Does social capital explain the Solow residual? A DSGE approach

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Abstract

Social capital has been credited with playing a role in many desirable economic outcomes. We analyze how these potentially beneficial effects translate into the performance of economies by developing a dynamic stochastic general equilibrium (DSGE) model featuring the role of social capital in the explanation of the Solow residual. We then simulate and estimate the model with Bayesian techniques using Italian data. Our framework fits actual data better than a standard DSGE model, suggesting that social capital may improve the economic performance via its impact on total factor productivity.

Keywords: social capital; total factor productivity; Solow residual; DSGE models.

JEL Classification: E12, E22, O11, Z1, Z13.

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1 Introduction

The literature has credited social capital with playing a role in many desirable economic outcomes such as loan repayment and access to credit (Karlan et al., 2009), financial development (Guiso et al., 2004), investments in education (Coleman, 1988) and innovation (Knack and Keefer, 1997), political accountability (Nannicini et al., 2013), and productivity in organizations (Costa and Kahn, 2003; Guiso et al., 2015), just to name a few.

How do these effects translate into the performance of economies? Empirical studies found evidence of a positive relationship between aspects of social capital - such as trust, networks and manifestations of prosocial attitudes - and growth across countries (e.g. Knack and Keefer, 1997; Algan and Cahuc, 2010) or regions (e.g. Tabellini, 2010; Guiso et al., 2016). However, our knowledge of the mechanisms allowing the effects of social capital to result in a better economic performance and, in the long run, growth is still limited.

In line with seminal studies (Bourdieu, 1986; Coleman, 1988), we assume that social capital is an asset that allows agents to internalize the benefits of cooperation. Social capital can be created as a by-product of disinterested activities such as prosocial behaviors like blood donation, or through rational investment decisions taken to the pursuit of particular goals. These decisions incidentally create a cooperation friendly environment, a common resource that has the feature of a public good. This resource is clearly multidimensional, as it can take many forms, productive, as it makes possible the achievement of specific ends that would not be possible in its absence, and not completely fungible, as it is specific to certain activities (Coleman, 1988). The multidimensionality and "situationality" (Coleman, 1988) of social capital led many authors to consider it as an umbrella concept that captures those societal features helping people to better work together for common purposes (Putnam, 1995) [1]. In this paper, we study how this multifaceted resource contributes to the economic performance by developing a dynamic stochastic general equilibrium (DSGE) model

[1] See Sabatini (2007) and Guiso et al. (2010) for a review of the literature.

that features the role of social capital in a constant returns to scale production function. The model is simulated and estimated using Bayesian techniques to match Italian data for total factor productivity over the period 1950-2014. We then compare the actual pattern of total factor productivity with the same time series simulated through the DSGE model in a benchmark case not including social capital and in our framework explicitly modeling the role of social capital. This exercise is aimed at improving our understanding of whether the accumulation of social capital supports the economic performance.

The empirical analysis shows that accounting for the role of social capital allows an otherwise standard DSGE model to better fit actual data in the long run. This result suggests that the macroeconomic outcomes of social capital may help explaining the Solow residual.

Our paper bridges two strands of literature. The first broadly studies the aggregate returns to social capital by empirically analyzing its correlation with growth (Algan and Cahuc, 2010; Guiso et al., 2016), and other macroeconomic outcomes, such as innovation (Knack and Keefer, 1997; Akçomak and ter Weel, 2009), financial development (Guiso et al., 2004), welfare spending (Bjørnskov and Svendsen, 2013), the quality of government (Putnam et al., 1993; Alesina and Zhuravskaya, 2011).

The second strand encompasses studies investigating the drivers of growth, such as innovation (Castellacci, 2008; Castellacci and Natera, 2016), access to credit (Skott and Gómez-Ramírez, 2018), trade (Sasaki, 2017), technological progress (Antoci et al., 2011b; Fiaschi and Fioroni, 2019), employment (Compagnucci et al., 2018), the quality of institutions (Acemoglu et al., 2001; Dias and Tebaldi, 2012), and the depletion of natural resources (Antoci et al., 2009a; Antoci et al., 2011a).

We contribute to these fields by developing and empirically testing the first DSGE model aimed at capturing social capital's macroeconomic effects.

The rest of the paper is organized as follows. Section 2 briefly reviews the literature about social capital's definition, measurement, and relationship with the economic performance. Section

3 describes the theoretical model. In Section 4 we describe our data, the methodology employed to estimate the parameters, the model's dynamics through the impulse response functions, and the related results. We discuss our ndings and their possible policy implications in Section 5 and conclude in Section 6.

2 Social capital and the economic performance

Despite the ambiguity in its definition and measurement, the concept of social capital has gained wide attention among economists for its ability to improve the understanding of the intangible factors of development. According to Coleman (1988), "Social capital is defined by its function. It is not a single entity but a variety of different entities, with two elements in common: they all consist of some aspects of the social structure, and they facilitate certain actions of actors within the structure" (Coleman, 1988, p. 98). Putnam (1995) referred to social capital as all the features of social life - networks, norms, civic engagement and trust - that enable individuals to act together more effectively to pursue shared objectives. These definitions view social capital as a multidimensional input in the objective functions of agents. In the view of Bourdieu (1986), this input has a residual nature as it encompasses all the means of production that cannot be institutionalized in the form of property rights, (as in the case of physical and natural capital) and it does not take the form of educational qualifications (human capital). The author defines social capital as the aggregate of the actual or potential resources that are linked to more or less institutionalized relationships of mutual acquaintance and recognition. Guiso et al. (2010) shift the focus from connections to "those persistent and shared beliefs and values that help a group overcome the free rider problem in the pursuit of socially valuable activities" (p. 419). Coleman (1988) suggests that investments in social capital can happen as an incidental by-product of disinterested activities, such as in the case of blood donation, or as rational investment decisions aimed at reaching the shared goals of a specific group, such as in the case of parents' associations in schools.

The definitions of social capital provided above share the emphasis on the aspects of the social structure that help members of a community or group to solve coordination issues. However, they also have in common the key weakness inherent in the difficulty to operationalize vague and multidimensional concepts. As summarized by Solow (2005) in his critique to Fukuyama (1995): "If 'social capital' is to be more than a buzzword, the stock of social capital should somehow be measurable, even inexactly". The literature has actually proposed many different measures of social capital, which capture its many dimensions. A strategy to synthesize them all in a single indicator is to focus on their hypothetical outcomes, such as those behaviors that reveal individuals' propensity for cooperation. One problem with these measures is that they can be contaminated by other factors (Guiso et al., 2010). For example, tax compliance is strictly linked to civic-mindedness, but may also depend on the tightness of tax surveillance and on the design of the tax system (Argentiero and Cerqueti, 2019; Cerqueti et al., 2019). However, there are cases in which the relationship between social capital and its hypothetical outcomes is not affected by confounding factors. Several authors suggest this is the case of blood donation (e.g. Guiso et al., 2004; Akçomak and ter Weel, 2012; Nannicini et al., 2013; Guriev and Melnikov, 2016). Guiso et al. (2010) explain that the decision to donate can be seen as a direct measure of how much people internalize the common good, as there is no economic payoff to donation and there is no legal obligation to donate. This is particularly true for Italy, where infrastructures for blood donation are widespread and mostly supervised by the Association of Voluntary Blood Donors (AVIS, acronym for *Associazione Volontari Italiani del Sangue*), which is responsible for the 90 percent of the whole blood donations in Italy and has branches in virtually every Italian municipality.

The stronger propensity for cooperation stemming from social capital can be beneficial for development in many ways. Cooperation reinforces trust and trustworthiness (Dasgupta, 2009), thereby improving the environment in which individuals and firms make their investment decisions, resulting in a more efficient allocation of resources and a higher total factor productivity. For example, since trust enhances access to credit (Karlan, 2005; Feigenberg et al., 2013), enrollment in higher education may be easier. At the firm level, higher credit opportunities might simplify the financing of innovative projects (Akçomak and ter Weel, 2009). The mitigation of agency problems typical of a more cooperative and trusting society improves the management of human resources and lowers monitoring costs both in the workplace and in inter-firm relationships (La Porta et al., 1997; Costa and Kahn, 2003). In high trust societies, hiring decisions are more likely to be influenced by talent and effort instead of the personal attributes of applicants, such as blood ties and personal knowledge - which are common surrogates of trustworthiness in low-trusting societies (Knack and Keefer, 1997; Alesina et al., 2015). As a result, social capital also increases the return to specialized and vocational education, resulting in stronger incentives to invest in human capital (Knack and Keefer, 1997; Guiso et al., 2010).

Overall, these mechanisms create a social infrastructure more favorable to high levels of output per worker, which, to use the words of Hall and Jones (1999): "Gets the prices right so that individuals capture the social returns to their actions as private returns" (p. 84).

