} = 0$	*F = 2.11 (p=0.143)*	*F = 1.13 (p=0.409)*	*F = 1.61 (p=0.222)*	*F = 0.01 (p=0.992)*	*F = 0.01 (p=0.986)*	*F = 0.31 (p=0.734)*	*F = 0.04 (p=0.957)*	*F = 0.03 (p=0.970)*	*F = 0.23 (p=0.795)*	*F = 0.19 (p=0.828)*
$H_0: \beta_{Cognitive} = \beta_{Structural}$	*F = 3.92 (p=0.060)*	*F = 0.01 (p=0.943)*	*F = 2.83 (p=0.107)*	*F = 0.00 (p=0.990)*	*F = 0.02 (p=0.885)*	*F = 0.61 (p=0.441)*	*F = 0.02 (p=0.902)*	*F = 0.05 (p=0.817)*	*F = 0.51 (p=0.491)*	*F = 0.35 (p=0.564)*
Observations	993	993	993	993	993	993	993	993	993	993
Studies	81	81	81	81	81	81	81	81	81	81

NOTE: The dependent variable is Fisher's z. Standard errors are estimated using the "CR2" cluster robust standard error estimator (Pustejovsky, 2016) and are reported in parentheses. The *, **, and *** indicate statistical significance at the 10-, 5-, and 1-percent level, respectively.

TABLE 8
Meta-Regression Analysis – All Variables

	BMA			*OLS*	
	Post Mean (1)	*Post SD (2)*	*PIP (3)*	*Coeff (4)*	*SE (5)*
DV_GrowthRate	-0.045	0.021	0.926	-0.054	0.045
SC_Cognitive	0.030	0.025	0.762	0.029	0.046
SC_Structural	-0.006	0.015	0.416	-0.012	0.045
PubYear	0.000	0.001	0.392	0.001	0.003
Published	0.023	0.022	0.709	0.030	0.042
LaggedDV	-0.057	0.042	0.788	-0.074	0.054
LaggedSC	-0.107	0.032	0.996	-0.103	0.060
NumberSCVars	-0.010	0.004	0.932	-0.011	0.005
Endog_IV	-0.041	0.027	0.834	-0.053	0.041
Endog_FE	-0.132	0.028	1.000	-0.140*	0.073
PanelData	-0.017	0.021	0.566	-0.031	0.073
CityLevel	0.025	0.050	0.457	0.071	0.121
RegionLevel	0.009	0.027	0.416	0.036	0.065
CountryLevel	-0.003	0.033	0.424	-0.016	0.086
Reg_OECDEurope	-0.027	0.035	0.577	-0.072	0.066
Reg_US	-0.148	0.046	0.997	-0.188*	0.096
Reg_Africa	-0.014	0.041	0.400	-0.058	0.078
Reg_Asia	-0.030	0.045	0.519	-0.082	0.071
se(z)	0.954	0.128	1.000	1.005***	0.221

NOTE: The dependent variable is Fisher's z. 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 6 in the text. The Bayesian Model Averaging (BMA) analysis was done using the R package BMS, described in Zeugner & Feldkircher (2015). The OLS standard errors in Column (5) are estimated using the "CR2" cluster robust standard error estimator (Pustejovsky, 2016).

