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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 957 estimates from 83 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 of the overall, mean effect of social capital on economic growth are positive, small to moderately sized, and consistently statistically significant. Correcting for publication bias reduces these estimates by half or more. Our preferred estimates indicate that the average effect of social capital on economic growth is statistically insignificant and very small. However, the meta-analysis identifies a large amount of heterogeneity, indicating that social capital may have substantive effects in particular circumstances. Further investigation of moderating effects find them consistent with expectations, though they are too small to explain the heterogeneity in estimates. Analysis of different kinds of social capital finds little evidence of disparate effects on growth.

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

Data Availability Statement: Program codes that allow push-button replicability of the results in this study are available here:
https://osf.io/suyxz/?view_only=7979e543d9254adbbee8aa626b1bd920.I

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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 also 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).

Although a large body of empirical research has attempted to quantify the contribution of social capital to economic growth, there still lacks an overall assessment of this effect. The purpose of this study is to synthesize that literature. We analyze 957 estimates from 83 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.

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 of overall, average effect are positive, generally small to moderately sized, and consistently statistically significant. Correcting for publication bias reduces these estimates by half or more. Our preferred estimate of the overall, average effect of social capital on economic growth is positive but very small and statistically insignificant. However, we estimate a wide range of true effects for social capital, extending from large negative to large positive effects. Analysis of the different types of social capital finds little evidence of differences in growth effects, nor are we able to identify any significant moderating factors.

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 and reports "best practice" estimates. Section 9 summarizes and concludes.

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

A search on Scopus for "social capital" and "economic growth" produces over 30,000 documents.[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. The numerical analysis consists of "vote counting"[2] 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.

One type of social capital that has received prominent attention in the economic growth literature is trust. 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.

[1] Search conducted on June 1, 2024.
[2] See McKenzie & Brennan (2023) for a discussion of the limitations of "vote counting".

Dearmon & Grier (2009) highlight the importance of trust in economic development by 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.

Other types of social capital have also received attention. 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, depending on the specific form it takes.

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 also explored finer categorizations of social capital within each category.

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. That search process was completed at the end of February 2020. We repeated and updated our search in April 2024. 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 957 estimates from 83 studies.[3] It includes both published and unpublished studies. 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

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

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 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 58 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 42 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 (*SC1_Cognitive*), structural (*SC1_Structural*), and other (*SC1_Other*), with the last category constituting the reference group for the later meta-regression analysis.[4] 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

[4] "SC1" stands for the upper "level" of social capital variables. Later we will break these down into subcategories, denoted by the prefix "SC2".

quantify structural social capital included membership in associations and professional organizations, volunteer activities, and voter participation. The most common type of "Other" social capital (*SC1_Other*) were measures that mixed both structural and cognitive social capital. Additional measures included ethnic fractionalization, social cohesion, and corruption; as well as measures of bridging, bonding, and linking 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 estimated coefficients 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) $$se(PCC_i) = \frac{1 - PCC_i^2}{\sqrt{df_i}}.$$

Meta-analyses typically use squared standard errors to weight estimates in calculating overall mean effects, with more precise estimates receiving greater weight. This causes a problem when using *PCCs*.

As can be seen from Equation (2.b), there is a mathematical relationship between *PCCs* and standard errors. Ceteris paribus, *PCC* values that are large in absolute value will have smaller standard errors and receive greater weight, potentially biasing estimates of the overall mean effect (Stanley and Doucouliagos, 2023; Hong and Reed, 2024). For this and other reasons, good practice uses a transformation of *PCC* called Fisher's z (van Aert, R.C.M, 2023):

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

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

Note that $se(z_i)$ is independent of the size of z.

A disadvantage of using either *PCC* or Fisher's *z* 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 to guide the interpretation of our subsequent estimates, though we are mindful that these are but rough guidelines.

Fortunately, for the range of estimates that we obtain in this study, Fisher's z is virtually identical to *PCC*. 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[6]. Thus, while our empirical analysis uses Fisher's z values, we will interpret the corresponding estimates as *PCC* values, using the threshold values of 0.10 and 0.23 to indicate "small" and "medium" values.

Other data characteristics. Before proceeding to synthesize the empirical literature's estimates of the effect of social capital on economic growth, we introduce the other variables we have collected for our analysis. *PubYear* records a study was published. Years of publication ranged from 1995 to 2021, with a mean publication year of 2010.4. This variable is useful in investigating whether there has been a trend in the size of the estimated social

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

[6] Fisher's z values can be converted back to PCC values using the following formula: $PCC = \frac{e^{2z}-1}{e^{2z}+1}$.

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).

Approximately 53 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 2 percent of the specifications 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/Fisher's z*. This implies a negative relationship between *Fisher's 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 70 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 (46 percent), with regional level data second (39 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 the part of the world the data come from (OECD/Europe, US, Africa, Asia). The reference category is "other" for countries that fall outside these categories or mix countries from different 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.

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

TABLE 3 summarizes the Fisher's *z* values that are the focus of our analysis. The mean and median Fisher's *z* values are 0.169 and 0.133. 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". As can be seen from the table, Fisher's *z* values and *PCC* values are closely matched across a broad range of values. The Fisher's *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 Fisher's *z* values (bottom panel). Given that the mean/median Fisher's *z* values are on the smallish side, one would expect the corresponding *t*-statistics also to be relatively small. That is indeed the case. Over half of the estimated social capital effects are statistically insignificant. However, when significant, the estimated effects are exclusively positive. Turning to the bottom panel of Fisher's *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.

Social capital exerts both direct and indirect effects on economic growth. Unfortunately, researchers typically do not make it explicit whether they are estimating direct or total (=direct+indirect) effects. Nor is there explicit acknowledgement, or even agreement, about the specific pathways by which social capital indirectly affects economic growth. As this is the current state of the empirical literature, our analysis takes the estimates in the literature as given. However, it should be remembered that, to the extent these estimates exclude positive (negative) indirect effects, they understate (overstate) the total effect of social capital on economic growth.

There are two further 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. Different estimators incorporate precision differently. As a result, we will employ a variety of estimators and select the one(s) that are most appropriate for 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) $z_i = \beta_0 + \theta_i + \varepsilon_i,\ \theta_i \sim N(0, \tau^2),\ \varepsilon_i \sim N(0, se(z_i)^2),\ i = 1, \ldots, S,$

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. The RE model allows for drawing unconditional inference which implies that the results can be generalized to comparable studies that are not included in the meta-analysis. However, there is some simulation evidence to indicate that the FE estimator is less biased and has a lower mean squared error in the presence of publication bias (Poole & Greenland, 1999; 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 63% of the weight in calculating the overall mean.[7] The top 10 studies – approximately 12% of the total number of studies – receive 90% of the total weight.[8] This heavy concentration on a small number of studies is concerning if social capital has heterogeneous effects.

However, RE is also problematic. Our sample of Fisher's *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 variance of estimated effects that is not explained by sampling error. The I^2 is 97.2% in our meta-analysis. This is relatively, but not extraordinarily, large for meta-analyses in economics. It implies that a significant portion of the differences in estimated effects is because social capital affects economic growth in varying ways. We shall have more to say about this later.

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[7] The studies with the 3 largest weights are (in order of weights) id = 10, 20, and 45. They count for 9.2% of the total number of estimates.

[8] The studies with the 10 largest weights (in order of weights) are id = 10, 20, 45, 61, 51, 59, 19, 54, 3, and 62 (in order of weights). They count for 36.3% of the total number of estimates.

One technical consequence of a large I^2 value for RE is that estimates tend to receive similar weights. Accordingly, we see in TABLE 4 that the top 3 and top 10 studies receive only 5% and 17% of the weight in calculating the overall mean. The difference between the minimum and maximum weights is slight: 0.3% versus 1.8%. 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 11.5, 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 Fisher's z variable is 0.435, 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 refers to the jth estimate, 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). The 3L-VCV model not only takes into account that true effects from the same study may be correlated, but also that the sampling errors may be correlated. However, it requires that the researcher make an assumption regarding the within-study correlation of the sampling errors, as correlation between sampling errors is not something that can be separately estimated. Our analysis assumes a correlation of 0.5, but we also run analyses with correlations of 0.3 and 0.7 as sensitivity checks. The 3L and 3L-VCV models are alternatively known as hierarchical effects meta-analysis and correlated and hierarchical effects meta-analysis, respectively.

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) using the R packages *metafor* (Viechtbauer, 2010) and *clubSandwich* (Pustejovsky, 2023). 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 Fisher's z estimates range from a low of 0.064 (FE) to a high of 0.194 (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.

The last three rows provide a means of selecting among the alternative estimators. According to the model selection criteria AIC and BIC (Burnham and Anderson, 2002), the

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

[10] The sensitivity analyses for 3L-VCV are reported in an online, supplemental document. The results using different values of ρ (= 0.3 and 0.7) are very similar to the results reported in the text (ρ = 0.5).

3L-VCV model fits the data best. This is as expected given that the 3L-VCV model is the only model that takes all the effect size dependencies into account that are present in the data.

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 next estimate the effect of publication bias and adjust the 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 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

[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.

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 0.024, 0.035, 0.021, 0.038, and 0.028 -- well below Doucouliagos' (2011) "small" threshold of 0.10. These compare with the unadjusted estimates in TABLE 5 of 0.169, 0.064, 0.145, 0.195, and 0.175. 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, Fisher's z, then what is being interpreted as publication bias may be nothing more than omitted variable bias.[13] 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

[13] 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 58.5%.

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). To estimate "Effect beyond bias", we set the value of $se(z)$ equal to 0 and multiply all the other estimated coefficients by the sample means of the respective variables. This provides a prediction of the overall mean effect when the effect of publication bias has been eliminated. Following this procedure produces "Effect beyond bias" estimates that are approximately twice the size of the estimates Columns (1) to (5), ranging from 0.042 to 0.060. Even so, these all fall short of Doucouliagos' "small" threshold.