The empirical literature on the drivers of economic development suggests that the private returns to social capital summarized above lead actors - whether individual or corporate - to create a cooperation friendly environment that supports growth. Knack and Keefer (1997) and Zak and Knack (2001) find that the share of people declaring to trust others is significantly associated to economic growth across countries. Guiso et al. (2004) show that in areas with more social capital - measured as voter turnout and the number of blood bags collected per inhabitant - households are more likely to use checks, invest less in cash and more in stock, have higher access to institutional credit, and make less use of informal credit. Algan and Cahuc (2010) find that changes in the level of inherited trust explain a substantial part of the differences in economic development across countries over the period 1935–2000. Nannicini et al. (2013) show that political accountability, a key determinant of the performance of institutions, is stronger in provinces with higher social capital, measured as average per-capita blood donations. Guiso et al. (2016) find evidence that the Italian cities that experienced a period of independence as free city-states in the Middle Ages, have higher endowments of social capital today - as measured by the the density of non-profit organizations and the presence of an organ donation organization in town - and that these indicators of social capital predict economic development across municipalities.

Our contribution to this literature consists in the development of a DSGE model that assesses the ability of social capital to explain the Solow residual, thus providing an explanation for the correlation between social capital and the economic performance. To simulate and estimate the model using Italian data, we follow the approach of measuring social capital as the volume of blood donations per inhabitants, as suggested in Guiso et al. (2004) and Guiso et al. (2010) and adopted in many other studies (see for example Akçomak and ter Weel, 2009; De Blasio and Nuzzo, 2010; Durante et al., 2011; Nannicini et al., 2013; Guriev and Melnikov, 2016).

3 The model

The economy is populated by infinitely living households, who maximize the expected discounted value of an inter-temporal utility function, i.e.:

$$E_0 \sum_{t=0}^{\infty} \beta^t U_t \left(C_t, N_t\right) \tag{1}$$

with β^t corresponding to the subjective discount factor, C_t is private consumption and N_t are the hours worked, E_0 is the expected value operator given the information at time 0, under the following inter-temporal budget constraint:

$$P_t C_t + K_t^p + K_t^s \leq R_t^p K_{t-1}^p + R_t^s K_{t-1}^s + W_t N_t \tag{2}$$

where K^p_{t-1} and K^s_{t-1} are the endowments of physical and social capital respectively at time $t-1$,, P_t is the consumer price index, W_t are nominal wages, and R^i_t $(i = s, p)$ are the gross rates of return

$$R^i_t = r^i_t + 1 - \delta^i \tag{3}$$

with r^i_t $(i = s, p)$ representing the net capital rentals and δ^i $(i = s, p)$ the capital depreciation rates[2].

Social capital is in part accumulated through rational investment decisions (Becker, 1974; Bourdieu, 1986). Agents invest in the creation of connections and social obligations, and in building a reputation of trustworthiness, to the purpose of pursuing particular or general goals that could not be achieved without coordination and cooperation. The stock resulting from these decisions is a shared resource having the nature of a public good. In line with the extensive literature on social capital and growth (see for example Francois and Zabojnik, 2005 and Antoci et al., 2011b), we assume this resource being an input of production. As suggested by Bourdieu (1986), agents can appropriate the outcomes of production to the extent of their personal or corporate wealth of social capital, which therefore determines the rental rate of this factor of production. Social capital, however, requires an endless and costly effort to produce and reproduce lasting relationships (Bourdieu, 1982; 1986). Like the other forms of capital, it is therefore subject to depreciation, as relationships, networks, trust and the individuals' propensity for cooperation can slacken over time as a result, for example, of the decline in social participation (Antoci et al., 2011b) and of negative shocks (Guriev and Melnikov, 2016).

Both physical and social capital, K^i_t $(i = s, p)$, evolve according to the standard law of motion, i.e.:

$$K^i_t - K^i_{t-1} = I^i_t - \delta^i K^i_{t-1} \tag{4}$$

where I^i_t $(i = s, p)$ are the incidental investments in physical and social capital for i at time t,

[2]The analytical derivation of the equilibrium characterization for the households and firms is reported in the Appendix A.

achieved through behaviors involving a contribution to the common good or promoting reciprocal trust and cooperation, such as blood donation.

Private consumption C_t is defined as follows

$$C_t = \left[\int_0^1 C_t\left(j\right)^{1-\frac{1}{\varepsilon}} di \right]^{\frac{\varepsilon}{\varepsilon-1}} \tag{5}$$

with j representing the variety of goods produced by each firm acting as a monopolistic competitor, $C_t\left(j\right)$ is the consumption of the good $j \epsilon [0;1]$ and $\varepsilon > 1$ indicating the elasticity of substitution between differentiated goods.

The optimal allocation of expenditures across the households reads as

$$C_t\left(j\right) = \left(\frac{P_t\left(j\right)}{P_t} \right)^{-\varepsilon} C_t \tag{6}$$

with $P_t\left(j\right)$ representing the price of the good j at time t implying that

$$\int_0^1 P_t\left(j\right) C_t\left(j\right) dj = P_t C_t \tag{7}$$

and

$$P_t = \left[\int_0^1 P_t\left(j\right)^{1-\varepsilon} dj \right]^{\frac{1}{1-\varepsilon}} \tag{8}$$

We assume that the period utility function follows a semi-logarithmic form:

$$U\left(C_t, N_t\right) = \log\left(C_t\right) - \frac{N_t^{1+\gamma}}{1+\gamma} \tag{9}$$

where γ is the inverse of the Frish elasticity of labor supply.

The aggregate output is defined as follows:

$$Y_t = \left(\int_0^1 Y_t(j)^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}} \tag{10}$$

where $j \in [0;1]$ is a continuum of firms, each one producing a different variety of final good with the same constant returns to scale technology:

$$Y_t(j) = A_t [N_t(j)]^{\zeta} \left[K_{t-1}^{p}(j)\right]^{\nu} \left[K_{t-1}^{s}(j)\right]^{1-\zeta-\nu} \tag{11}$$

where $Y_t(j)$ is the production function of good j, $N_t(j)$, $K_{t-1}^{p}(j)$ and $K_{t-1}^{s}(j)$ are labor, physical and social capital employed in the productive process of good j, whereas A_t is a productivity shifter common to all firms whose law of motion in logs reads as

$$a_t = \rho a_{t-1} + \epsilon_t^a \tag{12}$$

where $a_t = \log A_t, \rho \epsilon [0,1]$ is a persistence coefficient and ϵ_t^a is a white noise.

Moreover, each firm has a probability of resetting prices in any given period, $1-\theta$, independent across firms (staggered price setting, Calvo, 1983), with $\theta \in [0;1]$, indicating an index of price stickiness.

The aggregate price level reads as

$$P_t = \left[\theta (P_{t-1})^{1-\varepsilon} + (1-\theta)(P_t^*)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} \tag{13}$$

with P_t^* indicating the identical prices reset in period t. The expression (13) states that the aggregate level is a weighted average of reset and non reset prices across firms.

The (13) can be rewritten as:

$$(P_t)^{1-\varepsilon} = \left[\theta (P_{t-1})^{1-\varepsilon} + (1-\theta)(P_t^*)^{1-\varepsilon}\right] \tag{14}$$

Then, dividing each member of (14) by $(P_{t-1})^{1-\varepsilon}$ the following expression for the price dynamics $\left(\Pi_t = \frac{P_t}{P_{t-1}}\right)$ is obtained:

$$\Pi_t^{1-\varepsilon} = \theta + (1-\theta)\left(\frac{P_t^*}{P_{t-1}}\right)^{1-\varepsilon} \tag{15}$$

Inflation rate is only determined by the share $(1-\theta)$ of firms resetting their prices at a level P_t^*.

The log-linearization of (15) around zero inflation steady state produces the following equivalent results

$$\pi_t = (1-\theta)\left(p_t^* - p_{t-1}\right) \tag{16}$$

$$p_t = \theta p_{t-1} + (1-\theta)\, p_t^* \tag{17}$$

But how the firms choose the optimal price level P_t^*?

A firm in period t chooses a price P_t^* that maximizes the current market value of the profits Υ_t, i.e.

$$\max_{P_t^*} \sum_{k=0}^{\infty} \theta^k E_t \left\{ Q_{t,t+k} \left(P_t^* Y_{t+k|t} - \Psi_{t+k}\left(Y_{t+k|t}\right)\right)\right\} \tag{18}$$

subject to the sequence of demand constraints

$$Y_{t+k|t} = \left(\frac{P_t^*}{P_{t+k}}\right)^{-\varepsilon} C_{t+k} \tag{19}$$

for $k = 0, 1, 2, ...$ and where $Q_{t,t+k} = \beta^k \left(C_{t+k}/C_t\right)\left(P_t/P_{t+k}\right)$ is the discount factor, $\Psi_t(\cdot)$ is the cost function of the firm, whereas $Y_{t+k|t}$ represents output in period $t+k$ for a firm resetting its price in period t. Next, the first order condition associated with the problem (18) is given by:

$$\sum_{k=0}^{\infty} \theta^k E_t \left\{ Q_{t,t+k} Y_{t+k|t} \left(P_t^* - M \psi_{t+k|t}\right)\right\} = 0 \tag{20}$$

where $\psi_{t+k|t} = \Psi'_{t+k}\left(Y_{t+k|t}\right)$ indicates the nominal marginal cost in period $t+k$ for a firm resetting its price in period t and $M = \frac{\varepsilon}{\varepsilon - 1}$ that is the desired markup in the absence of constraints on the frequency of price adjustment. Note that in the absence of price rigidities ($\theta = 0$) the previous condition collapses to the optimal price setting condition under flexible prices:

$$P_t^* = M\psi_{t|t} \tag{21}$$

according to which the optimal price is a mark-up over the marginal costs. Then, the division of both the members of (20) by P_{t-1}^i reads as:

$$\sum_{k=0}^{\infty} \theta^k E_t \left\{ Q_{t,t+k} Y_{t+k|t} \left(\frac{P_t^*}{P_{t-1}} - M * MC_{t+k|t} \Pi_{t-1,t+k} \right) \right\} = 0 \tag{22}$$

where $MC_{t+k|t} = \frac{\psi_{t+k|t}}{P_{t+k}}$ is the real marginal cost in period $t+k$ for firms whose last price set is in period t.

