DOES SOCIAL CAPITAL PROMOTE INDUSTRIALIZATION?
EVIDENCE FROM A RAPID INDUSTRIALIZER

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Abstract—A new stylized fact in development economics is the importance of social capital in promoting economic growth. This paper examines the effect of social capital on industrialization in Indonesia. We analyze a rich set of social capital and social interaction measures, including voluntary associational activity and levels of trust and informal cooperation. The main finding is that initial social capital does not predict subsequent industrial development across 274 Indonesian districts. Though these findings are for only a single nation and may not apply everywhere, they call into question recent claims regarding social capital and economic development.

I. Introduction

Social networks affect a wide array of economic outcomes, ranging from informal credit and insurance, to contracting and the provision of local public goods.1 A provocative recent claim is that dense social networks, or social capital, can promote economic growth and industrialization. Perhaps most famously, Putnam (1993: 180) provides evidence from the history of economic growth across Italian regions that “networks of civic engagement contribute to economic prosperity.” Consistent with this view, Grootaert (1999) and Narayan and Pritchett (1999) also find a positive correlation between dense social networks and economic development on comparing cross sections of village, and Knack and Keefer (1997) provide similar correlations in a cross-country analysis.

We examine how the presence of several measures of social capital predict growth in manufacturing employment across Indonesian districts from 1985 to 1995. This was a period of extremely rapid industrial development in Indonesia, in which real per capita income grew by an impressive 70% and manufacturing employment doubled (World Bank, 2002). This paper uses new and larger data sets than previous single-nation studies to examine this question. We combine Indonesian household- and village-level nationwide surveys to create a panel data set of 274 districts. The data set contains a uniquely rich set of social networks measures following those outlined in the existing literature.

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1 Important early contributions in this literature include Besley, Coate, and Louloy (1993), Greif (1993), Udry (1994), and Alesina, Baqir, and Easterly (1999).

The vast majority of the population in the Indonesian archipelago live in cultures that historically have had a rich set of community organizations and rich informal networks. In this section we briefly describe the measures of social interactions that we employ in the analysis. These measures are found in a variety of data sources collected by Indonesia’s Central Bureau of Statistics (BPS), including the PODES community (desa) survey and the SUSENAS and SUPAS household surveys, as well as the Indonesian Family


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Life Survey (IFLS); the appendix describes these data sets in further detail.

A. Community Groups

Most Indonesian cultures are well known for their rich set of traditional community groups. Former president Suharto’s New Order regime built on this tradition, as well as on the community- and neighborhood-level structures established by the Japanese during their occupation of the archipelago during World War II, and mandated a large number of groups for each community (Grootaert, 1999). Beyond these government-sponsored groups, nongovernmental community groups are ubiquitous, often growing out of informal rotating savings and credit associations (ROSCAs) called arisan in Indonesian. During the period we study there was also a flowering of community groups sponsored by nongovernmental organizations. Eldridge (1995: 53) describes a typical Indonesian community self-help group:

Local income-generation programs operated by small local groups, either independently or in association with some larger [NGO], are fairly pervasive in Indonesia, most commonly in the form of informal or formal co-operative enterprises, arisan, savings and loan groups, and credit unions. Perhaps the most creative mode of income generation . . . is the revolving fund. This practice is commonly associated with small, informal co-operatives, which are often built on traditional-style associations such as arisan. . . . This process obviously depends on efficient organization and high levels of mutual support and reciprocity.

Such community credit groups have long been cited as an important manifestation of social capital (Putnam, 1993), and recent research by Anderson, Baland, and Moene (2003) confirms that strong local social ties are essential for their success in practice.

Beyond nongovernmental credit groups, we have also obtained detailed information on the number of state-led community credit groups (called KUD), traditional arts groups, sports groups, youth groups, farmers’ groups (called P3A), and both Muslim and non-Muslim religious institutions in Indonesian communities. These community-level survey measures are then aggregated up to district-level averages, where they are matched up with district-level industrialization measures, for the empirical analysis.