FIGURE 1
PRISMA Flow Diagram

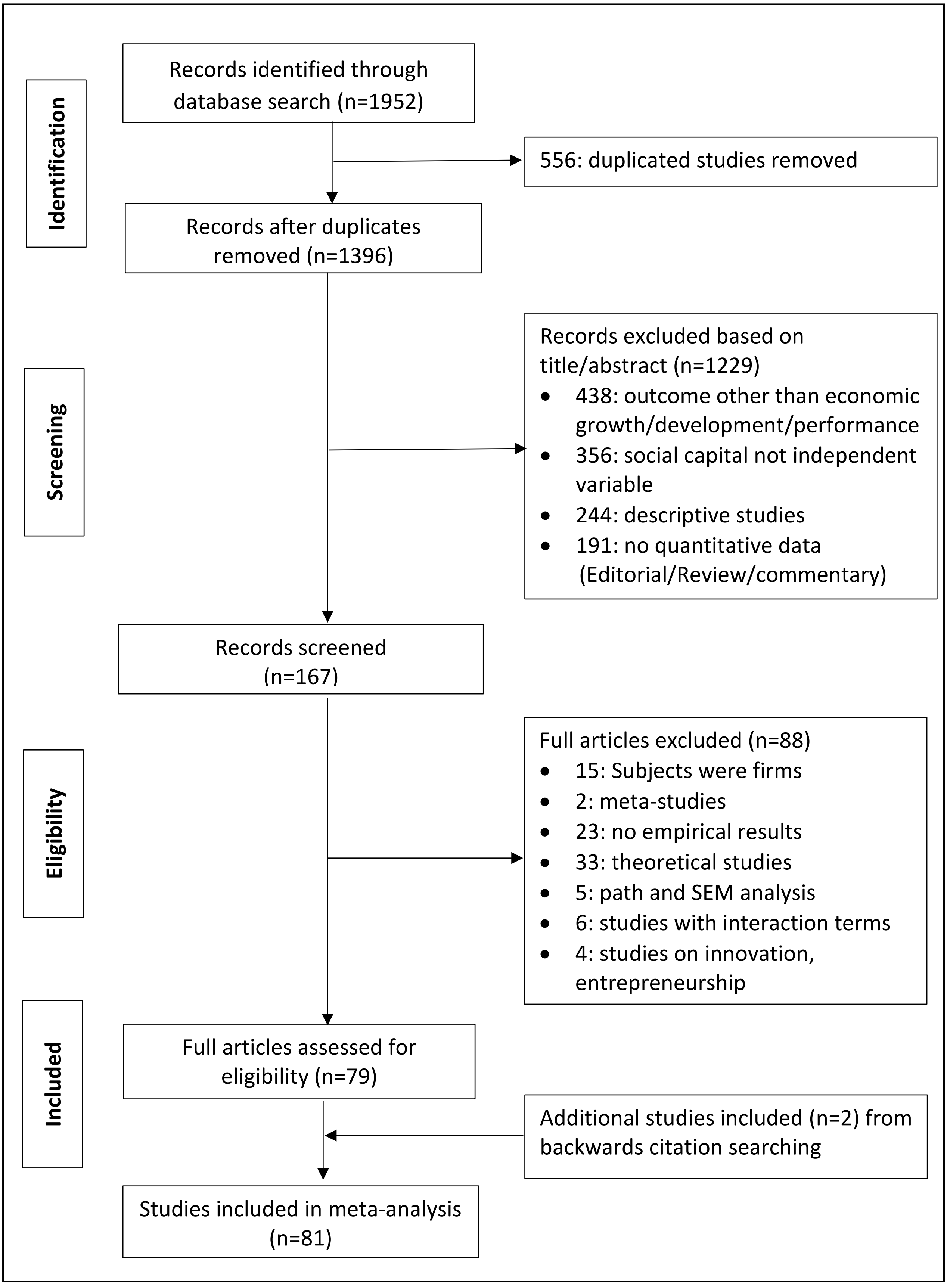
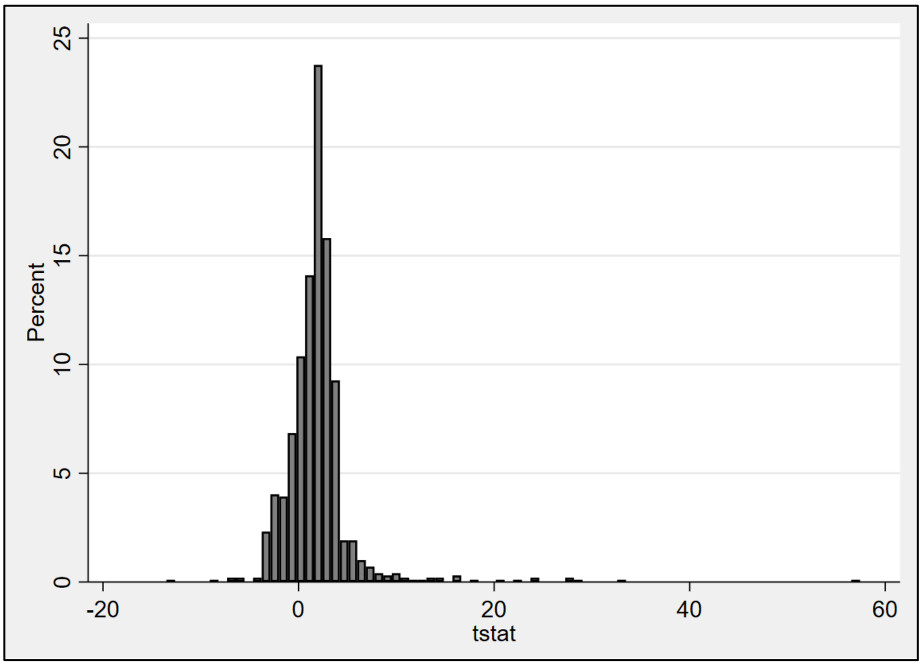