Finally, the log-linearization of (22) around the zero inflation steady state with a first-order Taylor expansion reads as

$$p_t^* - p_{t-1} = (1 - \beta\theta) \sum_{k=0}^{\infty} (\beta\theta)^k E_t \left[\widehat{mc}_{t+k|t} + (p_{t+k} - p_{t-1}) \right] \tag{23}$$

where $\widehat{mc}_{t+k|t} = mc_{t+k|t} - \overline{mc}$ is the log-deviation of marginal cost from its steady state value.

The optimal price setting strategy for the typical firm resetting its price in period t can be derived from (23), after some algebra:

$$p_t^* = \mu + (1 - \beta\theta) \sum_{k=0}^{\infty} (\beta\theta)^k E_t \left[mc_{t+k|t} + p_{t+k} \right] \tag{24}$$

with $\mu = \log \frac{\varepsilon}{\varepsilon - 1}$ representing the optimal markup in the absence of constraints on the frequency of price adjustment $(\theta = 0)$.

Hence, the price setting rule for the firms resetting their prices is represented by a charge over the optimal markup in the presence of fully flexible prices, given by a weighted average of their current and expected nominal marginal costs, with the weights being proportional to the probability of the price remaining effective $(\theta)^k$.

Note that, under the hypothesis of constant returns to scale, implicit in the production function of our model, the marginal cost is independent from the level of production, i.e. $mc_{t+k|t} = mc_{t+k}$ and, hence, common across firms; so, the expression (24) can be rewritten in the following way:

$$p_t^* - p_{t-1} = (1-\beta\theta)\sum_{k=0}^{\infty}(\beta\theta)^k E_t\left[mc_{t+k}\right] + \sum_{k=0}^{\infty}(\beta\theta)^k E_t\left[p_{t+k}\right] \tag{25}$$

Moreover, the equation (25) can be expressed in the following recursive form:

$$p_t^* - p_{t-1} = \beta\theta E_t\left[p_{t+1}^*\right] - (1-\beta\theta)\, p_t + (1-\beta\theta)\,\widehat{mc}_t \tag{26}$$

and combined with (16) in a log-linear form in order to obtain the domestic inflation equation:

$$\pi_t = \beta\pi_{t+1}^e + \frac{(1-\theta)(1-\beta\theta)}{\theta}\widehat{mc}_t \tag{27}$$

with $\pi_{t+1}^e = E_t\left[\pi_{t+1}\right]$.

Note that from (27) it emerges that the inflation rate of this economy depends on the discounted future expected inflation rate, $\beta\pi_{t+1}^e$ and the log deviation of real marginal costs from their steady state value $\widehat{mc}_t$ according to $\frac{(1-\theta)(1-\beta\theta)}{\theta}$, which is a strictly decreasing function in the index of price stickiness θ.

Solving (27) forward, inflation is expressed as the discounted sum of current and future log deviations of real marginal costs from their steady state level:

$$\pi_t = \frac{(1-\theta)(1-\beta\theta)}{\theta} \sum_{k=0}^{\infty} \beta^k E_t \left(\widehat{mc}_{t+k}\right) \tag{28}$$

The expression (28) shows that the fluctuations of inflation in this monopolistically competitive model with sticky prices à la Calvo result from price-setting decision of the firms linked to their expectations on marginal costs.

The level of output associated to a fully-flexible price scenario is $\bar{y}_t$ with the following corresponding log-linear definition of output gap

$$\tilde{y}_t = y_t - \bar{y}_t \tag{29}$$

The market clearing conditions for the good j can be expressed as follows:

$$Y_t(j) = C_t(j) + I_t^s(j) + I_t^p(j) \tag{30}$$

The previous relationship states that production of good j is allocated to private consumption, investments in social capital and physical capital .

Then, using the definitions of $C_t(j)$, equation (30) can be rewritten as follows:

$$Y_t(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\varepsilon} C_t + I_t^s(j) + I_t^p(j) \tag{31}$$

Finally, by plugging (31) into the definition of the aggregate output (10), the aggregate market clearing condition is obtained:

$$Y_t = C_t + I_t^s + I_t^p \tag{32}$$

In the case of absence of social capital (i.e. the benchmark case compared to a scenario where social capital is present, in order to evaluate which of the two models better matches the time series of Solow residual), the previous model collapses into the following equations:

$$
\begin{aligned}
U\left(C_t, N_t\right) &= \log\left(C_t\right) - \frac{N_t^{1+\gamma}}{1+\gamma} \\
P_t C_t + K_t^p &\leq R_t^p K_{t-1}^p + W_t N_t \\
\int_0^1 P_t\left(j\right) C_t\left(j\right) dj &= P_t C_t \\
Y_t\left(j\right) &= A_t\left[N_t\left(j\right)\right]^{\zeta}\left[K_{t-1}^p\left(j\right)\right]^{1-\zeta} \\
a_t &= \rho a_{t-1} + \epsilon_t^a \\
Y_t &= \left(\int_0^1 Y_t\left(j\right)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}} \\
\pi_t &= \beta \pi_{t+1}^e + \frac{\left(1-\theta\right)\left(1-\beta\theta\right)}{\theta}\widehat{mc}_t \\
Y_t &= C_t + I_t^p
\end{aligned}
\tag{33}
$$

4 Methodology, data and model dynamics

We empirically test the model using Italian annual data. Italy is a typical case study in the social capital literature since the pioneering study of Banfield (1958), in which the author shows how the backwardness of the Italian Mezzogiorno can be explained by the lack of civic spirit.

In order to estimate the parameters, simulate the time series and evaluate their dynamic responses in the presence of the total factor productivity shock, we adopt the inferential procedure based on the Monte Carlo Markow Chains (MCMC) methods and, in particular, on the Metropolis-Hastings algorithm, which belongs to the family of Bayesian estimation methods (see among others Canova, 2007, and Smets and Wouters, 2007). In particular, we build a multi-chain MCMC procedure based on four chains of size 100,000. The algorithm converges within 45,000 iterations to its expected value. Therefore, to remove any dependence from the initial conditions, we remove the first 45,000 observations from each chain. This high number of iterations, together with the 90% highest posterior density (HPD) credible interval for the estimates, ensures the robustness of our results[3]. All the calculations have been performed through the software DYNARE.

Below, we summarize the measurement equation considered, i.e. the relationship between the data (left side) and the model variables (right side):

$$[\Delta \ln Y_t] = [\Xi] + 100 * [y_t - y_{t-1}] \tag{34}$$

where $\Delta \ln Y_t$ is the real GDP annual growth rate for Italy expressed in percentage terms from 1950 to 2014 drawn from Fred Economic Data, and $\Xi = 100 * \ln(\upsilon)$ is the annual real GDP trend growth rate, expressed in percentage terms.

We choose the real GDP growth rate as the observable variable due to its important informative role: in fact, real GDP growth encompasses both Solow residual and the contribution to growth linked to the productive factors.

The parameters and their definitions are shown in Table 1.

The prior densities are consistent with the domain of the parameters. Following Del Negro and Schorfheide (2008), in the prior elicitation process we divided the parameters into three groups, on the basis of the information used to calibrate the priors.

The first group of parameters consists of those that determine the steady state $[\zeta, \nu, \delta^p, \delta^s]$ and whose calibration derives from macroeconomic 'great ratios' mainly referred to the sample informa-

[3]In detail, the estimation procedure is based on two steps. In the first, we have estimated the mode of the posterior distribution by maximizing the log posterior density function, which is a combination of the prior information on the structural parameters with the likelihood of the data. In the second, we have used the Metropolis-Hastings algorithm in order to draw a complete picture of the posterior distribution and compute the log marginal likelihood of the model. Moreover, following Brooks and Gelman (1998), we carried out the univariate convergence diagnostic based on a comparison between pooled and within MCMC moments, whose results are available upon request.

Table 1: Definitions of the parameters

Parameters	Definitions
ζ	output elasticity of labor
ν	output elasticity of private capital
δ^p	depreciation rate of private capital
δ^s	depreciation rate of social capital
γ	Frish elasticity of labor supply
β	Inter-temporal discount factor
θ	Price stickiness
Ξ	Annual real GDP growth rate
ρ	Persistence of total factor productivity
σ	Standard deviation of total factor productivity shock

tion. In the second group there are parameters that are related to policy, households, production $[\gamma, \beta, \theta, \Xi]$, taken either from micro-level data or from the literature or from out-of-the-sample information. The third group includes parameters describing the propagation mechanism of the stochastic shocks, such as standard deviations of them and autocorrelations $[\rho, \sigma]$. These last parameters are calibrated on the basis of the second moments of the observable variables, which are also consistent with the results found by the literature.