B. Informal Social Networks

Community group data capture relatively formal expressions of social networks and social interactions. It remains possible that informal forms of cooperation are better proxies for underlying social capital. This concern might be particularly important in Indonesia, where many formal social networks were encouraged or mandated by the state, and state influence could be correlated with later industrialization.

To partially address such concerns about formal social capital measures, we also analyze two proxies for informal social interactions. Although no single measure can adequately capture all that one might mean by informal social interactions, taken together these measures fill some of the gaps.

The first measure of informal social capital is the proportion of per capita expenditures on festivals and ceremonies, from the SUSENAS household survey. Intuitively, communities with frequent festivals are likely to have closer social connections; as Breman (2001: 261) argues, such expenditures are likely to be a good measure of underlying social networks in Indonesia because “the cycle of rituals and festivities . . . give meaning and articulation to the collective dimensions of [an Indonesian] locality.”

The second measure of informal social capital is derived from the traditional customs and law (adat) module of the Indonesia Family Life Survey. In 270 rural enumeration areas, village chiefs identified a local expert in adat, and these experts were asked to state whether a particular norm had held in traditional law, and whether it remained common practice at the time of the 1997 interview. These responses are best thought of as the opinions of influential community members. The adat survey instrument contains one retrospective question directly related to informal social capital, the extent of an “ethic of mutual cooperation” traditionally found in the community, which takes on a value of 1 if there was cooperation and 0 otherwise.

A number of influential commentators have argued that relations within the family should be included as an additional dimension of informal social capital (Costa and Kahn, 2001; Putnam 1995: 73). Two possible measures are the extent of elderly co-residence with children—which proxies for the strength of social ties within the family, and also constitutes a form of insurance for the elderly—as well as the divorce rate (in both cases we use SUPAS data for these measures). Although we analyzed these rates as predictors of future industrialization, we are concerned about how these measures relate to what is usually meant by social capital. For instance, divorce has many disparate causes. Thus we do not focus on family relations in the main empirical analysis.

C. The Economic and Political Environment in Indonesia

Upon independence Indonesia was one of the poorest nations in the world. Yet soon after the dictator Suharto took
power in 1965, Indonesia began a thirty-year spurt of extremely rapid economic growth, among the fastest in recorded history. Initially in the 1970s, much of this growth was driven by revenue from oil and other natural resources, and as late as 1980, manufacturing constituted a small share of the economy (Cribb & Brown, 1995). By the early 1980s, however, that situation began to change drastically as the government gradually relaxed restrictions on new businesses and investment, including those with foreign involvement. Importantly for the analysis in this paper, by the mid-1980s government investment policy no longer explicitly favored specific regions (Hill, 1996), and so patterns of investment and industrialization were increasingly determined by private-sector decisions rather than government regulation.

This policy change does not imply that there was a completely level playing field for all investors, or that political favoritism had been eliminated. Fisman (2001), among others, has documented the extent to which political connections to Suharto, his family, and cronies were crucial for firm success in Indonesia during the 1980s and 1990s, the full extent of which only became apparent in the aftermath of the Asian financial crisis.

Nonetheless, the magnitude of the Indonesian economic boom of the 1980s and 1990s meant that many regions of the country and many industrial sectors benefited from the increasingly open investment climate, and not just those with close ties to Suharto. To illustrate, manufacturing employment as a share of the full-time economically active population (those working over 20 hours per week, or unemployed) more than doubled between 1985 and 1995, rising from 6.3% to 13.1% (table 1A).5 The question this paper asks is whether initial social capital measures predict any of this surge in industrialization.

### III. Theories of Social Capital and Industrialization

We discuss several theories of how social capital might promote or hinder industrialization, highlighting only a few of the many proposed mechanisms, and then let the data speak in the following section.