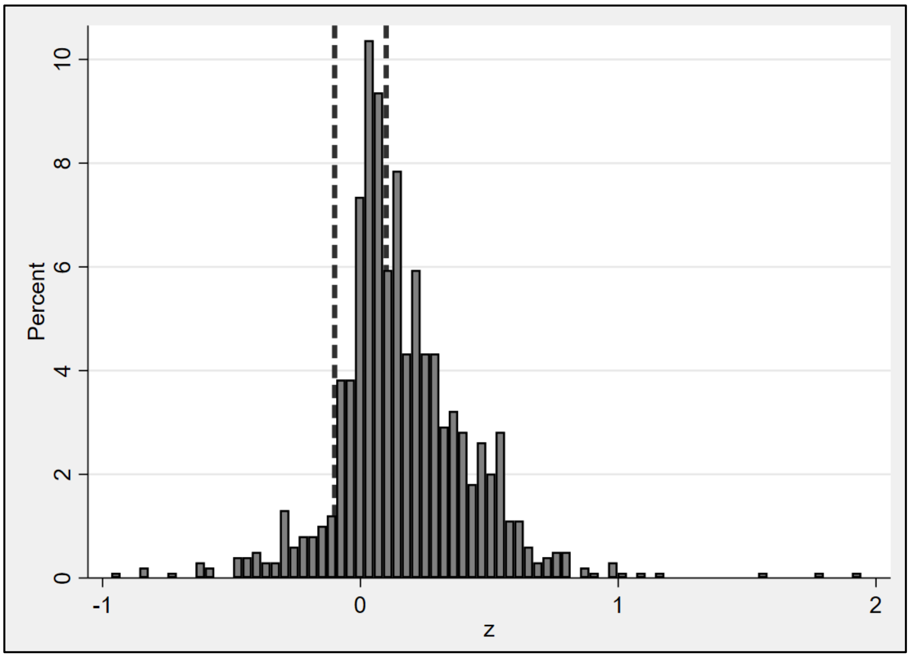
FIGURE 2
Distribution of *t*-and *PCC* Values

A. *t*-Statistics



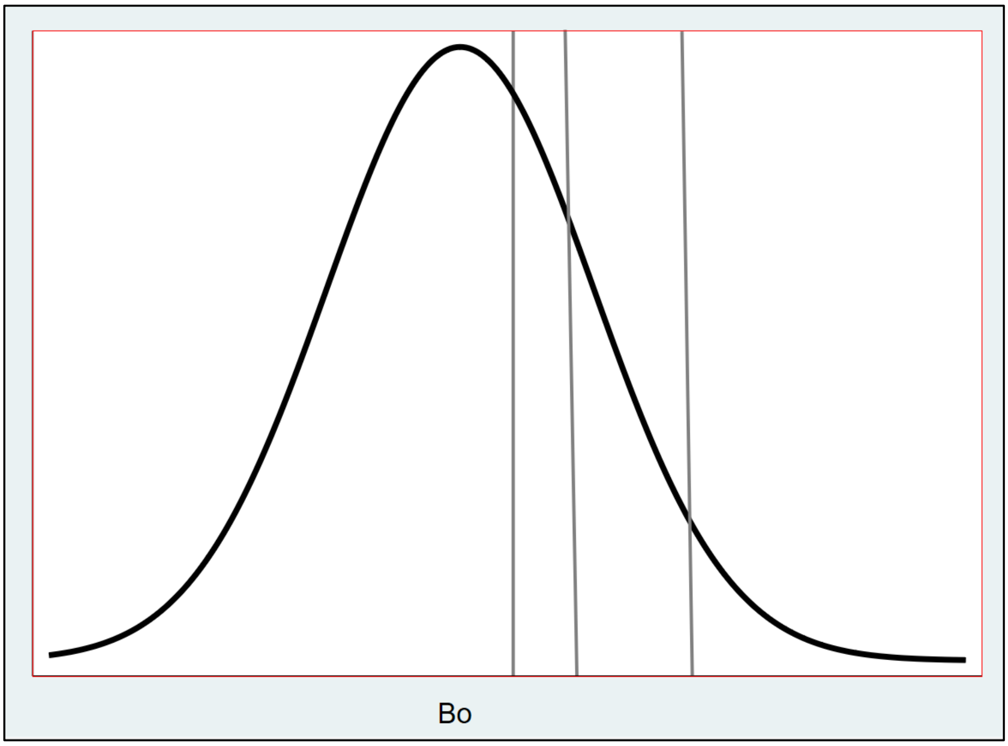
Distribution of t-statistics	*Percent*
t < -2.00	7.2
-2.00 ≤ t ≤ 2.00	48.3
t > 2.00	44.5