The calibrated values compared with the posterior ones are shown in Table 2.

The posterior values of the parameters are estimated using the observable variable (the real GDP annual growth rate) conditionally to the model. The posterior estimates of the parameters are composed of the posterior means together with the 90% HPD (Highest Posterior Density) credible interval for the estimated parameters obtained by the Metropolis-Hastings algorithm[4].

The elasticities of the production function (ζ, ν) are calibrated considering the average share of wages and capital rentals on GDP for Italy from 1980 to 2011 (provided by the Italian National Institute of Statistics, ISTAT) with a small standard deviation; the posterior value of labor share is

[4]We have increased the standard deviations of the prior distributions of the parameters by 50 percent in order to evaluate the sensitivity of the estimation results with the assumptions on prior estimates (Smets and Wouters, 2007). Overall, the estimation results are quite the same (results are available upon request).

Table 2: Prior and posterior distributions of the parameters

Parameters	Prior distribution			Posterior distribution		
	Distribution	Mean	St. Dev.	Mean	90% HPD interval	
ζ	beta	0.40	0.10	0.60	0.45	0.73
ν	beta	0.30	0.10	0.32	0.15	0.50
δ^p	beta	0.10	0.10	0.16	0.00	0.38
δ^s	beta	0.09	0.10	0.14	0.00	0.38
γ	gamma	3.00	0.75	2.55	1.32	3.67
β	beta	0.80	0.1	0.78	0.63	0.93
θ	beta	0.75	0.1	0.95	0.92	0.98
Ξ	normal	1.55	0.1	1.53	1.36	1.68
ρ	beta	0.90	0.10	0.98	0.95	1.00
σ	inv. gamma	0.10	2.00	0.04	0.02	0.06

higher than the prior one, showing the relative importance of labor input in the Italian production function, whereas the posterior estimate of physical capital is almost the same than the calibrated value. The prior value of the depreciation rates for physical and social capital is measured through the steady state ratio $\left(\delta^i = \frac{\bar{I}^i}{\bar{K}^i}\right)$ $(i = s, p)$: for physical capital we use Italian data on investments and capital stocks from 1980 to 2011. To measure social capital we follow the approach to use an indicator of its hypothetical outcomes that summarizes individuals' propensity for cooperation: blood donation. As explained in Guiso et al. (2004) and Guiso et al. (2010), the relationship between social capital and blood donation is unlikely to be affected by confounding factors , especially for the Italian case. In fact, blood donation in Italy is supervised by a unique association, the AVIS, which collects the totality of anonymous blood donations and manages a collection center in almost each Italian municipality. Our measure of social capital is the volume of blood donations as given by the number of 16-ounce blood bags collected per inhabitant. In particular, the parameter δ^s is calibrated by considering the yearly blood donations from 1980 to 2011 as a measure of I_t^s, i.e. the average level of social capital, and the accumulation over time of them as an indicator of the stock of social capital . The posterior values of δ^i are both higher than prior ones.

The prior value for the inverse of Frish elasticity of labor supply (γ) is able to match four empirical moments for the Italian data from 1980 to 2011 in accordance with Cho and Cooley (1994) and Argentiero and Bollino (2015): the ratio of standard deviation of total output to the standard deviation of total consumption, the correlation between total output and total consumption, the correlation between underground production and total consumption and the correlation between regular production and total consumption. The posterior value for γ is slightly lower than the prior one. The annual real GDP trend growth rate (Ξ) is normally distributed and is calibrated on Italian data with a prior mean of 1.55 that is almost the same of the posterior estimated value.

The price stickiness coefficient, i.e. the fraction of firms that does not reset its price in a period, is calibrated to a value of 0.75, following Galì and Monacelli (2008). The posterior value of this parameter is higher than the prior one, thus showing a higher degree of price stickiness for the Italian economy.

Following the real business cycle literature (see for example King and Rebelo, 1999) and the second moments of Italian total factor productivity data (provided by FRED Economic Data), we set a high value for the persistence coefficient of total factor productivity, which has also been confirmed by the estimation procedure, and a loose prior value for the standard deviation of the productivity shifter (σ).

The dynamic response of the main variables, in log-deviations from their steady state values, to a stochastic shock on total factor productivity is represented by impulse response functions (IRFs) in figure 1. Note that for all of the IRFs, the size of the standard deviations of the stochastic shocks and the variables' responses relate to the posterior average of the IRFs for each draw of the MCMC algorithm, together with 90% credible intervals.

In the aftermath of a positive technology shock, output increases, but less than the positive growth of total factor productivity. This stylized fact is consistent with the empirical findings of Galì (1999), Smets and Wouters (2003) and Galì and Monacelli (2008) according to which price stickiness determines an increase of aggregate demand (increase in private consumption) lower than

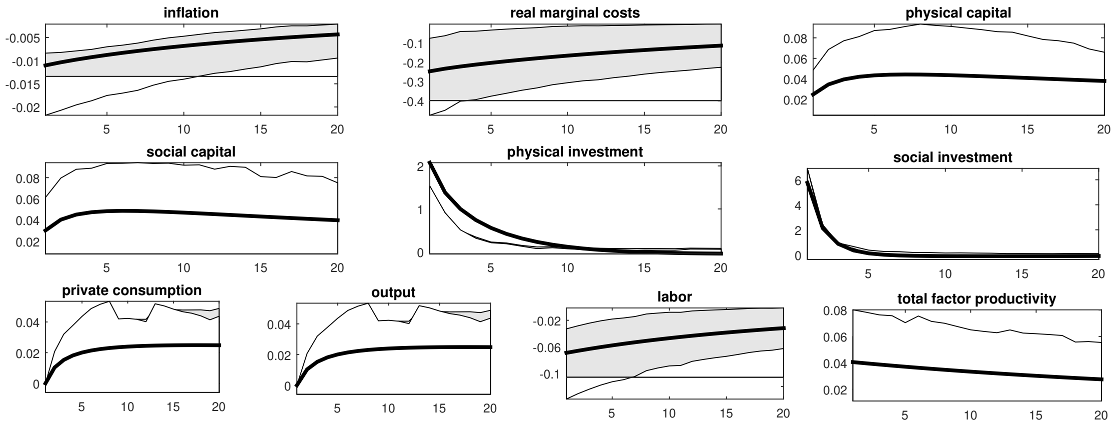

Figure 1: Impulse response functions for a positive productivity shock

the rise in supply. Hence, firms, due to the increased productivity, are able to produce the same quantity of goods with less hours worked, although capital stocks and investments increase due to the rise of capital rentals. Real marginal costs (mc) fall as well as inflation, but this last variable decrease less than in a fully flexible price scenario.

5 Analysis of the performance

In this section, we compare the empirical annual time series of the Italian total factor productivity from 1950 to 2014 with the series obtained by implementing the DSGE model in the benchmark case (33) of absence of social capital (*benchmark series, BS* hereafter) and in presence of social capital (*social capital series, SC* hereafter). In doing so, we want to understand if adding social capital to the productivity function allows the model to better fit actual data.

We use a MCMC method to generate the simulated time series for the BS and SC models. The simulated series span the same period of the original sample with the same periodicity, to allow the comparison experiments. Thus, we have 65 years for the period 1950-2014. We consider 100,000 realizations of the random shocks described in the considered DSGE models (see section 2). Next, the expected value of all the simulations at each time has been taken, and this will be the corresponding values at each year. Therefore, the length of the original sample and of the two simulated series will be $n = 65$.

We denote by $x = (x_i)_{i=1,\dots,n}$, $b = (b_i)_{i=1,\dots,n}$ and $s = (s_i)_{i=1,\dots,n}$ the original sample, the series of type BS and SC, respectively.

To discuss the models, we adopt three strategies. First, the distance between x and b is compared with the one between x and s. The times of the realizations will be included in this part of the analysis, so that the concept of distance between two series will involve the contemporaneous realizations of the series. As we will see, several concepts of distance are used, in order to obtain a satisfactory level of information from this procedure. Second, we adopt a data science perspective and discuss a rank-size analysis of the three series. In so doing, we are able to understand the possible presence of common regularities of the realizations of the three series when they are ranked in descending order. As a side analysis of data science type, the linear trends of the series are also compared. Third, the empirical distributions of the three series are considered and compared under the point of view of the descriptive statistics. In this framework, an entropy between the series distributions is also taken into account.

5.1 Time series distance approach

The distances employed in the first approach are the Euclidean one, the maximum, the minimum and the Euclidean one. They are defined, respectively, as follows

$$d_M(x,y) = \max_{i=1,\dots,n} |x_i - y_i|, \tag{35}$$

Distance d	$d(x,s)$	$d(x,b)$
$d = d_M$	0,524	1,814
$d = d_m$	0	0
$d = d_E$	0,038	0,445

Table 3: Distances between the original sample x and the two competing simulated series b and s, according to formulas in (35), (36) and (37).

$$d_m(x,y) = min_{i=1,\dots,n}|x_i - y_i|, \tag{36}$$

$$d_E(x,y) = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2, \tag{37}$$

where $y \in \{b, s\}$. The three concepts of distance are quite natural and jointly offer a panoramic view on how the original sample is close to the benchmark simulations or to the ones with social capital in a time-wise form.

