

Culture of Trust and Division of Labor*

Stephan Meier[†]
Matthew Stephenson[‡]

June 24, 2015

Abstract

Firms exhibit heterogeneity in size, productivity, and internal structure, and this is true even within the same industry. Our paper provides evidence of a link between an organization's culture—specifically the trust environment—and its level of specialization. We show experimentally that exogenously imposed culture endogenously leads to variation in organizational form. We prime trust and demonstrate that the level of trust within an organization affects division of labor and consequently productivity. This evidence is consistent with a cross-country link between trust and the division of labor that we observe in data from the European Social Survey.

JEL Classification: D03, D2, L2, Z1

Keywords: Trust, Culture, Organizational Structure, Division of Labor, Experiments

*We thank Roberto Weber, Evan Rawley, Phanish Puranam, Ernst Fehr, Bruce Kogut, Ko Kuwabara, Ernesto Reuben, Marlo Raveendran and participants at various workshops and conferences for very valuable comments.

[†]Columbia University, Graduate School of Business, 710 Uris Hall, 3022 Broadway, New York, NY 10027; sm3087@columbia.edu

[‡]Columbia University, Graduate School of Business, 7F Uris Hall, 3022 Broadway, New York, NY 10027; mhs2178@columbia.edu

1 Introduction

Organizations differ in observed performance but they also differ internally; for instance, in some organizations the division of labor is extensive while in other it is not. And internal differences between firms can help account for their performance differences, as when differing management practices within an organization affect firm productivity. While it has been known since Adam Smith that an organization’s internal structure, e.g. degree of division of labor, may profoundly affect its productivity, the process by which such structure evolves and is sustained is less understood. Part of this internal form may be determined by the production characteristics of its industry, but there exist substantial differences in organizational structures even within an industry (Almazan & Molina, 2005; Porter, 1979). Explaining differences in firms’ organizational structures is an important aspect of explaining differences in productivity differences.¹

This paper investigates whether some of the difference in organizational structure can be traced back to corporate culture. In particular, we argue and show empirically that changing an organization’s level of trust affects its division of labor and thus that exogenously imposed differences in culture endogenously lead to different organizational forms. Existing literature suggests that corporate culture might play an important part in explaining firms’ performance (e.g. Sørensen, 2002; Guiso et al., 2014) and that trust is crucial for cooperation within organizations (e.g. Fehr & List, 2004; Fehr et al., 1998). We want to extend those two strands of literature by arguing that the trust dimension of corporate culture affects performance through organizational structure, in particular the degree of division of labor. Theoretically, a link between trust (culture) and the division of labor (organizational structure) is evident when considering that the division of labor is limited by coordination costs, one of which is “whether workers trust

¹The organization of a firm has been argued to depend on many factors, including strategy (Chandler, 1990), technology (Woodward, 1965), and environment (Lawrence & Lorsch, 1967; Wan & Hoskisson, 2003). Additionally, factors such as identity (Kogut & Zander, 1996; Santos & Eisenhardt, 2005) social comparison (Nickerson & Zenger, 2008), and reciprocity (Akerlof, 1982; Fehr et al., 1998) can affect the organization and function of firms.

each other” (Becker & Murphy, 1992, p. 303).

To provide some intuition on how trust affects the division of labor, consider the example of a group of co-authors specializing in different sections of a paper. This can be efficient because 1) the person doing the literature review and write-up does not need to spend time decoding the proofs, re-focusing, and/or physically going from the field to the computer lab; and 2) the writer has familiarized herself with relevant literature, major papers, and authors to an extent beyond that of her co-authors.² Meanwhile, her co-authors have done the same *mutatis mutandis*. This efficiency has come at the expense of, for instance, the writer’s ability to understand and improve the proofs in the formal model that another co-author has been developing. Division of labor thus imposes an evident cost, and in a case where the value of the product is effectively the minimum effort in each subtask—so that a paper with a thorough literature review but a non-functioning model is not publishable—the cost can be great.

In light of such a cost we think the existence and sustainability of division of labor depend on whether the workers trust one another. Early sociological writing on the division of labor observes that “each in doing his specialized task must trust that others will do certain things... and will forbear from certain other things” (Ross, 1896, p. 525). In the absence of trust, workers can lose efficiency switching between tasks, thereby “de-specializing” the group.³ An East Asian engineering manager, describing team-based construction work, makes this process clear: “Those that can’t trust... end up doing everything themselves” (Girmscheid & Brockmann, 2009, p. 357). Another evocative example set in a firm comes from management guru Stephen Covey, who describes a circumstance in which a division he managed depended on another division to help meet a customer’s needs. Because Covey believed that the other division had a bad reputation, he

²These efficiencies are adapted from Smith & Nicholson (1887), which we will return to in Section 2.