A notable difference between the estimates in Columns (6)-(10) versus those in Columns (1)-(5) is that several of the estimates of "Effect beyond bias" are statistically significant. We can use the last three rows of TABLE 6 to select which estimates should be preferred. As before, the 3L-VCV model dominates the other models with respect to AIC and BIC model selection criteria. Further, we can test the model in Column (10) versus that in Column (5) since the latter is nested within the former. An *F*-test fails to reject the null hypothesis that the full set of control variables do not collectively affect the overall mean of estimated effects ($F_{16,10.3} = 1.41$, $p\text{-value} = 0.291$).[14]

Thus our preferred estimate of the overall mean effect of social capital on economic growth is statistically insignificant with *z/PCC* = 0.028, a negligibly small effect. We note that the reason TABLE 6 produces a different assessment than TABLE 5 of social capital's effect

[14] Note that the denominator degrees of freedom for the *F*-statistic is not an integer. This occurs because the CR2 estimator uses a Satterthwaite approximation to adjust the degrees of freedom, which can yield non-integer, degrees of freedom values (Pustejovsky & Tipton, 2018).

on growth is because it corrects for publication bias. We emphasize here is that this is only an estimate of the average social capital effect. We investigate heterogeneity in social capital's effect on economic growth below.

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 classify 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.[15]

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 differ from other types

[15] 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.

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 in TABLE 7.

The results are easily summarized. With one exception, we fail to reject the two null hypotheses at the 5 percent level. The exception occurs in the OLS estimates of Column (1), but these results are dominated by the 3L-VCV results in Column (5) on the basis of AIC and BIC. Thus, we find little evidence that different types of social capital have different effects on economic growth. As noted above, "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.[16]

A criticism of these results is that our categories of social capital are too broad and aggregated. Accordingly, we subdivided the respective categories into more finely delineated categories of social capital. The respective sub-categories are reported in TABLE 8, where the prefix "SC2" indicates that these are subcategories of the main "SC1" categories of cognitive, structural, and other social capital.

Cognitive social capital was divided into particularized trust (*SC2_PartTrust*), generalized trust (*SC2_GenTrust*), and norms (*SC2_Norms*). Particularized trust is trust that is directed towards a specific group(s) or institution(s), whereas generalized trust is refers to an individual's perceptions of a broad segment of society. In our sample, estimates of generalized trust were dominant, with 70% of the cognitive estimates belonging to this category. Less than 10% of the cognitive estimates measured particularized trust, and only 5 of the 304 cognitive social capital estimates belonged to norms. Generalized trust also had the largest, unadjusted

[16] At the suggestion of a reviewer, we also estimated the specifications in TABLE 7 using the Mundlak model (Mundlak, 1978; Churchill et al., 2022). The overall results were unchanged, and we found no difference between within- and between-effects for the social capital and standard error variables. The estimates are available in the online supplement to this paper.

effect on economic growth, with an average effect size of *PCC/z* = 0.220. This registers squarely as "medium-sized" according to Doucouliagos's (2011) size thresholds. The other types of cognitive social capital had smaller average effect sizes.

Estimates originally classified as measuring the effect of structural social capital were further divided into membership in organizations or collectives (*SC2_AssocGroup*), participation in voluntary social groups and activities (*SC2_SocialPart*), and voting. The largest category was *SC2_AssocGroup*, accounting for approximately two-thirds of the estimates in this category. It also had the largest average effect size of *PCC/z* = 0.245.

As one might expect, the remaining *SC1_Other* category consisted of a wide range of different types of social capital, of which the largest category was itself "other" (*SC2_Other*). Most of these had average effect sizes that did not achieve or barely met Doucouliagos's (2011) "small" threshold. We note that bonding and bridging social capital accounted for about 19 percent of *SC1_Other* estimates, and only 6 percent of all the estimates in our sample.

TABLE 9 repeats the analysis of TABLE 7, replacing the social capital measures *SC1_Cognitive* and *SC1_Structural* with the finer-grained subcategories above, using *SC2_Other* as the reference category.[17] The conclusions of TABLE 7 are unchanged. Evidence of positive publication bias is strong and robust across the different models. Further, once we account for publication bias, none of the individual social capital variables are statistically significant. And there is no evidence to indicate that any of the social capital variables have effects on economic growth that are different from the other social capital variables. The preferred model specification of Column (5) produces an associated test result of $F_{10,3.82}=0.710$ with a *p-value=0.701.*

[17] We dropped the five observations using "Norms" as a social capital variable since they were so few in number and could not be combined with either of the other Cognitive social capital categories.

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^{19} different models one can specify given the 19 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^{19} different models, so BMA uses a sampling procedure (Markov Chain Monte Carlo (MCMC) sampling) to efficiently select the variable combinations that provide the greatest explanatory power. The "B" in BMA refers to Bayesian and the fact that the researcher needs to identify prior beliefs over two distributions. The first prior that the researcher needs to specify is a distribution of probabilities over the different model specifications. One option is to give each model an equal, initial probability of $\frac{1}{2^{19}}$. 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.[18]

The second prior the researcher needs to specify is a distribution of probabilities over coefficient values. This is commonly done by positing a normal distribution with given mean

[18] Personal correspondence with Zeugner on October 15, 2015.

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 a "factor of proportionality" is given by Zellner's g (Zeugner & Feldkircher, 2015). That is the approach that we adopt.[19,20]

Columns (1) through (3) in TABLE 10 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 all posterior probabilities equals 1. PIP is the sum of the model probabilities for those models that include the respective variable.

We also show 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 10 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 (4) confirms the association between BMA and OLS.

[19] 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.

[20] 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.

In general, the signs of the respective coefficients accord with prior expectations as discussed in Section 4. Published studies have larger estimated effects than unpublished studies, consistent with the existence of positive publication bias. Specifications with lagged dependent variables have smaller estimated coefficients. This is consistent with the estimates representing short-run responses, which would be expected to be smaller than long-run responses. Further, correcting for endogeneity, both via instrumental variables and the inclusion of panel fixed effects, is associated with smaller estimated social capital effects.

In interpreting the sizes of the estimates in TABLE 10, it is useful to note that other than *PubYear, NumberSCVars,* and $se(z)$, 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 that none of the moderating effects even managed to achieve Doucouliagos' threshold value of "small" (= 0.10). This is noteworthy given that the estimated social capital effects have such a large I^2 value, indicating that most of the observed differences in estimated effects is due to real differences in the effects of social capital on growth, and not sampling error. Yet the analysis of TABLE 10 is unable to identify any factors that can explain this heterogeneity. This is an important finding of our meta-analysis.

Thus, a challenge for future studies is to identify the factors responsible for the heterogeneity in estimated social capital effects. The literature suggests a number of possibilities. Income is most prominently employed as a moderator variable in studies of social capital and growth (Algan & Cahuc, 2014; Andini & Andini, 2019; Knack & Keefer, 1997; Rupasingha et al., 2000). Education (Akcomak & ter Weel, 2009; Baliamoune-Lutz, 2005; Dearmon & Grier; 2009), and institutions (Dearmon & Grier, 2011; James, 2015) have also been used as moderators. Unfortunately, these variables could not be included in our analysis because these variables were not commonly reported by the respective studies.

“Best Practice” estimates. As a last exercise, we construct “Best Practice” estimates of the effect of social capital on economic growth. We report three sets of estimates. “Best Practice #1” predicts “Effect beyond bias” when $se(z)$ is set equal to 0 and all the other variables are set at their sample means. It is comparable to the “Effect beyond bias” value reported in Column (10) of TABLE 7.

“Best Practice #2” and “#3” also set $se(z)$ equal to 0. However, they predict the observed effect size of a study where the variable publication year is equal to the sample mean and the specification includes only one social capital variable and no lagged dependent variables or lagged social capital variables. They assume the underlying data come from a country-level, panel dataset with fixed effects, and where the social capital variable has been instrumented to address endogeneity. “Best Practice #2” focuses on estimates from Latin America and the Middle East, or studies that include estimates across a range of regions. “Best Practice #3” focuses on OECD/Europe. The estimates and associated prediction intervals are reported in TABLE 11.

For all three “Best Practice” predictions, the estimated, overall mean effect sizes (0.042, -0.022, and -0.043) are again well below Doucouliagos’ (2011) “small” threshold value of 0.10. Nevertheless, it needs to be noted that the prediction intervals allow for a wide range of effects, with *PCC* values ranging from as far negative as -0.441 to as large positive as 0.397. These lower and upper bound values meet or exceed Doucouliagos’ (2011) threshold value for “large”. Some portion of the wide range of the prediction intervals is due to sampling error and the fact that we have chosen to estimate standard errors using the conservative CR2 estimator. However, most of this comes from heterogeneity in true effects. We know this because TABLE 4 reported that 97.2% of the heterogeneity in estimated effects is attributable to heterogeneity in true effects, and only 2.8% is due to sampling error. This has important implications for how we interpret our empirical results.

It would be misleading to infer from the estimated, overall mean effects that social capital does not affect economic growth. The wide prediction intervals indicate that social capital can have substantial effects. In some circumstances, social capital can have substantial negative effects on economic growth. In other circumstances, it can have substantial positive effects on economic growth. Averaged together, however, the estimated effects roughly balance out.

9. Summary and Conclusion

We conduct the first meta-analysis of the empirical literature estimating the effect of social capital on economic growth. Accordingly, we collect and analyze 957 estimates from 83 studies. Because different studies use different measures of both economic growth and social capital, we transform estimates into partial correlation coefficients (*PCCs*), and then convert these 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.

Taken at face value, the estimates in the literature indicate that social capital has a "small" to "moderate" average effect on economic growth. However, we find robust evidence that, due to publication bias, these estimates overstate the true impact of social capital. Once we correct for publication bias, we consistently find that estimates of mean social capital effects become negligibly small, with our preferred estimates being statistically insignificant.

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 noteworthy given the importance many researchers have attributed to this factor (Banfield, 1958; Knack & Keefer, 1997; Zak & Knack, 2001; Beugelsdijk et al., 2004; Dearmon & Grier, 2009). Nor do we find evidence that any other type of social capital is significant.

Nevertheless, our analysis reveals that a substantial portion of the heterogeneity in estimated effects in the literature is due to real differences, and not sampling error. Further, while we estimate that the average effect of social capital is close to zero, the range of true effects is wide, with the 95% prediction interval stretching to include both large negative and large positive effects. Our analysis failed to identify any moderators that could explain this heterogeneity. It is hoped that the findings of this study will stimulate further research into factors that can explain when and how social capital can positively contribute to economic growth.

REFERENCES

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

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

Alesina, A., & La Ferrara, E. (2000). Participation in heterogeneous communities. *The Quarterly Journal of Economics*, 115(3), 847-904.

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

Algan, Y., & Cahuc, P. (2014). Trust, growth, and well-being: New evidence and policy implications. In *Handbook of Economic Growth* (Vol. 2, pp. 49-120). Elsevier.

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

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

Baliamoune-Lutz, M. (2005). Institutions, social capital, and economic development in Africa: an empirical study. International Centre for economic research working paper series, 18, 2007-05.