Results are reported in Table 3.

By looking at Table 3, it is clear that the model with social capital has a remarkably smaller distance from the empirical sample than the model without social capital. The average (Euclidean) distance $d_E(x,b)$ is more than eleven times greater than $d_E(x,s)$, while the maximum distance is more than three times bigger.

5.2 Data science approach

Time series are here viewed as collections of numbers. We aim at understanding whenever b and s share some regularity properties with x, and which one is closer to x in this respect.

The first step of this analysis is the assessment and the discussion of the linear trend of the three series. Time plays a relevant role, in that trend is intended on a temporal basis and allows to observe the overall behavior of the time series. To achieve our aim, a simple linear regression is

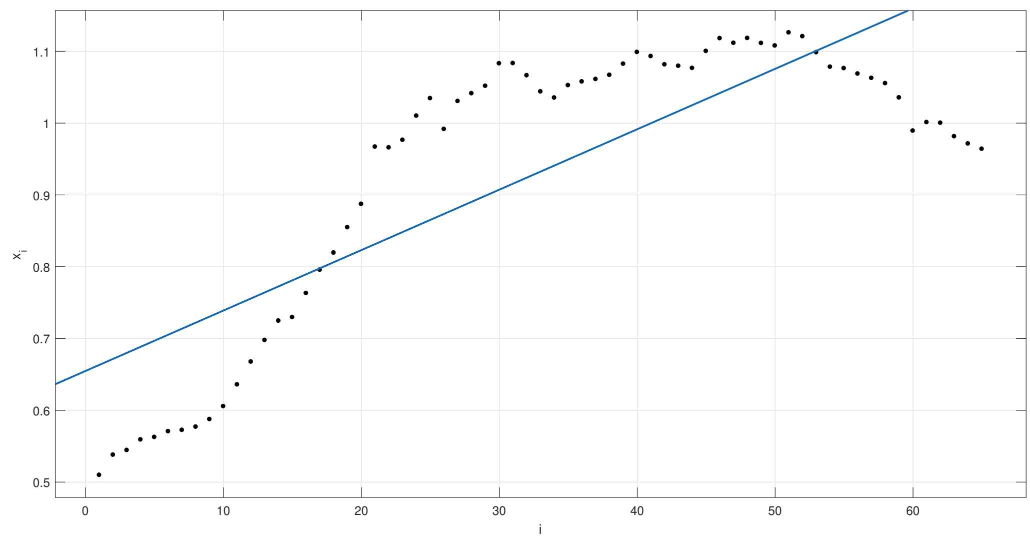

Figure 2: Linear trend for x. For a better visualization, the scatter plot is also presented.

Series y	$\hat{\alpha}$	$\hat{\beta}$	R^2
$y = x$	0.008415 (0.006849, 0.00998)	0.6549 (0.5954, 0.7143)	0.6468
$y = b$	0.0049 (-0.002205, 0.01201)	0.5171 (0.2474, 0.7869)	0.0293
$y = s$	0.01441 (0.01157, 0.01726)	0.3493 (0.2412, 0.4575)	0.6188

Table 4: The calibrated parameters $\hat{\alpha}$ and $\hat{\beta}$ of the linear regression exercise, according to formula (38), for the three cases of original sample, the benchmark series and the one with social capital. In brackets, the confidence interval at a 95% confidence level.

implemented over the three series, according to equation

$$y = \alpha t + \beta, \tag{38}$$

with $y \in \{x, b, s\}$ and $t > 0$ represents time. α and β are the parameters to be calibrated, and represent the slope and the intercept, respectively.

Results can be find in Figures 2, 3, 4 and Table 4.

Some insights can be derived from the linear trend exploration. First of all, it is rather evident

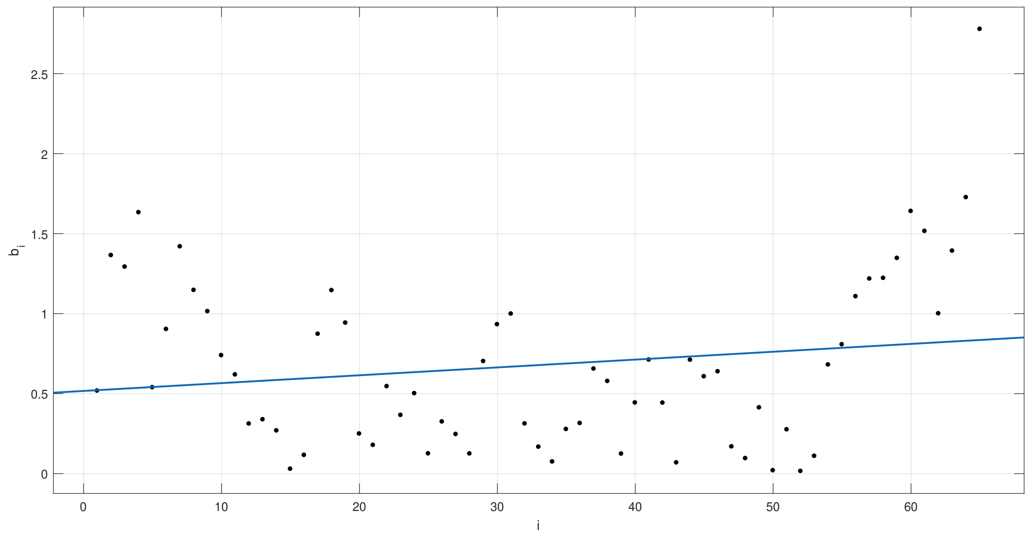

Figure 3: Linear trend for the benchmark series b. The scatter plot is juxtaposed to the best fit straight line.

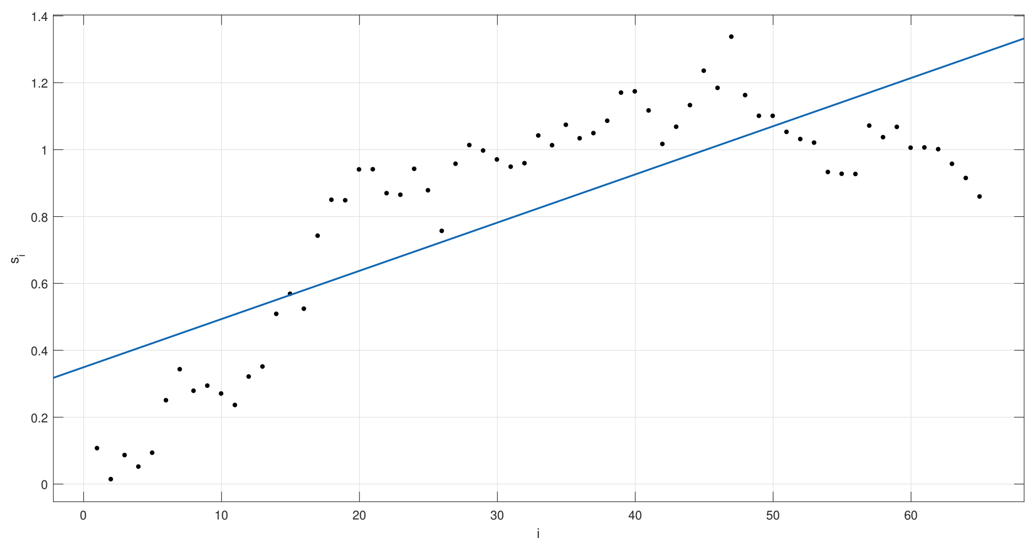

Figure 4: Linear trend for s. Also in this case, the scatter plot and the calibrated linear function are jointly shown.

that one can hardly observe a reliable linear trend for b, while x and s exhibit a better looking linear regression. This is confirmed also by the values of R^2, which are reported in Table 4. Notice also that the R^2 for the empirical case is around 60% and similar to that of SC, hence suggesting an analogous explanation power of the linear regression of the scatter plot. Moreover, both linear trends for x and s show an increasing behavior.

In the second step, a rank-size analysis approach is adopted. The elements of the series are ranked in decreasing order, so that $rank = 1$ is associated to the largest value of the series while $rank = n$ is the smallest one. In so doing, the temporal dimension of the considered series is lost. The scatter plot of the series realizations with respect to $rank$ is then fitted with a decreasing curve $y = f(rank)$ belonging to a preselected parametric family of functions. The comparison of the calibrated parameters obtained for x, b and s say much about the similarities of BS and SC with the empirical sample.

By a preliminary visual inspection of the rank-size scatter plot, we here consider a third degree polynomium of the type

$$f(rank) = \gamma_3 \cdot rank^3 + \gamma_2 \cdot rank^2 + \gamma_1 \cdot rank + \gamma_0 \tag{39}$$

where $\gamma_0, \gamma_1, \gamma_2, \gamma_3$ are real parameters to be calibrated.

Figures 5, 6 and 7 allows a visual inspection of the best fit, which is rather satisfactory for the three cases. Such an idea is confirmed by looking at the goodness of fit R^2, which is reported for completeness along with the calibrated parameters in Table 5.