³That is to say that trust affects task allocation. We focus here on “endogenous” task allocation by measuring actual effort provision in tasks, though delegation-based task allocation is also very important and plausibly affected by trust. For a review of these foundational concepts, see Puranam et al. (2014)

opted to take the “easy but expensive way out” by doing everything within his division, “creat(ing) our own redundant systems”. He added that “the whole organization was taxed for it in terms of the time and effort we had to put into something that should have been done by somebody else” (Covey, 2006, p. 264).⁴

The question of the impact of trust on the division of labor is difficult to study empirically since, first, data on trust levels within a large number of firms and their degrees of division of labor is difficult to obtain. Second and more importantly, a correlation between trust and division of labor could be due to omitted variables, e.g. the management team puts in place structure or institutions that affect both trust levels and division of labor. Reverse causality, i.e. the organizational structure affecting trust levels, makes it almost impossible to interpret a correlation between trust and division of labor as causal. Due to this problem, we provide two types of complementary evidence for the link between trust and division of labor. The main evidence comes from a laboratory experiment that establishes a causal effect between trust and division of labor.⁵ We also use cross-country evidence to establish a correlation between trust and division of labor.

In the laboratory experiment, individuals engage in a productive enterprise in groups of three and they are given the ability to alter how they divide labor among specialist and generalist task allocations. Performance is compensated at the group level, an arrangement “far more common than individual performance-based pay” within firms (Larkin et al., 2012, p. 1196). For simplicity we also assume a minimum-effort production process in which the group performance is the result of the least effort among the three tasks. Individuals can all specialize on their own task and if they do they will be maximally productive as a group. However, individuals are also given the

⁴Team sports presents another intuitive example: Dean Oliver, analyst for the NBA’s Denver Nuggets, notes that zone defense relies on “trust” that teammates will “cover their own zones” (Oliver, 2004). As in Covey’s example, a coach may have specified high division of labor—with each player defending a specialized zone—but players and employees can alter their tasks to de-specialize the group.

⁵For experimental methods used in answering questions in organizational studies and strategy, see Puranam et al. (2006), Camerer & Weber (2013), Croson et al. (2007), Chatterji et al. (2015).

ability to engage in a non-specialized task, which comes at a productivity cost but also confers the advantage of ensuring that non-specialized task is completed to some standard. This game effectively models the real world division of labor situations we describe above, in which members of a team can choose to “de-specialize” at a cost. Before the individuals engage in the real effort task we randomly manipulate their level of trust, allowing us to study whether exogenously changing a culture of trust endogenously creates different levels of division of labor.

Our laboratory findings show a significant effect of exogenously imposed trust on specialist behavior at the intensive and extensive margins. Specifically, we find positive and significant effects of trust on the level of realized specialization within a group, as well as the total performance of the group. Exogenously changing the trust level across our organizations, i.e. our groups of three, leads to the emergence of different forms of working together, i.e. extent of division of labor. We find that even exogenously imposed trust levels can minimize uncertainty about other co-workers. Furthermore, by repeating this experiment with feedback, we observe that these effects intensify over time, with high-trust groups increasing in specialization over time.

Cross-country evidence, using data from the European Social Survey, supports this finding in that the level of generalized trust within a country corresponds to a higher level of specialization within that country’s industries. The correlation between our proxy of division of labor—a measure of specialized job descriptions within a country’s industries—and generalized trust is robust to economic controls and country and time fixed effects. We also instrument for trust using the measure “feeling of safety” and find results consistent with the cross-country evidence. While the evidence is not interpreted as causal, it supports the experimental evidence by showing that trust level is correlated to the division of labor in observational data.