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.

Burnham, K. P., & Anderson, D. R. (Eds.). (2002). *Model selection and multimodel inference: a practical information-theoretic approach*. New York, NY: Springer New York.

Chan, J., To, H.-P., & Chan, E. (2006). Reconsidering social cohesion: Developing a definition and analytical framework for empirical research. *Social Indicators Research*, 75(2), 273-302.

Churchill, S. A., Luong, H. M., & Ugur, M. (2022). Does intellectual property protection deliver economic benefits? A multi - outcome meta - regression analysis of the evidence. *Journal of Economic Surveys*, 36(5), 1477-1509.

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.

Dearmon, J., & Grier, R. (2011). Trust and the accumulation of physical and human capital. *European Journal of Political Economy,* 27(3), 507-519.

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.

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.

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. (2024). Meta-analysis and partial correlation coefficients: A matter of weights. *Research Synthesis Methods*, 15(2), 303-312.

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.

James Jr, H. S. (2015). Generalized morality, institutions and economic growth, and the intermediating role of generalized trust. *Kyklos*, 68(2), 165-196.

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.

McKenzie, J. E., & Brennan, S. E. (2023). Chapter 12: Synthesizing and presenting findings using other methods. In J. P. T. Higgins, J. Thomas, J. Chandler, M. Cumpston, T. Li, M. J. Page, & V. A. Welch (Eds.), Cochrane Handbook for Systematic Reviews of Interventions (version 6.4, updated August 2023). Cochrane. Available from www.training.cochrane.org/handbook.

Mundlak, Y. (1978). On the pooling of time series and cross section data." *Econometrica*, 46(1), 69-85.

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.

Poole, C., & Greenland, S. (1999). Random-effects meta-analyses are not always conservative. American Journal of Epidemiology, 150(5), 469–475. https://doi.org/10.1093/oxfordjournals.aje.a010035

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/

Pustejovsky J (2023). clubSandwich: Cluster-robust (sandwich) variance estimators with small-sample corrections. R package version 0.5.10. https://CRAN.R-project.org/package=clubSandwich

Pustejovsky, J. E., & Tipton, E. (2018). Small-sample methods for cluster-robust variance estimation and hypothesis testing in fixed effects models. *Journal of Business & Economic Statistics*, 36(4), 672-683.

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.

Rupasingha, A., Goetz, S. J., & Freshwater, D. (2000). Social capital and economic growth: a county-level analysis. *Journal of Agricultural and Applied Economics*, 32(3), 565-572.

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.M. (2023). Meta-analyzing partial correlation coefficients using Fisher's z transformation. *Research Synthesis Methods*, 14(5), 768-773.

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.

Woolcock, M. (2001). The place of social capital in understanding social and economic outcomes. *Canadian Journal of Policy Research*, 2(1), 11-17.

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	0.580	0	1
*-- DV_GDPLevel**	=1, if dep. variable is level of income (GDP)	0.420	0	1
	SOCIAL CAPITAL VARIABLES-1			
2) SC1_Cognitive	=1, if social capital is cognitive	0.313	0	1
3) SC1_Structural	=1, if social capital is structural	0.366	0	1
*--SC1_Other**	=1, if social capital is other type	0.321	0	1
	STUDY CHARACTERISTICS			
4) PubYear	Year study was published	2010.4	1995	2021
5) Published	=1, if study is a published journal article	0.530	0	1
	SPECIFICATION			
6) LaggedDV	=1, if lagged DV included in equation	0.056	0	1
7) LaggedSC	=1, if lagged SC variable(s) included in equation	0.023	0	1
8) NumberSCVars	Number of SC variables included in equation	2.38	1	12
	ENDOGENEITY			
9) Endog_IV	=1, if instrumental variable estimator used	0.209	0	1
10) Endog_FE	=1, if fixed effects included in equation	0.096	0	1
*-- NoEndogeneity**	=1, if estimation did not address endogeneity	0.695	0	1
11) PanelData	=1, if data are panel data	0.718	0	1
	SPATIAL DATA CHARACTERISTICS			
12) CityLevel	=1, if data are city level	0.037	0	1
13) RegionLevel	=1, if data are regional level	0.386	0	1
14) CountryLevel	=1, if data are country level	0.461	0	1
*-- OtherLevel**	=1, if data are other level	0.117	0	1
	COUNTRIES			
15) Reg_OECDEurope	=1, if countries are in OECD or Europe	0.371	0	1
16) Reg_US	=1, if countries are in US	0.107	0	1
17) Reg_Africa	=1, if countries are in Africa	0.025	0	1
18) Reg_Asia	=1, if countries are in OECD or Europe	0.073	0	1
*-- Reg_Other**	=1, if countries outside the above regions	0.424	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	2.13	991	0.157	0.169
Median	1.89	189	0.133	0.133
Minimum	-13.51	6	-0.747	-0.967
Maximum	57.41	10,795	0.960	1.943
Std. Dev.	3.95	2353	0.203	0.236
1%	-3.93	14	-0.387	-0.409
5%	-2.08	23	-0.105	-0.106
10%	-0.93	30	-0.053	-0.053
90%	4.32	2,574	0.446	0.478
95%	7.00	9,727	0.501	0.551
99%	17.70	10,143	0.670	0.811
Obs	957	957	957	957

TABLE 4
Study Weights

	Fixed Effects	*Random Effects*
Mean	1.2%	1.2%
Median	0.6%	1.3%
5%	0.0%	0.5%
10%	0.1%	0.6%
90%	1.7%	1.7%
95%	4.8%	1.7%
Minimum	0.0%	0.3%
Maximum	36.4%	1.8%
Top 3	63.3% [a]	5.2%
Top 10	89.1% [b]	17.0%
I-squared	----	97.2%
Studies	83	83

[a] The studies with the 3 largest weights are id = 10, 20, and 45. See the Appendix to match id's with studies.

[b] The studies with the 10 largest weights are id = 10, 20, 45, 61, 51, 59, 19, 54, 3, and 62 (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	0.169*** (0.024)	0.064** (0.016)	0.145*** (0.023)	0.194*** (0.019)	0.175*** (0.018)
Observations	957	957	957	957	957
Studies	83	83	83	83	83
AIC	-42.2	8767.3	-150.9	-421.2	-434.9
BIC	-32.5	8772.2	-141.1	-406.6	-420.3
LR Test:	----[a]	----[a]	*p<0.0001*	*p<0.0001*	----[b]

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. The last row reports a likelihood ratio test of the full model versus the restricted model, where the restricted model is the model immediately to the left in the table.

[a] We do not report likelihood ratio test results for OLS and FE because these do not nest a simpler, restricted model.
[b] We cannot test 3L-VCV against 3L because these have the same number of parameters.

TABLE 6
Estimates of the Adjusted Overall Mean Effect

	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)***
Constant (Effect beyond bias)	0.024 (0.028)	0.035 (0.030)	0.021 (0.028)	0.038 (0.025)	0.028 (0.020)	0.053** (0.026)	0.059*** (0.018)	0.060* (0.026)	0.044** (0.030)	0.042* (0.032)
$se(z)$ ***(Bias)***	1.531*** (0.293)	1.310** (0.502)	1.563*** (0.296)	1.459*** (0.268)	1.574*** (0.252)	1.228*** (0.318)	1.184*** (0.271)	1.150*** (0.332)	1.299*** (0.353)	1.360*** (0.389)
Observations	957	957	957	957	957	957	957	957	957	957
Studies	83	83	83	83	83	83	83	83	83	83
AIC	-227.2	7879.0	-330.3	-463.6	-481.6	-288.2	4998.3	-369.2	-468.2	-478.7
BIC	-212.6	7888.7	-315.7	-444.1	-462.1	-186.1	5095.2	-267.5	-361.3	-372.2
LR Test:	----[a]	----[a]	*p<0.0001*	*p<0.0001*	----[b]	----[a]	----[a]	*p<0.0001*	*p<0.0001*	----[b]

<u>NOTE</u>: 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. *, **, and *** indicate statistical significance at the 10-, 5-, and 1-percent level, respectively. The last row reports a likelihood ratio test of the full model versus the restricted model, where the restricted model is the model immediately to the left in the table.

[a] We do not report likelihood ratio test results for OLS and FE because these do not nest a simpler, restricted model.
[b] We cannot test 3L-VCV against 3L because these have the same number of parameters.

TABLE 7
Meta-Regression Analysis - Social Capital-1 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)***
SC1_Cognitive	0.0.060 (0.048)	0.010 (0.036)	0.047 (0.044)	-0.040 (0.080)	-0.020 (0.075)	0.038 (0.050)	0.001 (0.025)	0.026 (0.047)	-0.061 (0.084)	-0.043 (0.083)
SC1_Structural	-0.046 (0.042)	0.034 (0.035)	-0.037 (0.042)	-0.075 (0.094)	-0.061 (0.084)	-0.050 (0.059)	-0.026 (0.034)	-0.037 (0.062)	-0.057 (0.096)	-0.048 (0.091)
$se(z)$	1.351*** (0.269)	1.406*** (0.468)	1.369*** (0.277)	1.518*** (0.283)	1.577*** (0.314)	1.228*** (0.318)	1.184*** (0.271)	1.150*** (0.332)	1.299*** (0.353)	1.360*** (0.389)
Constant	0.039 (0.035)	0.014 (0.016)	0.038 (0.035)	0.068 (0.055)	0.052 (0.049)	----	----	----	----	----
Observations	957	957	957	957	957	957	957	957	957	957
Studies	83	83	83	83	83	83	83	83	83	83
$H_0\colon \beta_{Cognitive} = \beta_{Structural} = 0$	*F = 2.78 (p=0.078)*	*F = 0.40 (p=0.698)*	*F = 1.96 (p=0.161)*	*F = 0.30 (p=0.743)*	*F = 0.25 (p=0.782)*	*F = 1.12 (p=0.340)*	*F = 0.25 (p=0.786)*	*F = 0.56 (p=0.576)*	*F = 0.29 (p=0.757)*	*F = 0.17 (p=0.841)*
$H_0\colon \beta_{Cognitive} = \beta_{Structural}$	*F = 5.71 (p=0.023)*	*F = 0.26 (p=0.648)*	*F = 4.08 (p=0.053)*	*F = 0.154 (p=0.701)*	*F = 0.26 (p=0.617)*	*F = 2.31 (p=0.140)*	*F = 0.48 (p=0.511)*	*F = 1.14 (p=0.297)*	*F = 0.00 (p=0.969)*	*F = 0.00 (p=0.957)*
AIC	-260.9	7636.6	-349.6	-471.9	-485.7	-288.2	4998.3	-369.2	-468.2	-478.7
BIC	-236.5	7656.1	-325.3	-442.7	-456.6	-186.1	5095.2	-267.5	-361.6	-372.2
LR Test:	----[a]	----[a]	*p<0.0001*	*p<0.0001*	----[b]	----[a]	----[a]	*p<0.0001*	*p<0.0001*	----[b]

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. The last row reports a likelihood ratio test of the full model versus the restricted model, where the restricted model is the model immediately to the left in the table.