One set of theories, currently very influential in development economics, stresses how some types of social networks can promote industrialization.6 As noted in the introduction, Putnam (2000) emphasizes that norms of reciprocity and trustworthiness are essential for economic growth, and that dense social networks help maintain such norms. Networks of mutual obligation may also encourage entrepreneurship; for example, individuals may be more willing to undertake promising but risky projects if there

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5 To control for possible changes in labor force participation due to industrialization, we focus on the change in manufacturing employment as a share of total adults in the district in 1985, which also doubled during the study period, from 3.3% to 6.7% (table 1A).

6 Dense social networks may also promote well-being through other channels, including better governance and a feeling of individual belonging to a community, but we focus on industrial development in this paper.
exists a strong community safety net. Informal financial institutions based on social capital, including rotating savings groups, may provide an important source of investment for such projects. Social networks can also provide access to distant markets and permit transactions that are separated in time and space; Greif (1993), for example, examines the role dense social networks played in permitting long-distance trade in the medieval Mediterranean. More generally, large networks make it more likely a potential entrepreneur can mobilize resources to start a new enterprise and find the necessary suppliers, customers, and employees.

At the same time, an extensive older literature suggests that, in at least some cases, traditional norms supported by dense social networks can impede industrialization. For an example from Indonesia, Geertz (1963) argued that traditional forms of Javanese social networks would produce continued economic stagnation by stifling saving and investment. Intuitively, if one’s social network always shares the returns to an investment, potential entrepreneurs’ return to hard work and savings is diminished, and this disincentive may prevent some profitable activities from being undertaken. This argument about the deleterious effects of strongly egalitarian social networks has been formalized by Platteau (2000) in the context of rural African underdevelopment. Strong traditional social networks and norms might also discourage the adoption of unfamiliar and unconventional new technologies and economic activities, further stifling growth (Akerlof, 1976).

IV. Estimation and Results

A. Estimation Strategy

We focus on the relationship between initial social capital measures and subsequent industrial change. These estimates help establish the extent to which manufacturing enterprises were formed in, or sought out, regions with dense initial social networks. The main specification is

\[ \Delta MFG_d = \alpha + \beta \cdot SOCIAL_{0,d} + Z_{0,d} + \delta + \epsilon_d. \]  

The change from 1985 to 1995 in the proportion of adults in manufacturing employment in district \( d \), \( \Delta MFG_{d} \), is the dependent variable. Initial measures of social capital, including both formal community groups and informal measures, are the key explanatory variables, \( SOCIAL_{0,d} \) (where “0” denotes initial values as close as possible to the year 1985). Extensive district characteristics \( (Z_{0,d}) \) are included as further controls, and these include geographic controls (indicator variables for island groups, district altitude, and whether the district is landlocked), initial infrastructure

including electricity and road quality, baseline educational attainment and earlier school construction in the district, and whether the district is urban. In some specifications we also control for baseline manufacturing employment, and typically find that these measures positively predict subsequent growth of manufacturing employment in the district. Because it remains possible that initial manufacturing intensity is a result of the same underlying social characteristics that affect future industrialization (and thus, to some extent, initial manufacturing proxies for social capital), we always present specifications that exclude initial manufacturing, as well.

It is important to acknowledge that we cannot definitively rule out the possibility that some unobserved district characteristic affects both initial social capital and later industrialization, leading to spurious results. However, the use of a rich set of baseline district controls, and the fact that the social capital measures predate the industrialization outcomes, reduce concerns about omitted variable bias and endogeneity.

Industrialization outcomes may be correlated among nearby districts due to (unobserved) common policy choices, political leadership, weather, and ethnic or religious influences. To allow for this possibility, in the analysis we allow for a common random effect across all districts in the same province, using clustered standard errors.

The former province of East Timor and the province previously known as Irian Jaya (before its division and subsequent name changes) are excluded from the analysis due to concerns over data quality, and because they suffered from civil conflict for parts of this period. We also combine districts that merged or split to reformulate them into the largest unit consistently defined from 1985 to 1995. The resulting data set contains complete industrialization information for 274 districts.