Our paper makes at least three important contributions to the literature:

First, our paper contributes to the debate about the effect of culture on organizational structure. A recent paper by Bloom et al. (2012) finds

that trust is associated with larger firm size and a flattening of hierarchical structures within the firm. We test a distinct but complementary theory: that trust affects the organization of production within firms, with higher-trust environments endogenously producing more specialized task allocations. The trust environment within a firm is an important feature of a company’s culture (Kreps, 1990). Zanini (2007) observes that “the function of corporate culture is to assure information for interactive partners...” and under incomplete contracts this is the “strategic function of trust embedded in the corporate culture of the firm.” We find that a culture of trust can help a firm to facilitate a stable division of labor. In particular, we show that initial differences in trust level can endogenously lead to different degrees of specialization within an organization. These initial differences are important for three reasons: 1) Firm structure is inertial (Nelson, 1991), so the early structure of an organization remains important even as a firm grows in size, 2) A firm’s culture is formed early and is difficult to change (Schein, 2010), and 3) Trust only increases by a small amount as a function of relationship duration, so the existence of relationships among individuals within a firm does not by itself impact trust substantially over time (Vanneste et al., 2013).

Second and related to the first contribution, our paper can shed light on a mechanism explaining the relationship between trust and growth. Trust levels within a country have been thought to affect a number of economic variables, most notably growth. A number of studies show a significant correlation between trust and economic growth (e.g., Knack & Keefer (1997); Algan & Cahuc (2010)). However, the precise mechanism through which trust affects growth is still an open question. Our evidence shows that a potential mechanism for the relationship between trust and growth is the organization of firms. If trust affects the division of labor as we observe in our study, and the division of labor affects the “wealth of nations”, this illuminates a plausible mechanism that links trust to growth: organizational structure.

Third, we contribute to the literature on the relationship between trust and economic behavior. There exists significant (mostly experimental) work

on the ways in which institutions and organizational forms causally foster the trusting and trustworthy behavior of individuals (Glaeser et al. (2000); Fershtman & Gneezy (2001); Bohnet et al. (2008); Falk & Zehnder (2013)). Our contribution lies in studying the converse of this research: addressing the manner in which individual's trust-levels causally impact institutions and organizational forms. The only other paper that we are aware of that studies the causal effect of trust on economic behavior is Bartling et al. (2013). This paper applies a very similar manipulation of high and low trust to the one we use, but investigates the role of trust and trustworthiness in inducing high and low effort equilibria in a gift exchange game, whereas we study the role of trust in the division of labor.

The paper proceeds as follows: Section 2 discusses concepts used within the paper and includes a model of the effects of trust on specialization. Section 3 presents evidence from cross-country data on the relationship between generalized trust and division of labor. Section 4 introduces the experimental design and the results of the experiment are exhibited in Section 5. Section 6 provides concluding thoughts and suggestions for further research.

2 Conceptual Considerations

The division of labor is thought to be paramount in accounting for the productivity of organizations going back to Adam Smith. However, the process by which the division of labor emerges has received, to the best of our knowledge, limited prior attention in the scholarly literature.⁶ Raveendran et al. (2015) constitutes a rare recent exception, focusing on factors that precipitate and sustain the division of labor.

Below we present a simple game theoretic model that illustrates how trust can affect division of labor. It shows that, in the presence of gains from

⁶Vernon Smith and coauthors have several important experimental papers that investigate aspects of the division of labor. They explore the role of specialization in the formation of long-distance trade under different institutional environments (Kimbrough et al., 2008), the discovery and emergence of specialization (Crockett et al., 2009), and the emergence of property rights due to specialization and gains from exchange Kimbrough et al. (2010).

specialization, trust makes division of labor more likely. Increasing trust also increases the payoff from specialization, as well the “risk dominance” profile of choosing to specialize vs. generalize.

Gains to Specialization

In order to analyze the division of labor, let there exist some set of tasks $y \in \{y_1, \dots, y_n\}$ divided among N workers. R_i is a switching variable denoting the number of tasks a worker engages in, $R_i \in \{1, \dots, N\}$. Thus if there are two workers who work on all tasks in y , then $R_i = N = 2$ whereas if they divide the tasks with no overlap $R_i = 1$. Effort for a worker i in task k is e_{ik} and their production in task k is as follows:

$$y_{ik} = \frac{e_{ik}}{R_i^\alpha}$$

Where α is a constant that determines the productivity effects of specialization. Smith’s classical treatment of gains from specialization identified distinct efficiencies that come with division of labor: saving on switching costs and the increase in skill that comes from repeating a task (1887).⁷ Arrow (1962) refers to this as “learning by doing”. Recognizing these efficiencies, we focus on the “gains from specialization” case in which $\alpha > 1$.⁸ In such a case, with fixed effort and two or more workers, individual productive output is decreasing in the number of tasks worked on, reflecting decreased switching costs and/or learning by doing. Under fully divided labor with no task overlap, overall productivity for worker i is $\sum_k y_{ik} = e_i$ whereas full generalization gives $\sum_k y_{ik} = e_i R_i^{1-\alpha} < e_i, \forall R > 1$.