[a] We do not report likelihood ratio test results for OLS and FE because these do not nest a simpler, restricted model
[b] We cannot test 3L-VCV against 3L because these have the same number of parameters.

TABLE 8
Description of Sub-Categories of Social Capital

Variable	Description	Mean z	Frequency	Percent
GROUP CATEGORY = COGNITIVE SOCIAL CAPITAL (Observations = 304)				
SC2_PartTrust	Particularized Trust. Particularized trust, also known as specific trust or strategic trust, refers to the trust that an individual has in specific people, groups, or institutions based on their past experiences, interactions, or knowledge of the trustee's characteristics. It is context-dependent and varies according to the specific relationship or situation (Uslaner, 2002).	0.088	84	28.0
SC2_GenTrust	Generalized Trust. Generalized trust is a broader, more abstract form of trust that extends beyond personal relationships. It refers to an individual's belief that most people, including strangers, can be trusted. Generalized trust is not based on specific knowledge or experiences with individuals but rather on a general expectation about the trustworthiness of people in society (Uslaner, 2002).	0.220	211	70.3
SC2_Norms	Norms. Norms refer to the informal rules, shared understandings, and expectations that govern behavior within a social network or community. These norms can be explicit or implicit and help to establish standards for what is considered acceptable or unacceptable conduct among members of the group (Putnam, 2000).	0.005	5	1.7
GROUP CATEGORY = STRUCTURAL SOCIAL CAPITAL (Observations = 354)				
SC2_AssocGroup	Associations or groups. Membership in organizations or collectives in which individuals participate for a common purpose, interest, or goal (Putnam, 2000).	0.245	234	66.9
SC2_SocialPart	Social participation. Voluntary involvement of individuals in formal and informal social networks, groups, and activities within a community (Putnam, 2000).	0.044	42	12.0

Variable	Description	Mean z	Frequency	Percent
SC2_Voting	Voting turnout. The percentage of eligible voters who cast a ballot in an election, often used as a measure of civic engagement and political participation (Putnam, 2000).	0.077	74	21.1
GROUP CATEGORY = OTHER (Observations = 317)				
SC2_Bonding	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).	0.028	27	8.8
SC2_Bridging	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).	0.033	32	10.4
SC2_EthnicFrag	Ethnic fragmentation. The degree to which a society or community is divided into distinct ethnic groups, often measured by the probability that two randomly selected individuals belong to different ethnic groups (Alesina & La Ferrara, 2000).	0.046	44	14.3
SC2_SCIndex	Social capital index. A composite measure that combines various indicators of social capital, such as trust, civic engagement, and social networks, to provide an overall assessment of the level of social capital within a community or society (Putnam, 2000).	0.026	25	8.1
SC2_SocialCoh	Social cohesion. The sense of togetherness, shared values, and willingness to cooperate and help others within a community or society (Chan, To, & Chan, 2006).	0.021	20	6.5
SC2_Other	Does not belong to any of the other types of social capital categories.	0.116	159	51.8

TABLE 9
Meta-Regression Analysis - Social Capital-2 Variables (With Correction for Publication Bias)

	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)***
SC2-PartTrust	-0.025 (0.087)	-0.018 (0.022)	-0,044 (0.078)	-0.065 (0.103)	-0.066 (0.110)	-0.039 (0.090)	-0.003 (0.034)	-0.060 (0.082)	-0.076 (0.108)	-0.072 (0.119)
SC2_GenTrust	0.098 (0.078)	0.062 (0.053)	0.075 (0.071)	0.002 (0.085)	0.017 (0.087)	0.080 (0.085)	-0.006 (0.067)	0.052 (0.078)	-0.012 (0.086)	0.002 (0.093)
SC2-AssocGroup	-0.075 (0.075)	-0.028 (0.040)	-0.078 (0.070)	-0.134 (0.119)	-0.120 (0.109)	-0.079 (0.092)	-0.064 (0.073)	-0.084 (0.090)	-0.119 (0.124)	-0.111 (0.118)
SC2_SocialPart	0.059 (0.099)	0.017 (0.047)	0.056 (0.101)	0.094 (0.110)	0.099 (0.112)	0.055 (0.100)	0.001 (0.030)	0.058 (0.102)	0.107 (0.103)	0.117 (0.107)
SC2-Voting	-0.010 (0.067)	0.065 (0.020)	-0.000 (0.057)	-0.066 (0.114)	-0.048 (0.101)	-0.072 (0.101)	-0.026 (0.083)	-0.049 (0.093)	-0.050 (0.120)	-0.042 (0.113)
SC2_Bonding	-0.079 (0.076)	-0.092 (0.021)	-0.097 (0.069)	-0.162 (0.102)	-0.138 (0.088)	-0.102 (0.105)	-0.153 (0.078)	-0.137 (0.101)	-0.124 (0.117)	-0.107 (0.108)
SC2-Bridging	0.037 (0.094)	0.123 (0.069)	0.044 (0.093)	-0.002 (0.104)	0.004 (0.099)	0.014 (0.108)	0.059 (0.101)	0.006 (0.106)	0.036 (0.116)	0.034 (0.115)
SC2_EthnicFrag	-0.042 (0.066)	0.000 (0.024)	-0.045 (0.063)	0.013 (0.024)	0.002 (0.032)	-0.019 (0.047)	-0.001 (0.036)	-0.031 (0.049)	0.013 (0.021)	0.007 (0.027)
SC2-SCIndex	0.112 (0.086)	0.059 (0.058)	0.091 (0.082)	0.052 (0.087)	0.027 (0.096)	0.091 (0.104)	0.039 (0.052)	0.062 (0.095)	-0.001 (0.083)	-0.013 (0.093)

	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)***
SC2_SocialCoh	0.018 (0.065)	0.028 (0.037)	0.011 (0.061)	-0.025 (0.071)	-0.020 (0.070)	0.060 (0.094)	-0.006 (0.090)	0.038 (0.087)	0.009 (0.080)	0.009 (0.085)
se(z)	1.354*** (0.297)	1.610*** (0.397)	1.395*** (0.302)	1.493*** (0.291)	1.574*** (0.336)	1.244*** (0.387)	1.270*** (0.401)	1.120*** (0.400)	1.261*** (0.350)	1.333*** (0.398)
Observations	952	952	952	952	952	952	952	952	955	952
Studies	82	82	82	82	82	82	82	82	82	82
H_0: SC2 variables have equal effects	*F = 1.25 (p=0.396)*	*F = 0.00 NA*	*F = 1.23 (p<0.423)*	*F = 0.86 (p=0.609)*	*F = 0.71 (p=0.701)*	*F = 0.99 (p=0.509)*	*F = 0.24 (p=0.939)*	*F = 1.01 (p=0.508)*	*F = 0.62 (p=0.754)*	*F = 0.51 (p=0.825)*
AIC	-294.0	6342.0	-378.9	-498.3	-508.4	-310.2	4466.4	-386.2	-489.8	-498.1
BIC	-230.8	6400.1	-315.9	-430.4	-440.5	-169.3	4601.6	-246.2	-344.9	-353.2
LR Test:	----[a]	----[a]	*p<0.0001*	*p<0.0001*	----[b]	----[a]	----[a]	*p<0.0001*	*p<0.0001*	----[b]

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. The last row reports a likelihood ratio test of the full model versus the restricted model, where the restricted model is the model immediately to the left in the table.

[a] We do not report likelihood ratio test results for OLS and FE because these do not nest a simpler, restricted model.
[b] We cannot test 3L-VCV against 3L because these have the same number of parameters.

TABLE 10
Meta-Regression Analysis – All Variables

	BMA			*OLS*	
	Post Mean (1)	*Post SD* (2)	*PIP* (3)	*Coeff* (4)	*SE* (5)
DV_GrowthRate	-0.058	0.016	0.993	-0.066	0.039
SC1_Cognitive	0.040	0.028	0.810	0.038	0.050
SC1_Structural	-0.042	0.025	0.854	-0.050	0.059
PubYear	0.000	0.001	0.316	-0.001	0.003
Published	0.033	0.021	0.834	0.034	0.040
LaggedDV	-0.058	0.043	0.765	-0.072*	0.033
LaggedSC	0.002	0.026	0.262	0.022	0.044
NumberSCVars	-0.004	0.004	0.652	-0.005	0.007
Endog_IV	-0.009	0.017	0.393	-0.025	0.037
Endog_FE	-0.046	0.033	0.783	-0.065*	0.033
PanelData	0.024	0.023	0.653	0.028	0.046
CityLevel	0.052	0.063	0.563	0.115	0.113
RegionLevel	0.014	0.031	0.371	0.050	0.061
CountryLevel	0.011	0.032	0.349	0.037	0.101
Reg_OECDEurope	0.006	0.018	0.349	-0.002	0.076
Reg_US	-0.060	0.042	0.806	-0.052	0.083
Reg_Africa	0.001	0.024	0.256	-0.012	0.085
Reg_Asia	-0.010	0.025	0.356	-0.018	0.080
se(z)	1.252	0.149	1.000	1.228***	0.319

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).