B. Results

The 1980s and early 1990s were a period of rapid industrialization in Indonesia, with sharp increases in manufacturing employment and per capita consumption expenditures (Table 1A), as well as major increases in educational attainment and urbanization (not shown). The map in figure 1 divides districts into three quantiles based on the extent of industrialization (measured by the percentage change in manufacturing employment) during the period 1985–1995. It is apparent that the increase in manufacturing employment was fairly evenly spread around the archipelago, with

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7 Glaeser, Laibson, and Sacerdotte (2002) develop a complementary theoretical approach to social capital based on the standard model of optimal investment over time. Other notable recent contributions to the theory of social capital include Woolcock (1998) and Francois (2002).

8 We also adjusted standard errors to allow disturbances to be correlated across districts as a general function of distance in certain specifications, using the GMM estimator in Conley (1999). Following Conley (1999), spatial standard errors were calculated with a weighting function that is the product of a kernel in each direction (north to south, east to west). The kernels start at 1 and decrease linearly until they are 0 at 600 kilometers from the district capital; results are robust to varying this cutoff. Standard error estimates obtained using this method are similar to the results using province clustering (regressions not shown).
high concentrations on Java, but also in Riau on Sumatra, West Kalimantan on the island of Kalimantan, and parts of the outer islands. The correlation of the change in industrialization between a district and other districts in the same province was only 0.29, again suggesting a relatively even spread.

The first social capital measure we focus on is the density of nongovernmental credit cooperatives, a community organization which many authors have argued is a particularly good proxy for underlying social capital, as discussed in section II A above. The density of nongovernmental credit cooperatives in 1986 is not a statistically significant predictor of industrialization from 1985 to 1995 in a basic specification without other explanatory variables ($-0.024$, standard error 0.064—table 2, regression 1), and the point estimate remains small and insignificant when island-group fixed effects are included ($-0.057$, standard error 0.061—regression 2). This specification is supplemented with the initial values of other potential determinants of manufacturing growth, including the proportion of the district population living in communities with access to electricity, which has a positive effect on subsequent industrialization as expected (0.073, standard error 0.037, statistically significant at 90% confidence, regression 3); as well as average

![Figure 1.—Industrial Development in Indonesia, 1985–1995](image)

**Notes:** Percentage change in the proportion of manufacturing workers, 1985 to 1995, among population aged 16–60 years, district averages, SUPAS. Light gray denotes the bottom third of districts in percentage change in industrialization, gray denotes the middle third of districts, and dark gray denotes the top third of districts. The white areas on the map—East Timor and Irian Jaya—are excluded from the analysis.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nongovernmental credit cooperatives per 1000 population, 1986</td>
<td>$-0.024$</td>
<td>$-0.057$</td>
<td>$-0.064$</td>
<td>$-0.047$</td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
<td>(0.061)</td>
<td>(0.077)</td>
<td>(0.069)</td>
</tr>
<tr>
<td>Proportion of population with access to electricity, 1986</td>
<td>$0.073^*$</td>
<td>$0.019$</td>
<td>$0.037$</td>
<td>$0.019$</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.019)</td>
<td>(0.037)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Average road quality ($1 =$ dirt, $2 =$ gravel, $3 =$ asphalt), 1986</td>
<td>$-0.019$</td>
<td>$0.003$</td>
<td>$0.013$</td>
<td>$0.007$</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.007)</td>
<td>(0.013)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Change (1973/74–1983/84) in primary and junior high schools per 1973 school-age population</td>
<td>5.5</td>
<td>4.2</td>
<td>4.3</td>
<td>3.6</td>
</tr>
<tr>
<td>Average years of schooling attained among ages 18–49, 1985</td>
<td>0.002</td>
<td>0.002</td>
<td>0.007</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Proportion of population living in urban area, 1986</td>
<td>$-0.005$</td>
<td>$-0.057^*$</td>
<td>$-0.017$</td>
<td>$-0.057^*$</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.033)</td>
<td>(0.017)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Proportion of population living in noncoastal areas, 1986</td>
<td>0.021</td>
<td>0.010</td>
<td>0.024</td>
<td>0.022</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.022)</td>
<td>(0.024)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Proportion of population in high-altitude areas, &gt;500 m, 1986</td>
<td>$-0.004$</td>
<td>$-0.017$</td>
<td>(0.006)</td>
<td>(0.014)</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.014)</td>
<td>(0.006)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Proportion of manufacturing workers among population aged 16–60 years, district average, 1985</td>
<td>1.09***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of manufacturing workers among population aged 16–60 years, other districts in the province, 1985</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Island fixed effects</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations (districts)</td>
<td>0.00</td>
<td>0.09</td>
<td>0.15</td>
<td>0.34</td>
</tr>
<tr>
<td>Mean of dependent variable</td>
<td>0.092</td>
<td>0.092</td>
<td>0.092</td>
<td>0.092</td>
</tr>
</tbody>
</table>