Rank-size analysis provides some information about the closeness of b and s to x. Figures 5, 6 and 7 highlight that x and s show a similar shape in terms of concavity of the best fitted curve, hence suggesting a common behavior of the elements of the original series and the SC one when they are ranked in descending order. Differently with such series, the curve associated to BS is convex at high rank and exhibits an inflection point at a middle rank.

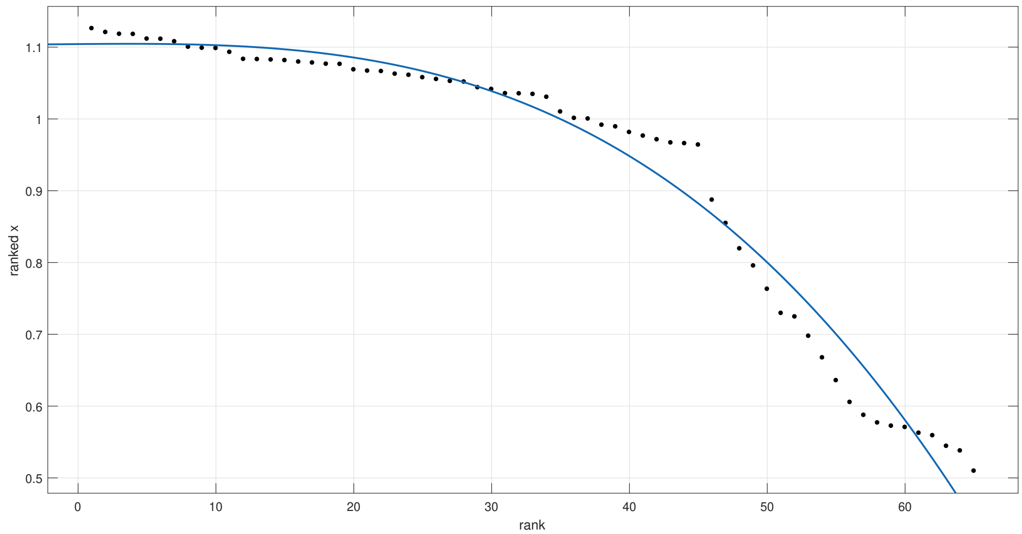

Figure 5: Rank-size best fit for x, according to formula (39), along with the scatter plot of the real data.

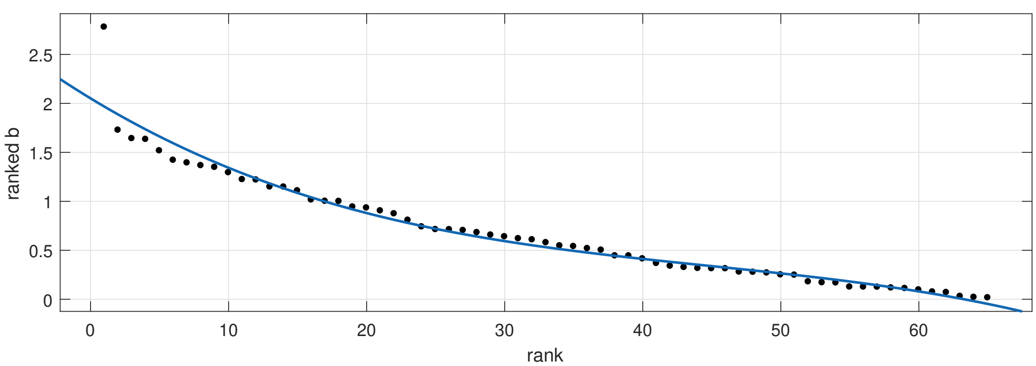

Figure 6: Rank-size best fit for b through function in (39) and related scatter plot.

Table 5: The calibrated parameters $\hat{\gamma}$ and $\hat{\delta}$ of formula (39), for the three series. In brackets, the confidence bounds at 95%. The R^2 is also shown (last column).

Series y	$\hat{\gamma}_3$	$\hat{\gamma}_2$	$\hat{\gamma}_1$	$\hat{\gamma}_0$	R^2
$y = x$	-2.334e-06	-8.21e-06	0.0001615	1.104	0.9723
	(-3.948e-06, -7.198e-07)	(-0.0001702, 0.0001538)	(-0.004458, 0.004781)	(1.069, 1.14)	
$y = b$	-1.18e-05	0.001587	-0.08558	2.052	0.9534
	(-1.754e-05, -6.069e-06)	(0.001011, 0.002163)	(-0.102, -0.06917)	(1.926, 2.178)	
$y = s$	-1.156e-05	0.0007569	-0.02142	1.26	0.9732
	(-1.435e-05, -8.779e-06)	(0.0004776, 0.001036)	(-0.02939, -0.01345)	(1.198, 1.321)	

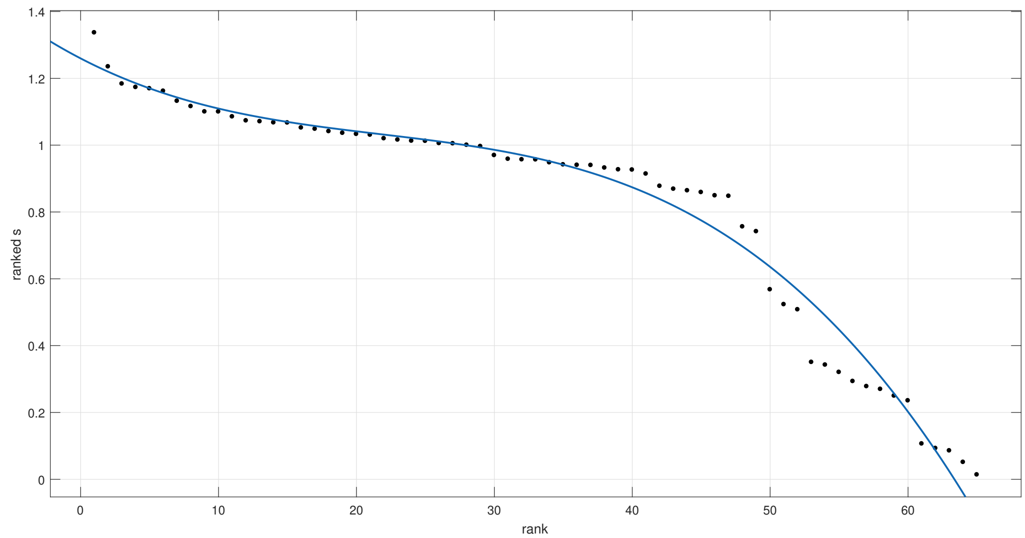

Figure 7: Rank-size best fit for s, obtained by using formula (39). The scatter plot is also shown for comparison purposes.

5.3 Empirical distribution approach

Time series are here discussed on the basis of their empirical distributions. As in the case of rank-size analysis, the time dimension is lost but a meaningful analysis of the macroscopic properties of the realizations can be carried out.

The main descriptive statistics are presented in Table 6.

By looking at Table 6, one can immediately argue that the series with social capital is much closer to the empirical sample than the series without social capital. Remarkably, skewness is negative and with very similar values for x and s while it is positive with a large value for b, hence leading to an evident violation of the symmetry property of the distributions when social capital does not intervene in the DSGE model. Analogously, kurtosis is negative for x and s and it is positive with a value close to three for b. This means that we are in presence of an original sample of platykurtic type – confirmed also for the series with the addition of social capital – while the case without social

Table 6: Main statistical indicators associated to the three series x, b and s.

Statistical indicator	x	s	b
Mean μ	0,93	0,83	0,68
Variance σ^2	0,04	0,12	0,29
Standard deviation σ	0,20	0,35	0,54
Skewness	-1,01	-1,09	1,18
Kurtosis	-0,55	-0,09	2,07
Median	1,03	0,96	0,58
Max	1,13	1,34	2,78
Min	0,51	0,01	0,01

capital leads to a leptokurtic distribution. Values of x and s are much closer to the mean than the one of b (smaller standard deviations) and the distance between the means is lower for x and s than for x and b. Moreover, x and s seem to span analogous intervals (quite the same maxima and minima) while the maximum between x and b are noticeably different.

The distance between the distribution of x and those of b and s has been also measured by using entropy. Such a measure is suitable for our scopes, because it is able to capture the overall features of the distribution of the data under investigation. In this respect, entropy summarize in a unified setting the position and variability indicators given by the descriptive statistics.

The considered entropy is given by:

$$\mathcal{E}(y) = -\sum_{i=1}^{n} \frac{|y_i|}{\sum_{k=1}^{n}|y_k|} \cdot \log\left(\frac{|y_i|}{\sum_{k=1}^{n}|y_k|}\right), \tag{40}$$

where $y = [y_i]_{i=1,\ldots,n}$. We use formula (40) for the original sample $y = x$ and when $y = b$ and $y = s$. The reference entropy is the one associated to the original sample x. The model – BS or SC – which fits the empirical data in a more convincing way is the one whose entropy is closer to the one of x. The reasoning behind this evidence lies in the thermodynamic definition of entropy, which is nothing but the disorder associated to the series. Basically, the value of the entropy can be associated to the distance of the distribution from the uniform case. This suggests that similar

Table 7: Computation of the entropy for the three series x, b and s, according to formula (40).

	x	s	b
Entropy	4,15	4,06	3,87

entropies are associated to analogous macroscopic properties of the probabilistic structure of the data, hence leading to similar series.