TABLE 11
Best Practice Estimates with Prediction Intervals

Best Practice #1 (“Sample Means”)	Best Practice #2 (“Region=Other)	Best Practice #3 (“Region=OECD/Europe”)
	Fisher’s *z* Values	
0.042 (-0.337, 0.420)	-0.022 (-0.417, 0.374)	-0.043 (-0.474, 0.387)
	PCC Values	
0.042 (-0.325, 0.397)	-0.022 (-0.394, 0.358)	-0.043 (-0.441, 0.369)
Evaluated at:	Evaluated at	Evaluated at
DV_GrowthRate=Mean	DV_GrowthRate=1	DV_GrowthRate=1
SC_Cognitive=Mean	SC_Cognitive=1	SC_Cognitive=1
SC_Structural=Mean	SC_Structural=0	SC_Structural=0
PubYear=Mean	PubYear=Mean	PubYear=Mean
Published=Mean	Published=1	Published=1
LaggedDV=Mean	LaggedDV=0	LaggedDV=0
LaggedSC=Mean	LaggedSC=0	LaggedSC=0
NumberSCVars=Mean	NumberSCVars=1	NumberSCVars=1
Endog_IV=Mean	Endog_IV=1	Endog_IV=1
Endog_FE=Mean	Endog_FE=1	Endog_FE=1
PanelData=Mean	PanelData=1	PanelData=1
CityLevel=Mean	CityLevel=0	CityLevel=0
RegionLevel=Mean	RegionLevel=0	RegionLevel=0
CountryLevel=Mean	CountryLevel=1	CountryLevel=1
Reg_OECDEurope=Mean	Reg_OECDEurope=0	Reg_OECDEurope=1
Reg_US=Mean	Reg_US=0	Reg_US=0
Reg_Africa=Mean	Reg_Africa=0	Reg_Africa=0
Reg_Asia=Mean	Reg_Asia=0	Reg_Asia=0
se(z)=0	se(z)=0	se(z)=0

NOTE: “Best Practice” predictions are derived from the estimates in Column (10) of TABLE 7. 95% prediction intervals are calculated using “CR2” cluster robust standard errors (Pustejovsky, 2016). Each prediction is conditioned on the variable values reported in the respective cells of the table. “Best Practice #1” predicts “Effect beyond bias” when se(z) is set equal to 0 and all the other variables are set at their sample means. It is comparable to the “Effect beyond bias” value reported in Column (10) of TABLE 7. “Best Practice #2” and “#3” also set se(z) equal to 0 and predict the effect of cognitive social capital on economic growth rates for estimates coming from journal articles published around 2010. They are based on a specification with only one social capital variable and no lagged dependent variables or lagged social capital variables. They assume the underlying data come from a country-level, panel dataset with fixed effects, and where the social capital variable has been instrumented to address endogeneity. “Best Practice #2” focuses on estimates from Latin America and the Middle East, or studies that include estimates across a range of regions. “Best Practice #3” focuses on OECD/Europe.

FIGURE 1
PRISMA Flow Diagram

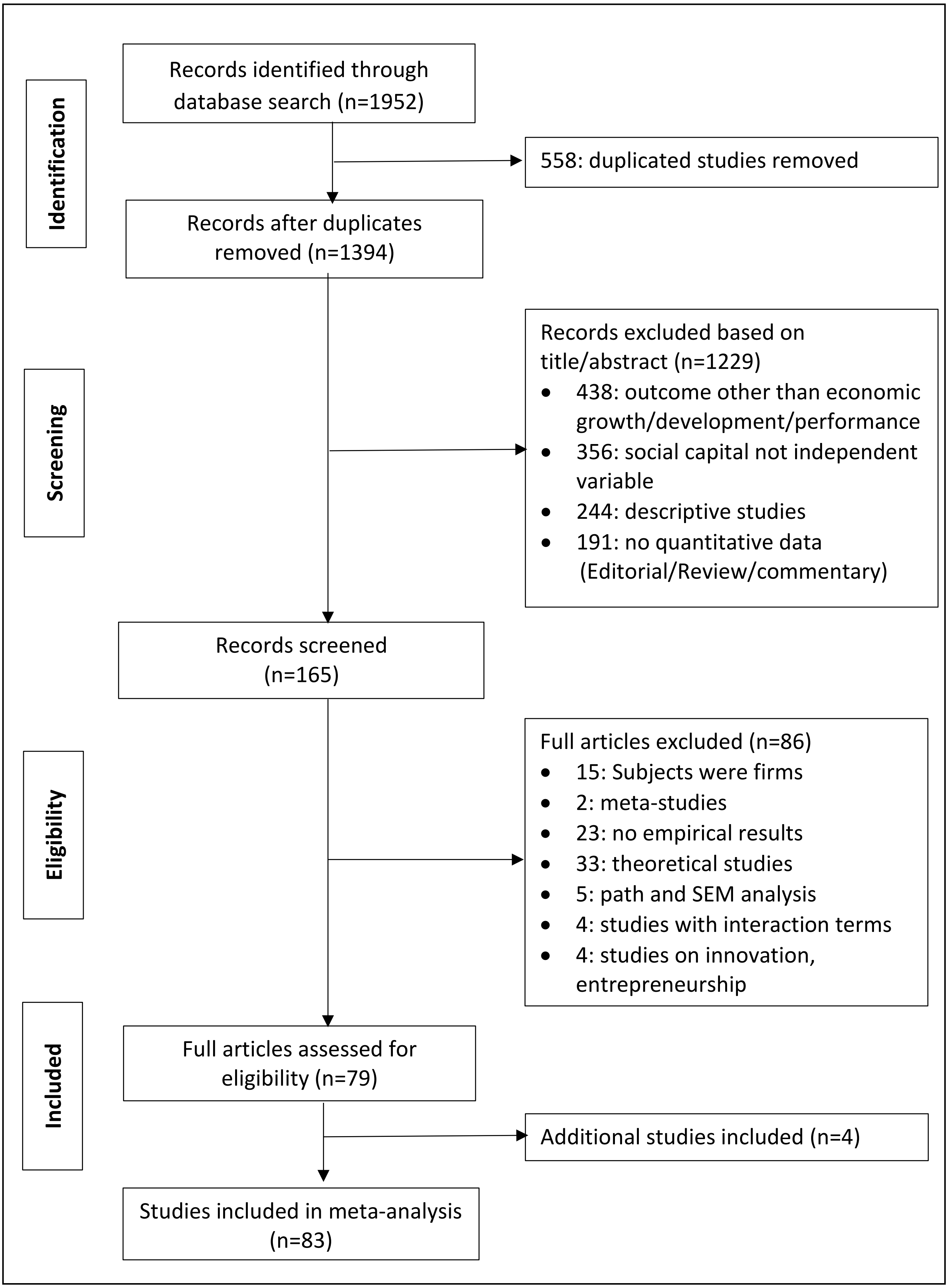
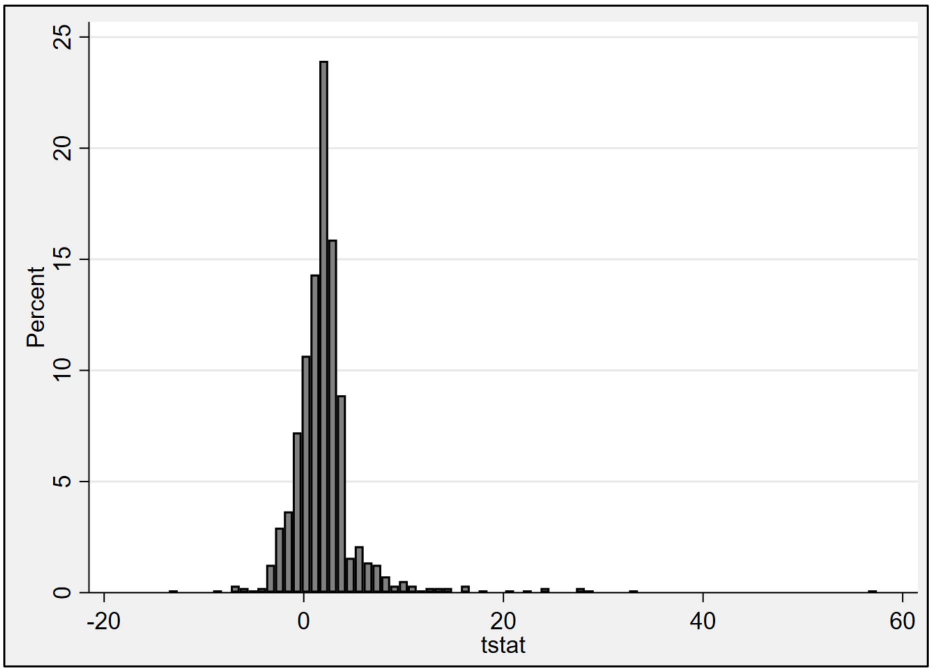


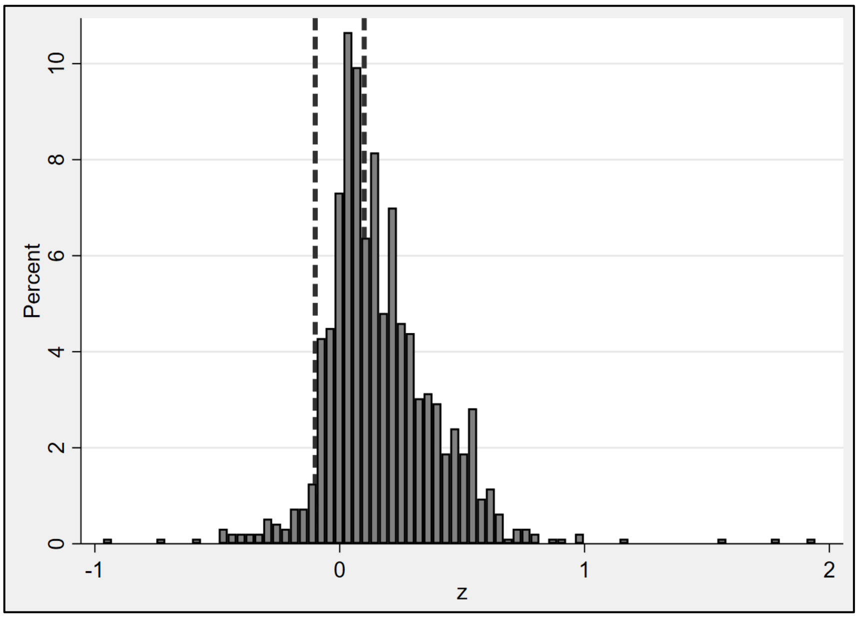
FIGURE 2
Distribution of *t*-and *PCC* Values