Note that α is not specialization but rather the productive benefits that accrue to specialization, benefits that vary by the productive technology available in a given industry for instance.

It is useful here to restrict attention to a simple case of two workers

⁷Smith identifies a third efficiency—the creation of productive tools—but this is outside the scope of our paper.

⁸Observe that with $\alpha = 1$ there would be no productivity losses from switching tasks.

and two tasks. We follow Becker & Murphy (1992)'s paper on the division of labor and specify a “minimum effort” production technology. Output Y is thus equal to the minimum production in either of the two tasks: $Y = \min((y_{11} + y_{21}), (y_{12} + y_{22}))$. That is, productivity is equal to either the sum of worker 1 and worker 2's production in task y_1 or the sum of worker 1 and worker 2's production in task y_2 , whichever is less. Payoffs are then split equally between the workers, and effort and task-allocation are non-contractible, so that $\pi_i = \frac{Y(y_{ik})}{N}$.

Trust

Having introduced a set of tasks with production benefits from greater division of labor, we will now consider the effect of trust. Trust is a notoriously hard concept to define, but within the existing definitions there appears to be a convergence on the role of belief as an important element. Gambetta (2000) summarizes an inter-disciplinary consensus as follows: trust is the “subjective probability with which an agent assesses that another agent or group of agents will perform a particular action, both before he can monitor such action and in a context in which it affects his own action.” Bénabou & Tirole (2003) propose that, in a productive context, a trusting belief can be thought of as one that regards the other's “cost or pleasure of accomplishing the task” (p. 494).⁹ Following this, we define trust as a probabilistic belief about another agent's incentive problem.

With respect to the productive tasks defined above, suppose that there exist two types of workers who differ only in effort provision for these tasks, type $\theta_i = \bar{\theta}$ sets $e_i = 1$ while $\theta_i = \underline{\theta}$ sets $e_i = 0$ in all cases. Effort is thus “all or none” and these types, respectively, are workers who find it profitable to exert effort given the potential payoffs or not at all.¹⁰ Workers have a trust parameter, a common prior $\theta = (0, 1)$ about the probability of a worker

⁹The “trust effect” in their model is about perceived incentive problems, which contrasts with a “profitability effect” regarding worker ability. We do not treat the profitability effect here.

¹⁰We will consider this assumption explicitly in Appendix D. Relaxing it does not substantively impact our conclusions.

being type $\bar{\theta}$. They also know their own type θ_i with certainty. The risk-neutral worker then sets a level of specialization based on the level of trust and their type, choosing $\hat{R}_i|(\theta, \theta_i)$ to maximize their expected payoffs in a simultaneous move game between workers.

Suppose that worker 1 is of type $\bar{\theta}$.¹¹ To see what values of θ produce a specializing ($R=1$) equilibrium, we check for profitable deviations by fixing worker 2's decision as being full specialization ($\hat{R}_2=1$) with $y_{22}=\theta$ and $y_{21}=0$.¹² This produces payoffs as follows:

$$\pi_1(\hat{R}_1) = \frac{Y(\hat{R}_1)}{N} = \min\left((y_{11} | \hat{R}_1), (y_{12} | \hat{R}_1) + \theta\right) N^{-1}$$

Because worker 1, as type $\bar{\theta}$, sets $e=1$ and worker 2 sets $e=1$ with probability θ , we can omit the subscripts on e . \hat{R} is a discrete choice variable that can equal 1 or 2 in the two-person case, so we have:

$$\pi_1(\hat{R}_1) = \begin{cases} \min(e, \theta e) N^{-1} = \frac{\theta e}{N} & \text{if } \hat{R}_1 = 1 \\ \min\left(\frac{e}{2\alpha}, \frac{e}{2\alpha} + \theta e\right) N^{-1} = \frac{e}{2\alpha N} & \text{if } \hat{R}_1 = 2 \end{cases}$$

Worker 1 will not find it profitable to deviate from $\hat{R}=1$ if $\theta e \geq \frac{e}{2\alpha}$. By symmetry, this is also the case for worker 2. Thus we can see then that the existence of equilibrium specialization benefits from increasing both gains from specialization (α) and trust (θ). Treating α as fixed by a technology, at a sufficient level of trust specializing constitutes a Bayesian Nash Equilibrium in pure strategies.