**Notes:** OLS regression results. Robust standard errors in parentheses. Disturbance terms are clustered by province; significance levels using the method in Conley (1999) are unchanged. Significantly different than 0 at 99% (***) and 90% (*) confidence. The island groups are: Kalimantan (0.050 of sample population), Java-Bali (0.634 of sample population), Sulawesi (0.064 of sample population), and Sumatra (0.206 of sample population); the omitted island group is Maluku and Nusa Tenggara (the outer islands, 0.046 of sample population).
road quality in the district, urbanization, and average educational attainment in the district in 1985, none of which is statistically significant at traditional confidence levels, perhaps surprisingly. We also find no effect from Dufo’s (2001) measure of the increase in access to schooling (measured by the change from 1973 to 1984 in schools per school-age population in the district); that is, rapid school-building in the decade before 1985 does not predict rapid industrialization after 1985.

The lack of an urbanization effect may be due to negative congestion effects. Overall, geographic factors—the island-group indicator variables, whether the district is coastal, and district altitude—do not strongly predict the expansion of manufacturing employment.

In contrast, initial local manufacturing employment in 1985 has powerful effects in predicting manufacturing growth from 1985 to 1995 (1.09, standard error 0.38—table 2, regression 4), although industrialization in other districts in the same province does not. The inclusion of these baseline industrialization controls does not substantially affect the point estimate on the measure of initial nongovernmental credit cooperatives (estimate −0.047, standard error 0.069).

We next carry out a similar analysis for nine other measures of initial social capital, both for a specification including the initial industrialization controls and for one excluding the industrialization controls. For the full specification including the initial industrialization controls, only one of the ten initial social capital measures is statistically significant at 95% confidence, the coefficient estimate on the existence of a traditional arts group (−0.056, standard error 0.019—Table 3, column 1); and only one other estimate is statistically significant at 90% confidence, the coefficient estimate on the density of mosques, that estimate being positive (0.0076, standard error 0.0042).

Taken together, there is no clear evidence in table 3 that social capital affects subsequent industrialization. Three of the ten point estimates in the specification with industrialization controls are positive (and one is marginally statistically significant, as discussed above), and seven are negative (one of which is significant at 95% confidence—table 3, column 1). This dispersion of estimates is roughly what would be expected from random sampling variation when the true effect of social capital is zero. When all ten measures are included simultaneously in a single regression, only the existence of a traditional arts group has a significant effect (regression not shown).

We create two indices in an attempt to combine information across the many distinct social interaction measures. The first index combines information from the eight community group measures (rows 1–8 in table 3) as follows: first, each of the community group measures is normalized to have mean 0 and standard deviation 1, and then these eight normalized variables are summed and again renormalized to generate the index. The second index is created similarly, but uses information for all ten initial social capital measures (rows 11–12) and the social capital index—all measures (N = 142). The social capital indices (rows 11–12) are constructed as follows: first, each of the measures (in rows 1–8 for the community groups index, and rows 1–10 for the all-measures index) is normalized to mean 0, standard deviation 1; the sum of these variables is normalized to mean 0, standard deviation 1 to generate the index.