A. *t*-Statistics



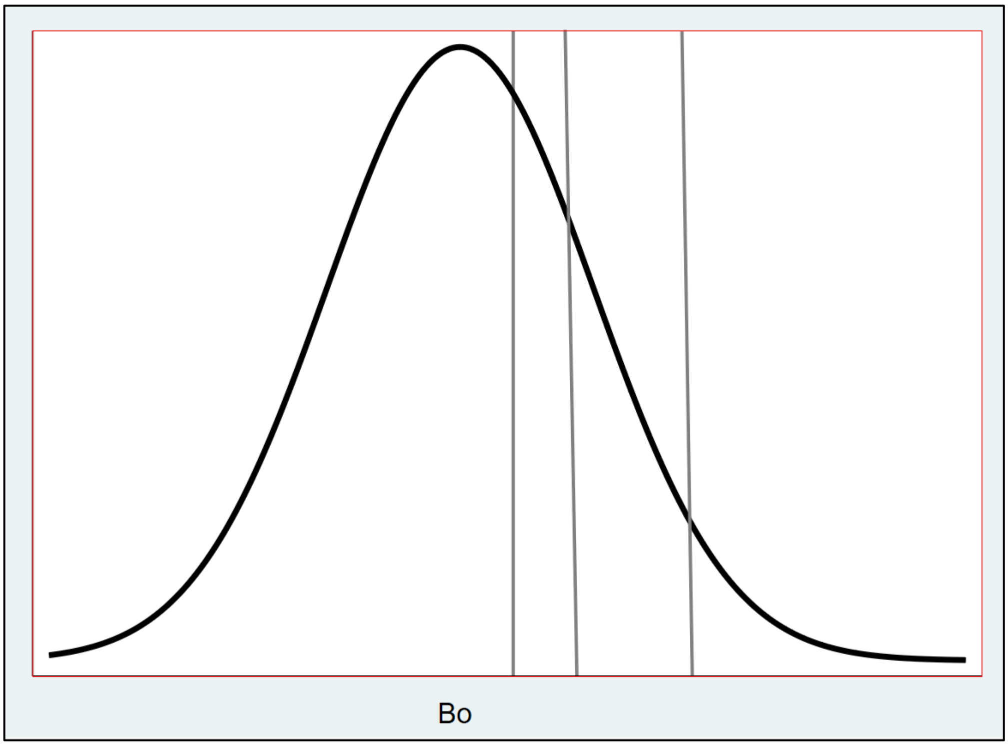
Distribution of t-statistics	*Percent*
Negative and significant	0
Insignificant	53.5
Positive and significant	46.5

B. *z* Values



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

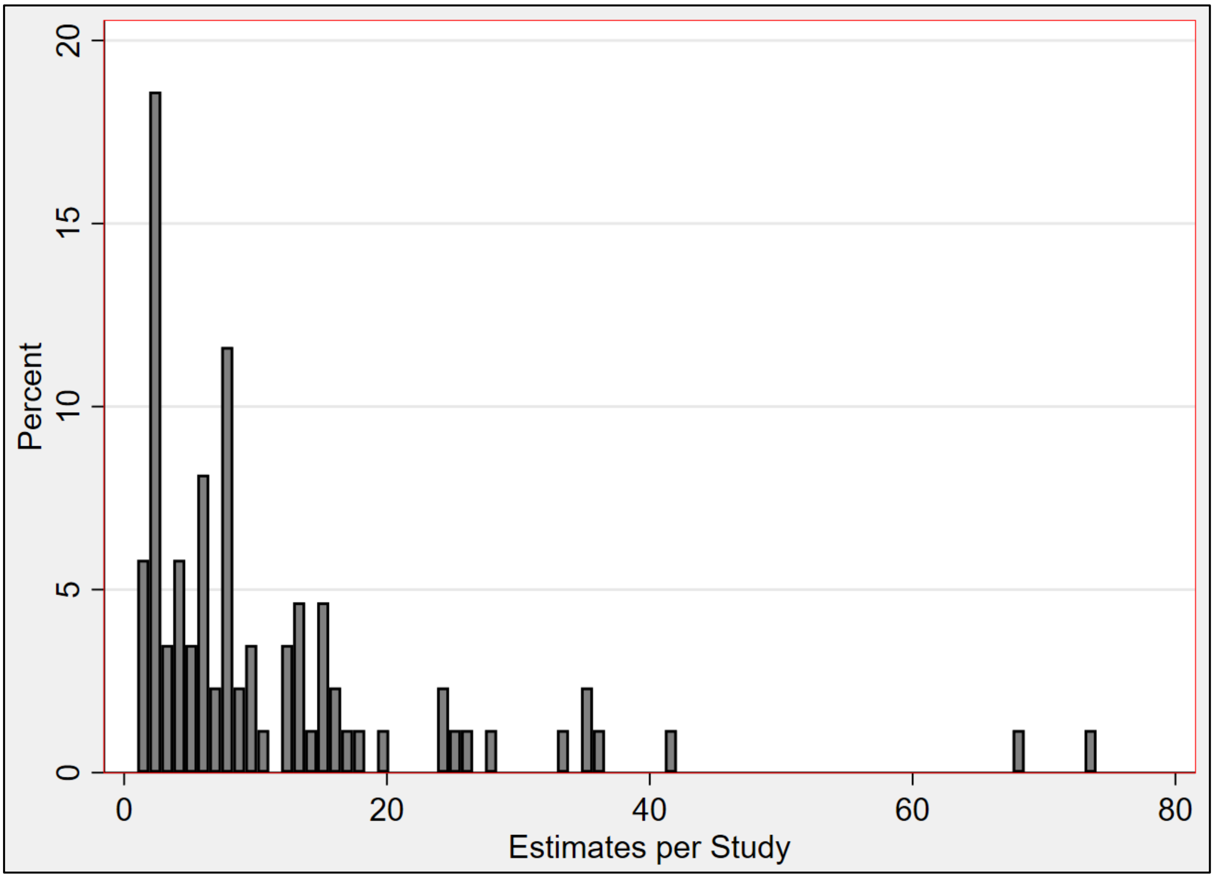
FIGURE 3
Distribution of True Effects



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	11.5	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] 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).

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

[7] Algan, Y., & Cahuc, P. (2013). Trust and Growth. *Annual Review of Economics*, 5(1), 521–549.

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

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

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

[11] Baliamoune-Lutz, M. (2005). Institutions, social capital, and economic development in Africa: an empirical study. International Centre for economic research working paper series, 18.

[12] Baliamoune-Lutz, M., & Mavrotas, G. (2009). Aid effectiveness: looking at the aid–social capital–growth nexus. Review of Development Economics, 13(3), 510-525.

[13] Baumann, S., Schneider, G. (1999). Bringing Putnam to the European regions: on the relevance of social capital for economic growth. Conference paper of ECSA, Pittsburgh.

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

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

[16] 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.

[17] 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.

[18] Beugelsdijk, S., & Smulders, S. (2009). Bonding and bridging social capital and economic growth. CentER Discussion Paper, 2009-27.

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

[20] Brito, J. A. (2015). Social Cohesion and Economic Growth: Small States vs Large States. MPRA Paper, No.66118

[21] 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.

[22] Dearmon, J., & Grier, K. (2009). Trust and development. Journal of Economic Behavior & Organization, 71(2), 210–220.
[23] Del, R. (2005). The Social Capital Effect on Economic Growth. Doctor thesis in The Ohio State University, Ohio.
[24] Dincer, O. & Uslaner, E.M. (2007). Trust and Growth. FEEM Working Paper No. 73.
[25] Dincer, O. C., & Uslaner, E. M. (2010). Trust and growth. Public Choice, 142(1), 59-67.
[26] 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.
[27] 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.
[28] Działek, J. (2014). Is social capital useful for explaining economic development in polish regions?. Geografiska Annaler: Series B, *Human Geography*, 96(2), 177-193.
[29] Dzialek, J. (2009). Social capital and economic growth in Polish regions. MPRA Paper No. 18287.
[30] Fafchamps, M., & Minten, B. (2002). Returns to social network capital among traders. *Oxford Economic Papers*, 54(2), 173-206.
[31] Forte, A., Peiró Palomino, J., & Tortosa Ausina, E. (2015). Does social capital matter for European regional growth? *European Economic Review*, 77, 47–64.
[32] 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.
[33] Guiso, Luigi, Paola Sapienza & Luigi Zingales. (2011). Civic Capital as the Missing Link. *Social Economics Handbook*, 1,417-480.
[34] Gupta, R. N. R. (2015). Economic Development: Is Social Capital Persistent? CES Working Papers, Available at halshs-01157891.
[35] Hall, S. G., & Ahmad, M. (2013). Can Trust Explain Social Capital Effect on Property Rights and Growth? *Procedia Economics and Finance*, 7, 55–64.
[36] Heller, L. (2009). Social Cohesion and Its Relationship to Endogenous Institutional Formation and Economic Growth. Journal of Private Enterprise, 25(1).
[37] 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.
[38] Hjerppe, R. (1998). Social Capital and Economic Growth. Discussion Papers 183, VATT Institute for Economic Research.
[39] Holthe, I. C. (2009). Tracking trust-Investigating how social capital influences economic development in Latin America. Master thesis in University of Bergen, Bergen.
[40] 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.
[41] Jackman, R. W., & Miller, R. A. (1996). A Renaissance of Political Culture? American Journal of Political Science, 40(3), 632.
[42] 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.
[43] 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.
[44] Kaldaru, H., & Parts, E. (2005). The Effect of Macro-level Social Capital on Sustainable Economic Development. *SSRN Electronic Journal*.
[45] Kanas, A. (2011). The economic performance of immigrants: The role of human and social capital. Ph.D. thesis in Utrecht University, The Netherlands.

[46] Kapan, L. (2019). Economic growth-A matter of trust?: The impact of social capital on economic growth. Doctor thesis in Jönköping University, Jönköping.
[47] 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.
[48] Knack, S. (2001). Trust, associational life, and economic performance. MRPA Paper No.27247.
[49] Knack, S. (2003). Groups, Growth and Trust: Cross-Country Evidence on the Olson and Putnam Hypotheses. Public Choice 117, 341–355.
[50] Komándi-Jánosi, K. (2016). How does trust affect economic growth through spurring innovation?. Analysis of nuts regions. Doctor thesis in Central European University, Budapest.
[51] Laughlin, T. W. (2012). The effects of social capital on local government performance and economic development. Ph.D. thesis in Auburn University, Alabama.
[52] 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.
[53] 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.
[54] Lyon, T. P. (2005). Making Capitalism Work: Social Capital and Economic Growth in Italy, 1970-1995. Available at SSRN 726201.
[55] Majeed, M.T.(2017) .Economic Growth and Social Cohesion: Evidence from the Organization of Islamic Conference Countries. Soc Indic Res 132, 1131–1144 .
[56] Manyasa, E. O. (2009). Social capital and rural economic development in western province of Kenya : An empirical analysis. Doctor thesis in Kenyatta University, Nairobi.
[57] Moesen, W., Puyenbroeck,T. & Cherchye, L. (2000). Trust as societal capital: economic growth in European regions, Public Economics Working Paper Series,1.
[58] Montolio, D., & Tur-Prats, A. (2018). Long-Lasting Social Capital and its Impact on Economic Development: The Legacy of the Commons. XREAP2018-08.
[59] Muringani, J., Fitjar, R. D., & Rodríguez-Pose, A. (2021). Social capital and economic growth in the regions of Europe. Environment and Planning A: Economy and Space, 53(6), 1412-1434.
[60] 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.
[61] 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.
[62] 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.
[63] Peiró-Palomino,, J. &Tortosa-Ausina, E. (2013). Can trust effects on development be generalized? A response by quantile. European Journal of Political Economy.32:377-390.
[64] 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.
[65] Peiró Palomino, J., & Tortosa-Ausina, E. (2015). Social Capital, Investment and Economic Growth. Evidence for Spanish Provinces. *Spatial Economic Analysis*, 10(1), 102-126.
[66] Pérez, F., Fernandez de Guevara, J., Serrano, L., & Montesinos, V. (2006). Measurement of social capital and growth: An economic methodology. *Fundación BBVA*, 4.
[67] 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.