Under what conditions is generalizing an equilibrium? Now suppose that worker 2 fully generalizes ($\hat{R}_2 = 2, y_{21} = y_{22} = \frac{\theta e}{2\alpha}$) and we thus check worker 1's incentive to deviate:

¹¹A worker of type $\underline{\theta}$ is indifferent in the choice of tasks so for simplicity we assume they follow the same decision rule as $\bar{\theta}$.

¹²We are here assuming that the "task coordination" problem is solved. Including problems of task coordination makes specialization less profitable and this is discussed in Appendix D.

$$\pi_1(\hat{R}_1) = \begin{cases} \min\left(e + \frac{\theta e}{2^\alpha}, \frac{\theta e}{2^\alpha}\right) N^{-1} = \frac{\theta e}{2^\alpha N} & \text{if } \hat{R}_1 = 1 \\ \min\left(\frac{e(1+\theta)}{2^\alpha}, \frac{e(1+\theta)}{2^\alpha}\right) N^{-1} = \frac{e(1+\theta)}{2^\alpha N} & \text{if } \hat{R}_1 = 2 \end{cases}$$

Generalizing is always an equilibrium since $e(1+\theta) \geq \theta e \rightarrow e \geq 0$ and $e_i \geq 0 \forall i$. If trust is low ($\theta e \leq \frac{e}{2^\alpha}$) and $\theta_i = \bar{\theta}$ then generalizing constitutes the unique equilibrium.¹³ With the level of trust greater than or equal to $\frac{e}{2^\alpha}$ we have multiple equilibria, one in which both specialize and one in which both generalize.

Trust and organizational form

At a level of trust such that two organizational forms are feasible ($\theta e \geq \frac{e}{2^\alpha}$), we can say more about the equilibrium properties of these forms. Specializing will payoff dominate generalizing only if $\theta e > \frac{e(1+\theta)}{2^\alpha} \rightarrow \theta(2^\alpha - 1) > 1$. The relative payoff of the specialized form of organization is greater with more gains the specialization α and trust θ .

To clarify these relationships, Figure 1 displays a graph of the existence and dominance properties of the specialization ($R=1$) equilibrium. Any combination of values for trust and gains to specialization that lies above the solid line creates a specializing equilibrium in the game. Specializing is payoff dominant for values above the dashed line, and is risk dominant¹⁴ for values above the dotted line. To observe the effect of trust on division of labor, it is useful to pick a value for α , supposing a fixed production technology. With $\alpha=4/3$, an individual's productivity gains from specialization are ≈ 25 percent for a constant level of effort.¹⁵ At this value of α , specialization is only an equilibrium if trust ≈ 0.4 or greater. Specialization is only payoff dominant with trust greater than ≈ 0.7 , and generalizing always risk dominates regardless of the level of trust.

¹³For $\theta_i = \bar{\theta}$, all choices of \hat{R} produce Nash Equilibria, since they exert no effort and don't affect payoffs. This is a less interesting case.

¹⁴It is risk dominant if it provides a higher payoff on the assumption that the opponent completely randomizes. In this case, that means $\theta > \frac{2}{2^\alpha - 1}$.

¹⁵Recall from earlier that overall productivity under generalization is $e_i R_i^{1-\alpha}$ while productivity under specialization is e_i .