Table 3.—Predicting Industrialization: Social Capital Measures

<table>
<thead>
<tr>
<th>Initial Social Capital Measure (Explanatory Variable)</th>
<th>Coefficient Estimate on Initial Social Capital Measure (S.E.):</th>
</tr>
</thead>
<tbody>
<tr>
<td>With Initial Manufacturing Controls (1)</td>
<td>No Initial Manufacturing Controls (2)</td>
</tr>
<tr>
<td>1. Nongovernmental credit cooperatives per 1000 people, 1986</td>
<td>−0.047 (0.069) −0.064 (0.077)</td>
</tr>
<tr>
<td>2. Total credit cooperatives (state, nongovernmental) per 1000 people, 1986</td>
<td>−0.056 (0.060) −0.069 (0.069)</td>
</tr>
<tr>
<td>3. Existence of traditional arts group in community, 1986</td>
<td>−0.056*** (0.019) −0.075*** (0.025)</td>
</tr>
<tr>
<td>4. Number of distinct types of arts and sports groups in community, 1986</td>
<td>−0.0010 (0.0024) −0.0041** (0.0020)</td>
</tr>
<tr>
<td>5. Existence of scout youth group in community, 1986</td>
<td>0.004 (0.015) 0.002 (0.019)</td>
</tr>
<tr>
<td>6. Mosques per 1000 people, 1986</td>
<td>0.0076 (0.0042) 0.0049 (0.0054)</td>
</tr>
<tr>
<td>7. Non-Muslim places of worship per 1000 people, 1986</td>
<td>−0.0061 (0.0052) −0.0068 (0.0065)</td>
</tr>
<tr>
<td>8. Existence farmers’ irrigation group (FSA) in community, 1986</td>
<td>0.003 (0.012) 0.018 (0.027)</td>
</tr>
<tr>
<td>9. Share of household expenditure on ceremonies and festivals, 1985</td>
<td>−0.24 −2.01**</td>
</tr>
<tr>
<td>10. Community “ethic of mutual cooperation” in traditional times</td>
<td>−0.13 −0.23</td>
</tr>
<tr>
<td>11. Social capital index—community groups (normalized measures 1–8)</td>
<td>−0.0048 −0.0105</td>
</tr>
<tr>
<td>12. Social capital index—all measures (normalized measures 1–10)</td>
<td>−0.0133 −0.0244*</td>
</tr>
</tbody>
</table>

Notes: OLS regression results. The dependent variable is the change (1985–1995) in the proportion of manufacturing workers among population aged 16–60 years, district average. Robust standard errors in parentheses. Disturbance terms are clustered by province; significance levels using the method in Conley (1999) are unchanged. Significantly different than 0 at 99% (**), 95% (**), and 90% (*) confidence.

Each coefficient estimate is from a separate regression. The specification in column 1 is analogous to table 2, regression 4, and column 2 is analogous to table 2, regression 3 (with the social capital measures included as explanatory variables one at a time).

Village-level data are from PODES 1986, 1993, and 1996. District-level industrialization data are from SUPAS 1985, 1995. All regressions are for the sample of 274 districts, except for the share of household expenditures on ceremonies (N = 262), the community “ethic of mutual cooperation” (N = 142), and the social capital index—all measures (N = 142). The social capital indices (rows 11–12) are constructed as follows: first, each of the measures (in rows 1–8 for the community groups index, and rows 1–10 for the all-measures index) is normalized to mean 0, standard deviation 1; the sum of these variables is normalized to mean 0, standard deviation 1 to generate the index.

9 Specifically, the specifications in table 3, column 1, are analogous to table 2, regression 4, and those in table 3, column 2, are analogous to table 2, regression 3.
tutes on ceremonies and festivals in 1985 (—2.01, standard error 0.84)—are statistically significantly negatively related to industrialization. Overall, only one of the ten point estimates—the coefficient estimate on mosque density—is positively correlated with subsequent industrialization; the other nine are negatively correlated (column 2).