Results are reported in Table 7.

The comparison between the entropies gives that both the simulated series underestimate the reference entropy of the original sample x. However, the entropy of s is much closer to the reference one than the entropy of b. This outcome goes in the same direction of what said by the analysis of the descriptive statistics, hence stating the supremacy of the DSGE model with social capital in capturing the real data with respect to the benchmark model without social capital. In Appendix B we provide a detailed explanation of how the ISTAT measures TFP and we measure the contribution of social capital to its determination.

6 Discussion

Our study provides the first evidence that social capital supports the economic performance in a DSGE framework. Several economic mechanisms provide reasons why the inclusion of social capital allows the model to explain the residual total factor productivity and to fit actual data better. There is evidence that social capital fosters a better allocation of human and financial resources. The mitigation of agency problems typical of a more cooperative and trusting society improves the management of human resources (La Porta et al., 1997; Costa and Kahn, 2003) and lets hiring decisions to be driven by the human capital of applicants instead of personal attributes such as blood ties and personal knowledge, which are common surrogates of trustworthiness in low-trusting societies. This mechanism makes investments in human capital more profitable and allows workers to exploit their potential fully, possibly resulting in higher labor productivity (Knack and Keefer, 1997; Guiso et al., 2010; Alesina et al., 2015). According to several authors, social capital also fosters the accumulation of human capital with a further beneficial effect on the productivity of labor. For example, since trust enhances access to credit (Karlan, 2005; Feigenberg et al., 2013), enrollment in higher education may be more accessible. People may exploit their networks of contacts to exploit better opportunities for the education of their children (Coleman, 1988). Parents with strong relational skills may create associations advocating for improved teaching at their children's schools (Coleman, 1988). Overall, the empirical literature in economics suggests that societies rich in social capital provide stronger incentives for investing in human capital, making workers more productive.

The higher financial development (Guiso et al., 2004) and improved access to credit (McMillan and Woodruff, 1999; Karlan, 2005; Karlan et al., 2009) connected to social capital also stimulate the entrepreneurial activity possibly conducting to the creation of new firms and a more competitive and efficient allocation of financial resources across firms (Dasgupta, 2001). More dense networks imply a higher probability of repeating economic interactions that raise the importance of reputation. This makes the behavior of agents more easier to foresee, reducing monitoring and transaction costs (Nahapiet and Ghoshal, 1998; Antoci et al., 2011b).

The literature has also credited social capital with a beneficial role in reducing litigiousness in industrial relations (Westlund, 2006), fostering knowledge transfer (Inkpen and Tsang, 2005) and the adoption of new technologies (Fafchamps and Minten, 2001), improving search for investment opportunities (Lindner and Strulik, 2014), enhancing the assignment of workers to tasks (Fafchamps, 2011), acquiring competitive capabilities (McEvily and Zaheer, 1999), facilitating the development of industry networks (Walker et al., 1997) and strategic alliances (Koza and Lewin, 1998; Kale et al., 2000).

Overall, higher levels of cooperation (the specific dimension of social capital we measure in our empirical analysis) reinforce trust and trustworthiness and improve the environment in which workers and firms make their investment decisions, being them in human, financial, or physical capital (Dasgupta, 2009).

Our framework does not allow us to identify which mechanism, among the ones mentioned above, is crucial in making social capital able to improve the fit of the model. Instead, the outcomes of the empirical analysis call for a more profound effort in the retrieval of time-series measures for the various social capital dimensions and the assessment of their role in explaining total factor productivity in a DSGE framework. Social capital, however, is not the only addendum that may improve the fit of our model. Other factors could well be missing from the picture, and future research should address their possible role. Benhabib and Spiegel (1994) show that human capital plays a role in the growth rate of total factor productivity. Technology-skill mismatches can lead to sizable differences in total factor productivity and output per worker (Acemoglu and Zilibotti, 2001). Hall and Jones (1999) document that institutions and government policies, which they call social infrastructure, drive differences in capital accumulation, productivity, and output per worker across nations. Openness to trade (Edwards, 1998), the quality of institutions (Alcala and Ciccone, 2004), and the level of financial intermediaries development (Beck et al., 2000), are also likely to play a role in explaining the total factor productivity, to name a few examples. We should not consider social capital as a substitute for these factors but rather as a complement. While all forms of capital are essential for growth and development, none of them are sufficient in and of themselves (Ostrom, 2000). Seminal literature stresses the complementarity between human and social capital in particular. Bourdieu (1982; 1986) explains that the individuals' ability to invest in social capital crucially depends on their human capital: "The reproduction of social capital presupposes an unceasing effort of sociability, a continuous series of exchanges in which recognition is endlessly affirmed and reaffirmed. This work ... is not profitable or even conceivable unless one invests in it a specific competence (knowledge of which connections are valuable and skills at using them) and an acquired disposition to acquire and maintain this competence" (Bourdieu and Wacquant, 1992: 119). Such knowledge is a form of human capital that contributes to the creation of social capital. In other words, investments in social capital always require human capital in precise forms, and people who invest in human capital also invest in social capital (Glaeser et al., 2002).

Although a multitude of factors may concur in explaining the Solow residual, we are confident our contribution captures the role of social capital explicitly. The time-series measure we employ in the empirical analysis is unlikely to be affected by confounding factors such as human capital, especially for our specific case study. Blood donation in Italy is supervised by a unique association, the AVIS, which collects the totality of anonymous blood donations and manages a collection center in almost every Italian municipality. The volume of donations has proved to be uncorrelated with indicators of education, public spending for welfare, health expenditure, health conditions, and indicators of the local economic performance across provinces and regions of Italy (Guiso et al., 2004).

The downside of this way of measuring social capital lies in the lack of time-series of equivalent indicators in other countries to the purpose of cross-country comparisons. The most common source of social capital indicators consists of survey data, which provide short series (starting in the 1990s in the best case scenario), with relatively few observation points and not always comparable indicators. Despite this weakness, our study provides the first attempt to explain productivity dynamics through a DSGE framework featuring the role of social capital. Our results suggest a new possible direction in the study of the Solow residual, thus providing a contribution that advances the literature at the intersection between social capital and productivity studies.

7 Conclusions

In this paper, we developed a DSGE model with sticky prices to assess the role of social capital in explaining the Solow residual. We dealt with social capital as a productive factor that directly enters a constant returns to scale production function. We estimated, simulated, and dynamically evaluated the model for Italy through Bayesian techniques. We then compared the annual time series for the Solow residual generated by the DSGE model with social capital and the one of a standard DSGE model without social capital from 1950 to 2014 with the Italian TFP empirical data in the same sample.

Overall, the empirical analysis shows that our model fits the actual pattern of total factor productivity for the period we study better than a standard DSGE model, not featuring the role of social capital. This result is consistent with the many studies crediting social capital with a role in the creation of a cooperation friendly environment that helps to solve coordination issues, thereby supporting a better allocation of resources and, more in general, the economic activity.

The take-home message for policymakers is straightforward. Public policy can improve the environment in which agents make transactions and investment decisions in previously unsuspected ways. Nurturing cooperative behavior, social trust, and trustworthiness strengthen a shared resource that has the feature of a public good. Such a shared asset can improve the allocation of factors and their productivity in many ways. For example, encouraging investments in human capital (Coleman, 1988), sustaining financial development (Guiso et al., 2004), fostering access to credit and a competitive allocation of financial resources (Karlan et al., 2009), lowering monitoring and transaction costs (Nahapiet and Ghoshal, 1998), removing barriers to knowledge transfer (Inkpen and Tsang, 2005) and the adoption of new technologies (Fafchamps and Minten, 2001), enhancing the assignment of workers to tasks (Fafchamps, 2011), facilitating the development of competitive capabilities (McEvily and Zaheer, 1999), the incubation of industry networks (Walker et al., 1997) and the formation of strategic alliances (Koza and Lewin, 1998; Kale et al., 2000).

Perhaps most importantly, governments and, in general, policymakers should consider that, like the other factors of production, social capital is “fragile” (Antoci et al., 2009b), in that trust and civic spirit can be eroded by the lack of procedural fairness (Rothstein, 2011) and opportunistic and anti-social behaviors (Guiso et al., 2010). If citizens perceive the political process as unfair, the policy outcomes as illegitimate, and public institutions as untrustworthy, they will adapt to the environment by not trusting anyone and behaving accordingly (Frey et al., 2004; Feld and Frey, 2007; Rothstein, 2011). Several authors suggested that agents project the fairness and trustworthiness they perceive in the state onto their fellow citizens, implying that the efficiency and fairness of institutions are crucial for the preservation of social capital (Frey et al., 2004; Feld and Frey, 2007; van Dijke and Verboon, 2010; Rothstein, 2011; Gobena and van Dijke, 2017; Cerqueti et al., 2019).

Understanding how any proposed policy intervention will affect social cohesion, trust, trustworthiness, the propensity for cooperation and the perceived fairness of institutions is of vital importance since public policy occurs in a social context characterized by a delicate mix of informal organizations, networks, and institutions (Woolcock and Narayan, 2000). Also, it is critical to invest in bridges between communities and social groups and to contrast discrimination and segregation associated with gender, ethnicity, religion, or socio-economic status (Antoci and Sabatini, 2018). To this end, Woolcock and Narayan (2000) suggest that participatory processes can facilitate social interaction and convergence among stakeholders with diverse interests or identities: "Finding ways and means by which to transcend social divides and build social cohesion and trust is crucial for economic development" (Woolcock and Narayan, p. 242).