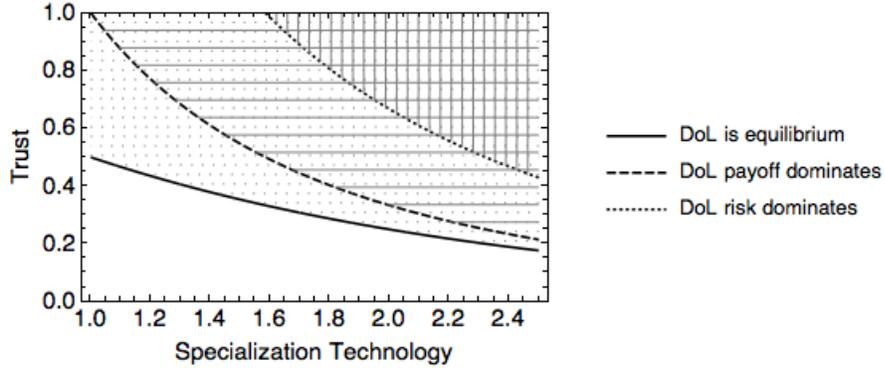


Figure 1: Properties of the Specialization Equilibrium

Fehr (2009) observes that the belief component of trust can have lasting effects “only as an equilibrium selection device”. In our model, as trust increases, we observe that division of labor becomes a Bayesian Nash Equilibrium and thus a viable organizational form. This is because at low-trust workers want to safeguard against low-effort by generalizing whereas when trust increases workers no longer find it preferable to deviate to generalization. However, workers might still receive higher payoffs when both generalize. With trust increasing to a high level, a specialized equilibrium can produce the greatest expected payoff but there are still often “risk dominance” advantages to the generalist equilibrium.

3 Illustrative Evidence on Trust and Division of Labor across Countries

In order to motivate the relevance of our idea and experimental results outside the lab, we present cross-country evidence from a repeated panel survey that sheds light on the relation between trust levels and division of labor. A culture of trust in a country can affect a firm’s structure for at least two reasons: First, the level of trust within an organization can act as a constraint on its form, as shown in the model. Thus a firm might see greater potential production under high levels of specialization but is constrained

by the trust environment that makes such an arrangement unstable. Hence we have a within-country hypothesis suggesting that the division of labor will respond to changes in trust. The model suggests that this effect should be observed at a given specialization technology, and thus industry-level observations are relevant. Secondly, the nascent structure of a firm is often team-production (Alchian & Demsetz, 1972) and, because firm structure is inertial and resistant to change (Nelson, 1991), trust’s effects on division of labor could be expected to persist. Thus we would predict a cross-sectional correlation between trust and the division of labor. While we find support for both hypotheses, controlling for time-invariant factors on the country level and instrumenting for trust, we consider the evidence correlational and suggestive. We therefore couple these findings with our experimental evidence investigating the causal effect of trust on division of labor. Nevertheless, the evidence provided in this section resembles evidence on trust and growth (Knack & Keefer, 1997; Algan & Cahuc, 2010) and we see it as a complementary illustration to our experimental evidence.

Data sets: We draw on data from the European Social Survey (ESS) for the available years of 2002-2012. The range provides 217,250 individual observations drawn from 35 countries.¹⁶ We then pair this data with country-level economic measures from the Penn World Tables (Feenstra et al., 2013).

Proxy for division of labor: We exploit a unique feature of the data in the European Social Survey (ESS) to construct a measure of division of labor. The ESS contains classifications for both an individual’s occupation as well as the industry in which they are employed, using the International Standard Classification of Occupations (ISCO-88) and Nomenclature of Economic Activity (NACE) codes respectively. Within our sample we have 492 unique ISCO-classified occupations and 91 NACE-classified industries. Using this data we use an idea from Gibbs & Poston (1975) and construct an index of

¹⁶ Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Kosovo, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Russian Federation, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, and the United Kingdom.

division of labor, d , for each industry j within a country from this data as follows (for more details, see Appendix A):

$$d_j = \frac{\sum_{i=1}^n x_{ij}^2}{(\sum_{i=1}^n x_{ij})^2}$$

Where n is the number of possible occupations and x_i is the number of individuals in a given occupation i . This form is maximized when x is constant for all i , suggesting a uniform distribution of individuals among the possible occupations within an industry. If we suppose that each possible occupation within an industry is a “bucket” which can be filled by employees, d measures how levelly those buckets are filled within a country’s given industry. As described above, our division of labor index d is computed for each year within a domestic industry. That is, within a country, each industry has a unique division of labor score for a given year of the ESS.

To provide intuition on this measure, consider the forestry industry in Greece and Finland. These countries differ substantially in generalized trust, with Finland having a high average and Greece a low one. We also observe that Greece and Finland have different occupational structures within their forestry industries: a majority (61 percent) of Greek forestry workers classify their occupation as “manufacturing laborer”, a classification which denotes no obvious specialized skill. Compare this with Finland, in which there are no observed “manufacturing laborers” but instead there are “wood processing plant operators”, “wood products machine operators”, “wood treaters”, “woodworking machine setters”, “motorized forestry plant operators”, “lifting truck operators” and so on.¹⁷ Moreover, these occupations are flatly distributed in the Finnish sample and no clear majority occupation is evident. As we would expect, these observations are reflected in the industry d score, within Finland’s forestry industry being much higher than Greece’s. We maintain that the differentiation of skills and specific tasks form the

¹⁷In principle using more specific job titles could be explained by the hypothesis that trust increases the thoroughness of the ESS survey and thereby results in more specific answers. However a spearman correlation finds no evidence for a link between interview time and trust ($p=0.769$).

basis on which a worker chooses to either classify themselves as a general laborer or a machine operator.¹⁸ Thus our measure d captures an element of division of labor within industries.