When information across these measures is combined in the indices, the community group index is not statistically significant at traditional confidence levels, and the index using all ten social capital measures is negative and marginally statistically significant (−0.0244, standard error 0.0134, column 2, row 12). In both cases, nonetheless, the negative point estimates are modest: a 1-standard-deviation increase in the social capital indices translates into a 0.3–0.8-standard-deviation decrease in manufacturing employment growth. This is suggestive, but ultimately inconclusive, evidence that initial social capital actually had a slightly negative effect on industrial development in Indonesia, perhaps along the lines suggested by Geertz (1963).

Finally, to cast our net as wide as possible, we also examined the effects of two aspects of family relations which some consider a dimension of social capital: the extent of elderly coresidence with children, and the divorce rate of women. Neither is significantly related to subsequent industrialization at traditional confidence levels in the two main specifications (all point estimates on initial family relations are positive but statistically insignificant, regressions not shown)—further evidence of the weak link between initial social capital and industrialization in Indonesia during the 1980s and 1990s.

V. Conclusion

This paper’s empirical results provide new insights into the current debate on the role of social capital in economic development. Using a unique data set of district-level data that we assembled, we find that the initial density of social networks does not predict subsequent industrial development in Indonesia, across a variety of econometric specifications and for multiple measures.

This finding does not imply that social networks and social interactions can never affect industrial development; it merely shows that in the Indonesian case during the study period any benefits of dense social networks were counteracted by their costs, or that other local economic, institutional, or political factors were the prime drivers of industrial development. Nonetheless, because Indonesia was among the world’s fastest-growing economies during the 1980s and 1990s, the fact that social capital appears to play little role in understanding which Indonesian districts industrialized is noteworthy, and perhaps calls for a partial reevaluation of the now widespread view that social capital is a crucial determinant of economic development.

In a companion paper (Miguel, Gertler, & Levine 2003), we show that Indonesian districts that experienced rapid industrialization also experienced significant increases in most social capital measures during the period 1985–1997. In a second main finding of that paper, districts that neighbor rapidly industrializing areas exhibited high rates of out-migration, which appear to have led to significantly fewer credit cooperatives and a reduction in “mutual cooperation” as assessed by village elders in those districts. Together with the results of the current paper, these findings challenge well-known empirical studies which use observed positive cross-sectional correlations between income levels and social networks to claim that denser social networks promote economic development. These findings thus directly relate to Sobel’s (2002) critique that existing research often confuses the causes and effects of social capital. Although strong social networks may (or may not) be essential for achieving collective action and good governance and for improving human welfare more broadly, we find no evidence that they promoted industrial development in Indonesia.10

The results of this paper thus provide a new perspective on Putnam’s (1993) seminal research on Italy. Putnam’s stylized facts are that northern Italy has a dense network of community groups and a prosperous industrial economy, whereas southern Italy currently has relatively few groups and is poor. To sort out causality, Putnam employs historical evidence to argue that social capital has in fact been a key driver of Italian economic and political development over the past centuries. However, as Putnam himself acknowledges, large-scale out-migration from southern Italy to northern Italy in the twentieth century—in response to differential rates of industrial development—may also have contributed to lower current levels of social capital in southern Italy, as we claim occurred in Indonesia.

At the same time, it is important to recall that, like Putnam’s classic study of Italy, ours is a case study of one nation during one era. And it is possible that the corruption that pervaded Suharto’s regime—especially by the end of the study period—led noneconomic factors to often become important determinants of investment patterns. The prominence of the ethnic Chinese minority among Indonesian entrepreneurs is another plausible explanation why social capital measures for the population as a whole do not predict industrialization.11 If so, these results might not completely generalize to other settings with different economic and political institutions or ethnic makeup. Nonetheless, the high degree of state economic intervention, widespread corruption, and ethnic diversity in Indonesia are hardly unique among less developed countries, and this suggests that the findings of this paper could be relevant elsewhere.