[68] Pervaiz, Z., & Chaudhary, A. R. (2015). 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.
[69] Roth, F. (2007). Social Capital, Trust, and Economic Growth—A cross-sectional and panel analysis. Doctor thesis in Universität Göttingen, Göttingen.
[70] Roth, F. (2009). Does Too Much Trust Hamper Economic Growth? Kyklos 62 (1), 103-128.
[71] 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.
[72] Schmidt, K. (2003). Is trust important for economic development and growth?. Berlin Disponível Science and Politics, 28, 664-83.
[73] 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.
[74] 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.
[75] Tabellini, G. (2010). Culture and Institutions: Economic Development in the Regions of Europe. Journal of the European Economic Association, 8(4), 677–716.
[76] Temple, J. (1998). Initial conditions, social capital and growth in Africa. *Journal of African Economies*, 7(3), 309-347.
[77] Vizitei, C. C. (2012). Can trust substitute for quality institutions to promote economic growth?. Master thesis in University of Missouri-Columbia, Columbia.
[78] Volland, B. (2010). Trust, confidence and economic growth: An evaluation of the Beugelsdijk Hypothesis. Jena Economic Research Papers, 80.
[79] 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.
[80] Westlund, H. & Kobayashi, K.(2013). *Social capital and rural development in the knowledge society*. Edward Elgar Publishing.
[81] Whiteley, P. F. (2000). Economic Growth and Social Capital. *Political Studies*, 48(3), 443–466.
[82] Yokoyama, S., & Sakurai, T. (2006). Potential of social capital for community development. Available from APO's web site.
[83] Zak, P. J., & Knack, S. (2001). Trust and growth. The Economic Journal, 111(470), 295-321.

ONLINE SUPPLEMENT

for

Social Capital and Economic Growth: A Meta-Analysis

TABLE	DESCRIPTION
S1	Reproduces TABLE 6 in the text except it estimates them separately for two subsets: (i) social capital effects where the dependent variables is the growth rate; (ii) social capital effects where the dependent variable is measured in levels.
S2	Reproduces TABLE 7 in the text except it estimates them separately for two subsets: (i) social capital effects where the dependent variables is the growth rate; (ii) social capital effects where the dependent variable is measured in levels.
S3	Reproduces TABLE 6 in the text (with no control variables) using only the sample of unpublished studies.
S4	This analysis is patterned after TABLE 7 in the text except that it estimates the model using the Mundlak model, allowing estimates of both within- and between-effects for the social capital and publication bias variables.
S5.A, S5.B	TABLE S5.B is identical to TABLE 9 in the text. TABLS S5.A reproduces the estimation of S5.B except that it omits the publication bias term. A comparison of TABLES S5.A and S5.B allow one to see the difference that correcting for publication bias makes for the estimated coefficients of the SC2 social capital variables.
S6	Sensitivity check to alternative values of rho for the 3L-VCV estimator in TABLE 5.

TABLE S1
Estimates of the Adjusted Overall Mean Effect (Subsample Analysis)

	Subsample = DV_GrowthRate					***Subsample = DV_GDPLevel***				
Variable	***OLS (1)***	***FE (2)***	***RE (3)***	***3L (4)***	***3L-VCV (5)***	***OLS (6)***	***FE (7)***	***RE (8)***	***3L (9)***	***3L-VCV (10)***
Constant (Effect beyond bias	0.032 (0.023)	0.055 (0.034)	0.033 (0.022)	0.019 (0.032)	0.018 (0.025)	-0.005 (0.060)	-0.006 (0.011)	-0.006 (0.060)	0.045 (0.037)	0.031 (0.035)
$se(z)$ ***(Bias)***	1.365*** (0.246)	0.992** (0.439)	1.348*** (0.225)	1.533*** (0.312)	1.568*** (0.275)	2.067** (0.831)	2.075*** (0.580)	2.084** (0.805)	1.546** (0.548)	1.700*** (0.544)
Observations	555	555	555	555	555	402	402	402	402	402
Studies	58	58	58	58	58	32	32	32	32	32
AIC	-213.5	3597.2	-307.4	-361.8	-365.2	-30.1	3846.9	-61.2	-126.3	-132.2
BIC	-200.5	3605.9	-294.5	-344.6	-348.0	-18.1	3854.9	-49.3	-110.4	-116.2
LR Test:	----[a]	----[a]	*p<0.0001*	*p<0.0001*	----[b]	----[a]	----[a]	*p<0.0001*	*p<0.0001*	----[b]

NOTE: This table reproduces the analysis of TABLE 6 in the text except that it splits the full sample into two subsamples. One where the economic growth is measured as a growth rate. And one where economic growth is measured in terms of levels. 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. The last row reports a likelihood ratio test of the full model versus the restricted model, where the restricted model is the model immediately to the left in the table.

[a] We do not report likelihood ratio test results for OLS and FE because these do not nest a simpler, restricted model
[b] We cannot test 3L-VCV against 3L because these have the same number of parameters.

TABLE S2
Meta-Regression Analysis - Social Capital-1 Variables (Subsample Analysis)

	Subsample = DV_GrowthRate					*Subsample = DV_GDPLevel*				
Variable	***OLS (1)***	***FE (2)***	***RE (3)***	***3L (4)***	***3L-VCV (5)***	***OLS (6)***	***FE (7)***	***RE (8)***	***3L (9)***	***3L-VCV (10)***
SC1_Cognitive	0.0.053 (0.035)	0.035 (0.041)	0.049 (0.032)	-0.055 (0.044)	-0.036 (0.043)	0.097 (0.107)	-0.006 (0.037)	0.080 (0.093)	0.110 (0.133)	0.127 (0.143)
SC1_Structural	-0.013 (0.044)	0.065** (0.015)	0.024 (0.037)	0.011 (0.051)	0.015 (0.049)	-0.080 (0.074)	-0.040 (0.036)	-0.087 (0.070)	-0.134 (0.136)	-0.128 (0.132)
$se(z)$	1.275*** (0.260)	1.259*** (0.325)	1.218*** (0.231)	1.644*** (0.369)	1.697*** (0.350)	1.501* (0.787)	2.178*** (0.664)	1.526* (0.745)	1.275* (0.708)	1.250 (0.774)
Constant	0.026 (0.023)	0.009 (0.014)	0.020 (0.015)	0.031 (0.035)	0.017 (0.027)	0.051 (0.077)	0.008 (0.022)	0.056 (0.077)	0.070 (0.088)	0.067 (0.090)
Observations	555	555	555	555	555	402	402	402	402	402
Studies	58	58	58	58	58	32	32	32	32	32
$H_0: \beta_{Cognitive} = \beta_{Structural} = 0$	*F = 1.14 (p=0.340)*	*F = 8.46 (p=0.031)*	*F = 1.40 (p=0.278)*	*F = 0.91 (p=0.437)*	*F = 0.34 (p=0.716)*	*F = 2.77 (p=0.103)*	*F = 0.43 (p=0.693)*	*F = 3.18 (p=0.080)*	*F = 1.21 (p=0.359)*	*F = 1.29 (p=0.335)*
$H_0: \beta_{Cognitive} = \beta_{Structural}$	*F = 1.45 (p=0.243)*	*F = 0.42 (p=0.540)*	*F = 0.24 (p=0.634)*	*F = 0.59 (p=0.472)*	*F = 0.40 (p=0.547)*	*F = 4.97 (p=0.044)*	*F = 0.48 (p=0.545)*	*F = 5.91 (p=0.030)*	*F = 2.81 (p=0.116)*	*F = 2.96 (p=0.107)*
AIC	-221.0	3079.9	-306.8	-362.0	-363.1	-56.3	3735.7	-85.6	-151.0	-156.9
BIC	-199.4	3097.2	-285.2	-336.1	-337.3	-36.3	3751.6	-65.7	-127.0	-132.9
LR Test:	----[a]	----[a]	*p<0.0001*	*p<0.0001*	----[b]	----[a]	----[a]	*p<0.0001*	*p<0.0001*	----[b]

NOTE: This table reproduces the analysis of TABLE 7 in the text except that it splits the full sample into two subsamples. One where the economic growth is measured as a growth rate. And one where economic growth is measured in terms of levels. 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. The last row reports a likelihood ratio test of the full model versus the restricted model, where the restricted model is the model immediately to the left in the table.

[a] We do not report likelihood ratio test results for OLS and FE because these do not nest a simpler, restricted model
[b] We cannot test 3L-VCV against 3L because these have the same number of parameters.

TABLE S3
Estimate of the Adjusted Overall Mean Effect (Unpublished Studies)

Variable	*OLS (1)*	*FE (2)*	*RE (3)*	*3L (4)*	*3L-VCV (5)*
Constant* *(Effect beyond bias)	0.011 (0.047)	-0.005 (0.007)	0.012 (0.048)	0.030 (0.050)	0.017 (0.042)
$se(z)$ ***(Bias)***	1.438*** (0.434)	1.694*** (0.521)	1.425*** (0.437)	1.569** (0.512)	1.725*** (0.501)
Observations	450	450	450	450	450
Studies	35	35	35	35	35

NOTE: This table is identical to TABLE 6 in the paper except that only estimates from unpublished sources are included.