Trust measure: The ESS includes a measure of trust. It is based on the question “Generally speaking would you say that most people can be trusted or that you need to be very careful in dealing with people”. Responders provide an answer on a 10-point scale with the lowest category being “You can’t be too careful” and the highest “Most people can be trusted”. The mean response to the generalized trust question in our sample is 4.83 with a standard deviation (s.d.) of 0.986, and a range of 2.7-6.9.¹⁹ Sapienza et al. (2013) note that the “trust in strangers” survey question that we use is most relevant to beliefs within a laboratory, rather than preferences. McEvily et al. (2012) find that, when the “target of trust” is a stranger, surveyed measures of trust do correlate with trusting behavior in a controlled environment. Because our model and experiment treats an interaction among strangers in a productive context, these surveyed measures of trust (and production activities) are relevant.

Results: We evaluate the relationship between the division of labor and trust using the measures described above. Figure 2 displays the results for the aggregated d scores plotted against generalized trust at the country level with a linear fit line projected on the data. Trust and d are positively correlated ($p < .01$)²⁰ and indicating that an increase of one s.d. in measured trust results in a .45 s.d. increase in the observed d -score.

In Table 1 we explore the robustness of the association between trust and division of labor by making use of the panel structure of our data and fitting several models with a variety of controls. The specification controls for growth as well as population size, trade openness, and capital investment which are variables commonly used to explain growth. We also include

¹⁸So a worker charged with the task of treating the wood, driving the truck, and setting the machine for operation should be more apt to describe their occupation in general terms (“laborer”) than a worker whose entire job consists of treating wood.

¹⁹These statistics are reported at the country level.

²⁰Results in this section are from a OLS regressions unless otherwise specified.

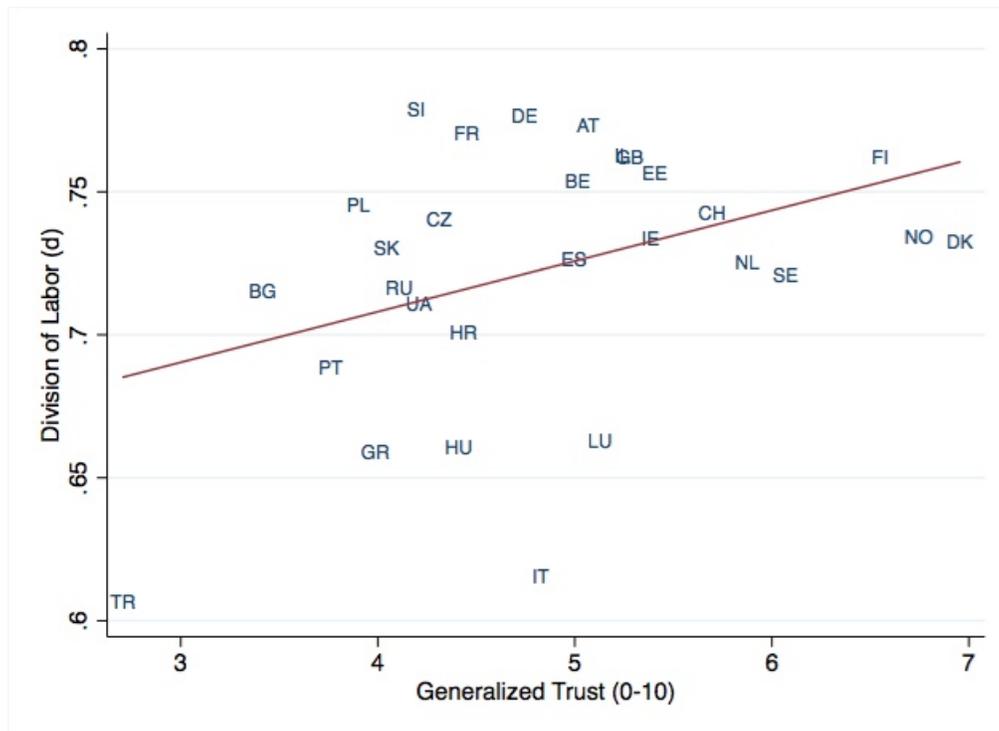


Figure 2: Trust and Division of Labor

Note: Data taken from European Social Survey and measures averaged across countries from 2002-2012. Plot omits graphical outliers Cyprus (CY), Israel (IS), and Kosovo (XK). These countries are not omitted from the statistical analysis.

controls plausibly related to division of labor: the number of industries in a country, number of individuals self-employed, and number of family firms. We instrument for trust using the "feeling of safety after dark"²¹, a measure that should only affect the division of labor through its effect on trust.