10 In a related point, Gertler, Levine, and Moretti (2001) find that Indonesian individuals with richer social networks do not have better informal insurance against adverse health shocks (as measured by consumption smoothing).

11 We thank a referee for this point.
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APPENDIX

Data Sources

1. Village Potential Statistics (PODES)

The Village Potential Statistics (PODES) survey provides detailed information about the characteristics of villages and urban neighborhoods. We analyze the 1986 PODES survey. Over 60,000 village heads or neighborhood leaders filled out the survey about their area in each year in all districts, excluding East Timor and Irian Jaya. We also use PODES data of geographic characteristics, including altitude, being landlocked, and community land area, as well as infrastructure, including road quality and access to electricity.

2. National Socio-Economic Survey (SEUSENAS)

The National Socio-Economic Survey (SEUSENAS) is an annually repeated cross section. It surveyed between 20,000 and 50,000 households per year in the mid-1980s, and approximately 200,000 households per year by the mid-1990s. We focus on the 1987 SEUSENAS survey, which contains information on per capita household spending on “ceremonies and festivals”, which we use as a measure of the strength of informal social networks. The SEUSENAS sample was selected to be representative for each of Indonesia’s districts. Smaller districts were oversampled to improve statistical precision. [This section draws heavily on Surbakti (1995).]

3. Intercensal Population Survey (SUPAS)

The Intercensal Population Surveys (SUPAS) are carried out every ten years, in the midperiod between complete population censuses. We analyze the 1985 and the 1995 SUPAS. The 1985 SUPAS covered 126,696 households and 609,858 individuals; the 1995 survey covered 216,946 households and 948,380 individuals. Sampling rules generally follow those of the SEUSENAS. The specific variables we use from SUPAS include the proportion of elderly individuals (at least 60 years old) co-residing with adult children (at least 18 years old), and most importantly, the proportion of the adult population working in manufacturing occupations—the principal measure of district industrialization. (Macy Federman kindly created several SUPAS variables for us.)

4. The Indonesia Family Life Survey (IFLS)

The IFLS is a representative sample of 83% of the population of Indonesia as of late 1993, covering 13 of Indonesia’s 27 provinces (Frankenberg & Thomas, 2001). The smallest provinces and politically unstable regions – such as Irian Jaya and the former East Timor — were not sampled. We use 1997 information across several hundred communities. In each community the IFLS interviewed an expert in local customs and laws (udar). We have udar information on 142 of the 274 districts we analyze, and these districts contain over two-thirds of Indonesia’s 1995 population.

A possible concern with our focus on the number of community groups reported in the PODES, rather than individual group membership, in the analysis is whether village head reports correlate well with memberships reported by households. We examined this question using the second wave of the Indonesian Family Life Survey, which asked households about
membership in twelve different types of community groups. The IFLS separately surveyed village heads and leaders of local women’s groups about the presence of community groups, ten of which were also included on the households’ list. These groups include: voluntary labor groups; community meetings; cooperative groups (of any kind); neighborhood improvement programs; neighborhood security organizations; drinking water systems; washing water systems; garbage disposal systems; contraceptive acceptors groups; and child development programs. We cumulated individual responses to the household level by summing the number of the ten overlapping community groups in each household that at least one household member belonged to. The village leadership reports strongly predicted whether households belonged to groups, with an elasticity of roughly 0.4; that is when the village head reported having two standard deviations above the average number of groups in the village, the average household belonged to roughly 0.5 more groups ($p < 0.01$) than average (2.0). Thus, village leader reports on the presence of community groups appears to be a valid proxy for individual group membership.

5. School Construction

We have district-level data from the Ministry of Education and Culture on the number of primary, middle, and high schools per school-aged child in both 1973/4 and 1983/4, the decade preceding our period of study, and use these data to predict subsequent industrialization. Indonesia pursued a massive school construction program in the 1970s (Duflo, 2001). We are grateful to Esther Duflo for generously providing these data.