Efficiency in the provision of public services, the inclusiveness of institutions, and the accountability of public actors can strengthen the belief that the political process is fair and the policy outcomes legitimate, which could, in turn, further underpin confidence in institutions and social trust. By contrast, exacerbating divisions across social groups, neglecting the efficiency and accountability of public institutions, and carrying out policy measures that the public may perceive as unfair are likely to erode the social capital of the economy (Frey et al., 2004; Feld and Frey, 2007; Rothstein, 2011; Rothstein and Charron, 2018). For example, a tax pardon, which grants immunity for past tax evasions in exchange for a small fee, can be a smart fiscal policy in the short term, since it will increase tax revenues without increasing the marginal tax rates, but it might deteriorate the stock of social capital (Guiso et al., 2010).

Our framework cannot shed light on which policy actions can more effectively strengthen, or preserve, the forms of social capital that enhance total factor productivity. Nonetheless, our results urge public actors to devote to the strengthening of social capital the same attention and effort they usually pay to the accumulation of the other factors of production.

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Appendix A

Equilibrium Characterization

Households

The (9) is maximized under (2) by using the method of Lagrange multipliers[5], i.e.:

$$L = \max_{\left[C_t, N_t, K_t^p, K_t^s\right]_{t=0}^{\infty}} E \left[\begin{array}{c} \sum_{t=0}^{\infty} \beta^t \left(\log\left(C_t\right) - \frac{N_t^{1+\gamma}}{1+\gamma} \right) + \\ + \chi_t \left(R_t^p K_{t-1}^p + R_t^s K_{t-1}^s + W_t N_t - P_t C_t - K_t^p - K_t^s \right) \end{array} \right] \quad (41)$$

where χ_t is the dynamic Lagrange multiplier, with the following three necessary conditions:

$$\frac{\partial L}{\partial C_t} : \frac{1}{\left(C_t\right) P_t} = \chi_t \quad (42)$$

$$\frac{\partial L}{\partial N_t} : \frac{N_t^{\gamma}}{W_t} = \chi_t \quad (43)$$

$$\frac{\partial L}{\partial K_t^p} : -\chi_t + \beta E_t \left[\chi_{t+1} R_t^p \right] = 0 \quad (44)$$

$$\frac{\partial L}{\partial K_t^s} : -\chi_t + \beta E_t \left[\chi_{t+1} R_t^s \right] = 0 \quad (45)$$

where (44) and (45) state that in equilibrium the value of marginal utility of consumption at time t is equal to the discounted expected value of marginal utility of consumption at time $t+1$.

The following equation is a result of the combination of (42) and (43), i.e.:

$$N_t^{\gamma} \left(C_t\right) = \frac{W_t}{P_t} \quad (46)$$

[5]The use of dynamic programming technique would produce the same results.

The combination of (42) with (44) and (45) reads as:

$$\beta R_t^p E_t \left[\left(\frac{C_t}{C_{t+1}} \right) \left(\frac{P_t}{P_{t+1}} \right) \right] = 1 \tag{47}$$

$$\beta R_t^s E_t \left[\left(\frac{C_t}{C_{t+1}} \right) \left(\frac{P_t}{P_{t+1}} \right) \right] = 1 \tag{48}$$

The previous equations imply the following non arbitrage condition between the gross rates of return

$$R_t^p = R_t^s \tag{49}$$

that in steady state reads as

$$\overline{R}_t^p = \overline{R}_t^s = \frac{1}{\beta} \tag{50}$$

Firms

Given $(W_t, R_t^p, R_t^s)_{t=0}^{\infty}$, since the representative final producer faces a common price for the productive factors, each firm faces the following problem:

$$\min_{\left[N_t(j), K_{t-1}^p(j), K_{t-1}^s(j)\right]_{t=0}^{\infty}} - \left(W_t N_t (j) + R_t^p K_{t-1}^p (j) + R_t^s K_{t-1}^s (j) \right) + \tag{51}$$

$$+ \varphi (j) \begin{bmatrix} A_t \left[N_t (j) \right]^{\zeta} \left[K_{t-1}^p (j) \right]^{\nu} \left[K_{t-1}^s (j) \right]^{1-\zeta-\nu} + \\ + \left(1 - \delta^p \right) K_{t-1}^p (j) + \\ + \left(1 - \delta^s \right) K_{t-1}^s (j) - \left(\frac{P_t(j)}{P_t} \right)^{-\epsilon} Y_t \end{bmatrix} \tag{52}$$

where the Lagrange multiplier $\varphi (j)$ is associated to the marginal costs.

The problem (51) yields to the following FOCs:

$$W_t = \varphi(j)\left[\zeta A_t\left[N_t(j)\right]^{\zeta-1}\left[K^p_{t-1}(j)\right]^{\nu}\left[K^s_{t-1}(j)\right]^{1-\zeta-\nu}\right] \tag{53}$$

$$R^p_t = \varphi(j)\left[\nu A_t\left[N_t(j)\right]^{\zeta}\left[K^p_{t-1}(j)\right]^{\nu-1}\left[K^s_{t-1}(j)\right]^{1-\zeta-\nu} + (1-\delta^p)\right] \tag{54}$$

$$R^s_t = \varphi(j)\left[\begin{array}{c}(1-\zeta-\nu)A_t\left[N_t(j)\right]^{\zeta}\left[K^p_{t-1}(j)\right]^{\nu} * \\ * \left[K^s_{t-1}(j)\right]^{-\zeta-\nu} + (1-\delta^s)\end{array}\right] \tag{55}$$

from which an expression for the marginal costs MC_t can be derived

$$MC_t = \zeta^{-\zeta}\nu^{-\nu}(1-\zeta-\nu)^{-(1-\zeta-\nu)}(W_t)^{\zeta}(R^p_t)^{\nu}(R^s_t)^{1-\zeta-\nu}\frac{1}{A_t} \tag{56}$$

Appendix B

The Italian National Institute of Statistics (ISTAT) measures TFP through a methodology based on economic growth accounting (see e.g., Barro, 1999) and the Tornqvist index (Morrison and Diewert, 1990 and Kohli, 2004). The technology is described by a production function whose inputs are labor and capital. This latter is broken down into three components: non-ICT capital (all the physical capital goods excluding products related to Information and Communication Technologies), ICT capital (capital goods that incorporate Information and Communication Technologies, i.e., hardware, software, and communications equipment) and non-ICT immaterial capital (intellectual property products other than software, i.e., research and development, mineral and original exploration of artistic, literary or entertainment works). The ISTAT measures productive factors as well as gross domestic product on a sectorial basis. The Solow residual of this production function is assumed with Hicks-neutrality, and any adjustment cost is absent. Social capital, intended as a public good resulting from cooperative behaviors, is not explicitly considered in the measures of capital mentioned above. Nevertheless, our DSGE model incorporating social capital matches Italian TFP data better than a standard DSGE model with only capital and labor.

We interpret this result in light of the evidence that social capital fosters a better allocation of human and financial resources - through the channels summarized in Section 6 - that improves the productivity of the factors of production accounted for in the ISTAT methodology.

By following ISTAT's procedure and using the data generated by our DSGE model, we can measure the contribution of social capital to the determination of TFP. In particular, the TFP growth rate is given by

$$\ln\left(\frac{A_t}{A_{t-1}}\right) = \ln\left(\frac{Y_t}{Y_{t-1}}\right) - \ln\left(\frac{ID_t}{ID_{t-1}}\right) \tag{57}$$

where

$$ID_t = \varsigma\left(sl_t + sl_{t-1}\right)*\ln\left(\frac{L_t}{L_{t-1}}\right) + \nu\left(sk_t^p + sk_{t-1}^p\right)*\ln\left(\frac{K_t^p}{K_{t-1}^p}\right) + \left(1-\varsigma-\nu\right)\left(sk_t^s + sk_{t-1}^s\right)*\ln\left(\frac{K_t^s}{K_{t-1}^s}\right) \tag{58}$$

is the composite index of inputs' volume (Tornqvist index) and sl_t, sk_t^p and sk_t^s are the elasticities of GDP concerning labor, private capital, and social capital, which are assumed to be equal to the shares of the cost of each productive factor of nominal GDP, i.e.

$$\begin{aligned} sl_t &= \frac{W_t L_t}{P_t Y_t} \\ sk_t^p &= \frac{R_t K_t^p}{P_t Y_t} \\ sk_t^s &= \frac{W_t K_t^s}{P_t Y_t} \end{aligned}$$

The average contribution of social capital to TFP growth along the period 1950-2014 is equal to (57) measured through the model with social capital minus the value of (57) in the model where social capital is absent. The numerical results according to our model with the presence of social capital indicate an average TFP growth for Italy from 1950 to 2014 of 1.15% (the empirical data feature an average value of 1.02%), whereas the model without social capital indicates a TFP growth of 0.7%. Hence, based on our analysis, the contribution of social capital to the TFP growth, can be quantified around 0.45%.