TABLE S4
Meta-Regression Analysis (Mundlak Model) - Social Capital-1 Variables

Variable	*No Control Variables (1)*	*Full Set of Control Variables (2)*
SC1_Cognitive (within)	-0.057 (0.120)	-0.048 (0.117)
SC1_Cognitive (difference)	0.097 (0.131)	0.078 (0.129)
SC1_Structural (within)	-0.075 (0.095)	-0.053 (0.095)
SC1_Structural (difference)	0.000 (0.114)	-0.024 (0.113)
se(z) (within)	1.133*** (0.266)	0.927*** (0.328)
se(z) (difference)	0.640 (0.619)	0.972 (0.848)
$H_0: \beta_{Cognitive-Diff} = \beta_{Structural-Diff} = 0$	$\chi^2 = 0.73$ *(p=0.694)*	$\chi^2 = 0.71$ *(p=0.701)*
Observations	957	957
Studies	83	83

NOTE: This analysis is patterned after TABLE 7 in the manuscript. The dependent variable is Fisher's z. Standard errors are estimated using the "CR1" cluster robust standard error estimator and are reported in parentheses. The *, **, and *** indicate statistical significance at the 10-, 5-, and 1-percent level, respectively.

TABLE S5.A
Meta-Regression Analysis - Social Capital-2 Variables (No Correction for Publication Bias)

Variable	*OLS (1)*	*FE (2)*	*RE (3)*	*3L (4)*	*3L-VCV (5)*	*OLS (6)*	*FE (7)*	*RE (8)*	*3L (9)*	*3L-VCV (10)*
SC2-PartTrust	0.072 (0.082)	-0.016 (0.040)	0.053 (0.076)	-0.028 (0.109)	-0.021 (0.118)	0.016 (0.085)	0.000 (0.022)	-0.005 (0.076)	-0.057 (0.110)	-0.049 (0.121)
SC2_GenTrust	0.184** (0.081)	0.149** (0.052)	0.160* (0.078)	0.021 (0.090)	0.038 (0.094)	0.131 (0.080)	0.043 (0.070)	0.101 (0.074)	0.003 (0.087)	0.017 (0.094)
SC2-AssocGroup	-0.024 (0.074)	0.002 (0.036)	-0.042 (0.075)	-0.129 (0.128)	-0.121 (0.122)	-0.035 (0.086)	-0.023 (0.076)	-0.047 (0.090)	-0.112 (0.126)	-0.104 (0.121)
SC2_SocialPart	0.073 (0.092)	0.012 (0.068)	0.072 (0.097)	0.120 (0.113)	0.131 (0.118)	0.078 (0.103)	0.005 (0.036)	0.082 (0.105)	0.124 (0.103)	0.137 (0.108)
SC2-Voting	-0.020 (0.053)	0.051* (0.021)	-0.015 (0.049)	-0.067 (0.129)	-0.059 (0.121)	-0.033 (0.093)	0.018 (0.089)	-0.014 (0.094)	-0.044 (0.126)	-0.035 (0.120)
SC2_Bonding	-0.042 (0.112)	-0.074 (0.048)	-0.063 (0.112)	-0.151 (0.129)	-0.124 (0.121)	-0.033 (0.099)	-0.144 (0.087)	-0.073 (0.100)	-0.105 (0.123)	-0.079 (0.113)
SC2-Bridging	0.062 (0.083)	0.139 (0.065)	0.064 (0.078)	0.007 (0.111)	0.016 (0.104)	0.075 (0.099)	0.072 (0.091)	0.059 (0.099)	0.054 (0.120)	0.062 (0.115)
SC2_EthnicFrag	-0.070 (0.063)	0.002 (0.025)	-0.063 (0.060)	0.009 (0.027)	0.006 (0.028)	-0.056 (0.059)	-0.000 (0.041)	-0.059 (0.059)	0.006 (0.030)	0.003 (0.032)
SC2-ScIndex	0.242* (0.081)	0.181 (0.120)	0.226* (0.088)	0.083 (0.093)	0.070 (0.103)	0.143 (0.093)	0.095 (0.087)	0.113 (0.091)	0.003 (0.086)	-0.005 (0.093)
SC2_SocialCoh	0.049 (0.064)	0.131*** (0.022)	0.056 (0.061)	-0.047 (0.076)	-0.021 (0.085)	0.122 (0.079)	0.079 (0.074)	0.096 (0.075)	0.054 (0.073)	0.060 (0.087)

Variable	*OLS (1)*	*FE (2)*	*RE (3)*	*3L (4)*	*3L-VCV (5)*	*OLS (6)*	*FE (7)*	*RE (8)*	*3L (9)*	*3L-VCV (10)*
se(z)	----	----	----	----	----	----	----	----	----	----
H_0: SC2 variables have equal effects	*F = 36.40 (p<0.001)*	*F = 0.00 NA*	*F = 31.10 (p<0.001)*	*F = 0.57 (p=0.785)*	*F = 0.34 (p=0.913)*	*F = 2.07 (p=0.145)*	*F = 0.26 (p=0.928)*	*F = 1.86 (p=0.200)*	*F = 0.68 (p=0.719)*	*F = 0.53 (p=0.805)*
Observations	952	952	952	952	952	952	952	952	955	952
Studies	82	82	82	82	82	82	82	82	82	82

NOTE: This table is identical to TABLE 9 in the text except that it does not include the publication bias term, *se(z),* in the specification. By comparing it to the table below (TABLE S5.B), one can see the difference to the estimated coefficients for the social capital variables when including the publication bias term. 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.

TABLE S5.B
Meta-Regression Analysis - Social Capital-2 Variables (With Correction for Publication Bias)

Variable	*OLS (1)*	*FE (2)*	*RE (3)*	*3L (4)*	*3L-VCV (5)*	*OLS (6)*	*FE (7)*	*RE (8)*	*3L (9)*	*3L-VCV (10)*
SC2-PartTrust	-0.025 (0.087)	-0.018 (0.022)	-0,044 (0.078)	-0.065 (0.103)	-0.066 (0.110)	-0.039 (0.090)	-0.003 (0.034)	-0.060 (0.082)	-0.076 (0.108)	-0.072 (0.119)
SC2_GenTrust	0.098 (0.078)	0.062 (0.053)	0.075 (0.071)	0.002 (0.085)	0.017 (0.087)	0.080 (0.085)	-0.006 (0.067)	0.052 (0.078)	-0.012 (0.086)	0.002 (0.093)
SC2-AssocGroup	-0.075 (0.075)	-0.028 (0.040)	-0.078 (0.070)	-0.134 (0.119)	-0.120 (0.109)	-0.079 (0.092)	-0.064 (0.073)	-0.084 (0.090)	-0.119 (0.124)	-0.111 (0.118)
SC2_SocialPart	0.059 (0.099)	0.017 (0.047)	0.056 (0.101)	0.094 (0.110)	0.099 (0.112)	0.055 (0.100)	0.001 (0.030)	0.058 (0.102)	0.107 (0.103)	0.117 (0.107)
SC2-Voting	-0.010 (0.067)	0.065 (0.020)	-0.000 (0.057)	-0.066 (0.114)	-0.048 (0.101)	-0.072 (0.101)	-0.026 (0.083)	-0.049 (0.093)	-0.050 (0.120)	-0.042 (0.113)
SC2_Bonding	-0.079 (0.076)	-0.092 (0.021)	-0.097 (0.069)	-0.162 (0.102)	-0.138 (0.088)	-0.102 (0.105)	-0.153 (0.078)	-0.137 (0.101)	-0.124 (0.117)	-0.107 (0.108)
SC2-Bridging	0.037 (0.094)	0.123 (0.069)	0.044 (0.093)	-0.002 (0.104)	0.004 (0.099)	0.014 (0.108)	0.059 (0.101)	0.006 (0.106)	0.036 (0.116)	0.034 (0.115)
SC2_EthnicFrag	-0.042 (0.066)	0.000 (0.024)	-0.045 (0.063)	0.013 (0.024)	0.002 (0.032)	-0.019 (0.047)	-0.001 (0.036)	-0.031 (0.049)	0.013 (0.021)	0.007 (0.027)
SC2-ScIndex	0.112 (0.086)	0.059 (0.058)	0.091 (0.082)	0.052 (0.087)	0.027 (0.096)	0.091 (0.104)	0.039 (0.052)	0.062 (0.095)	-0.001 (0.083)	-0.013 (0.093)
SC2_SocialCoh	0.018 (0.065)	0.028 (0.037)	0.011 (0.061)	-0.025 (0.071)	-0.020 (0.070)	0.060 (0.094)	-0.006 (0.090)	0.038 (0.087)	0.009 (0.080)	0.009 (0.085)

Variable	*OLS (1)*	*FE (2)*	*RE (3)*	*3L (4)*	*3L-VCV (5)*	*OLS (6)*	*FE (7)*	*RE (8)*	*3L (9)*	*3L-VCV (10)*
se(z)	1.354*** (0.297)	1.610*** (0.397)	1.395*** (0.302)	1.493*** (0.291)	1.574*** (0.336)	1.244*** (0.387)	1.270*** (0.401)	1.120*** (0.400)	1.261*** (0.350)	1.333*** (0.398)
H_0: SC2 variables have equal effects	*F = 1.25 (p=0.396)*	*F = 0.00 NA*	*F = 1.23 (p<0.423)*	*F = 0.86 (p=0.609)*	*F = 0.71 (p=0.701)*	*F = 0.99 (p=0.509)*	*F = 0.24 (p=0.939)*	*F = 1.01 (p=0.508)*	*F = 0.62 (p=0.754)*	*F = 0.51 (p=0.825)*
Observations	952	952	952	952	952	952	952	952	955	952
Studies	82	82	82	82	82	82	82	82	82	82

NOTE: This table is identical to TABLE 9 in the text. By comparing it to the table above (TABLE S5.A), one can see the difference from including the publication bias term, *se(z)*. 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.

TABLE S6
Sensitivity Check of Alternative Values of *ρ* for 3L-VCV Estimates (TABLE 5)

Variable	*3L-VCV (ρ = 0.3) (1)*	*3L-VCV (ρ = 0.5) (2)*	*3L-VCV (ρ = 0.7) (3)*
Constant (Effect beyond bias)	0.182*** (0.019)	0.175*** (0.018)	0.169*** (0.018)
Observations	957	957	957
Studies	83	83	83
AIC	-432.2	-434.9	-432.5
BIC	-417.6	-420.3	-417.9

NOTE: Column (2) reproduces the results reported in Column (5) of TABLE 5 in the text, where ρ was set equal to 0.5 for the 3L-VCV model. Columns (1) and (3) show the effect of changing ρ to 0.3 and 0.7, respectively.