B. *z* Values



NOTE: Vertical dashed lines are set at ±0.10 to indicate "small" effects.

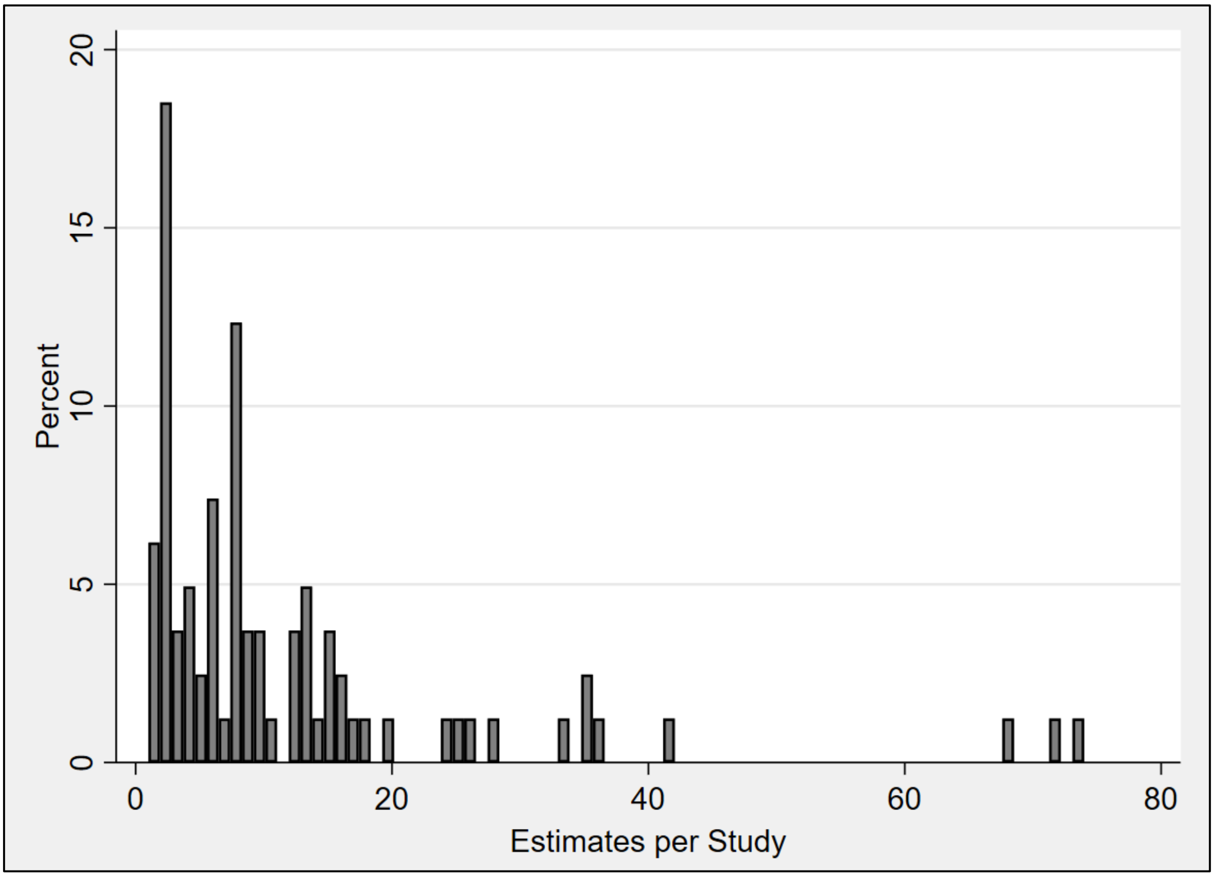
FIGURE 3
Distribution of True Effects



NOTE: This figure illustrates a hypothetical situation where true effects are normally distributed but large weights are given to three studies that do not represent the underlying population of effect sizes.

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.