Column 1 reports results on a model which considers the smallest unit of analysis given our data: the yearly domestic industry. Column 2 reports results at the country level, pooling industries within countries and years, and this exhibits a similar coefficient on trust. In columns 3 and 4 we report the same specifications but using controls. In both specifications we find a similarly significant and positive relationship between trust and the division of labor with roughly similar effect sizes. In columns 5 and 6 we add time and group level fixed effects and, while the industry-level specification remains significant, the country-level specification is only significant at the 10 percent level. Thus the result is largely robust to controlling for time-invariant effects. Columns 7 and 8 display the results of a two stage least squares regression, with column 7 reporting the first stage results and column 8 reporting the results with instrumented trust. We use the ESS survey measure "feeling of safety" as in instrument for trust ($F < 0.01$). This instrument helps alleviate concerns about endogeneity, and the coefficient is significant and similar in size to the other results.

In sum, we observe that trust is positively and significantly associated with the division of labor within the ESS dataset. This finding is not simply due to time-invariant country and country-industry factors, and a plausible instrument helps to rule out questions of reverse causality. Prominent research on trust and organizations treats the level of trust within a region as being primarily determined by historical particulars and thus "largely exogenous" with respect to the organization of firms (Bloom et al. 2012a). Trust has been found to depend on weather conditions (Durante 2010), past literacy rates and institutions (Tabellini, 2008) and "crucial events in city-states during the medieval period and earlier" (Guiso et al., 2008, cited in Bloom et al. 2012) Nevertheless, we are sensitive to the possibility of endogeneity

²¹"How safe do you - or would you - feel walking alone in [your neighborhood] after dark?", surveyed on a scale from 0-5.

Table 1: Trust and the Division of Labor in the ESS Dataset

Dependent Variable	(1) <i>d</i>	(2) <i>d</i>	(3) <i>d</i>	(4) <i>d</i>	(5) <i>d</i>	(6) <i>d</i>	(7) Trust	(8) <i>d</i>
Trust	0.0782*** (0.0125)	0.0683** (0.0310)	0.109*** (0.0161)	0.0639** (0.0287)	0.105*** (0.0143)	0.179* (0.0983)		0.0713** (0.0339)
Feeling of Safety							0.228*** (0.00840)	
Constant	0.585*** (0.0199)	0.724*** (0.0515)	0.203 (0.134)	0.497*** (0.176)	0.512 (1.377)	0.947 (1.302)	0.355*** (0.122)	0.247** (0.116)
Controls	N	N	Y	Y	Y	Y	Y	Y
Fixed effects	N	N	N	N	Y	Y	N	N
Observations	9,123	150	6,406	110	6,406	110	6,406	6,406
R-squared	0.009	0.092	0.031	0.433	0.015	0.286	0.162	0.029

Note: Data from the European Social Survey, 2002-2012. Results from an OLS multiple regression, robust errors in parentheses, clustered at the domestic industry (1,3,5,7) and country (2,4,6) levels. Control variables are population size, trade openness, capital investment, the number of industries in a country, number of individuals self-employed, and number of family firms. All independent variables in logs. Column 7 reports the first stage of two-stage least squares regression instrumenting Trust with "Feeling of Safety", and column 8 reports the second stage with instrumented trust. Fixed effects are time and group-level: domestic industry (5) and country (6). Change in observation is due to level of analysis and some missing data for the control variables. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

given our sample and we prefer to present the results as correlational. We believe that the findings are suggestive and point to external validity for our experiment demonstrating a causal effect of trust on division of labor.

4 Experimental Design

To test whether the level of trust in an organization causally affects division of labor, we need (1) a task that measures the extent of specialization and (2) a way to randomly assign individuals/teams into high or low trust environments. We will describe the operationalization of our experiment in turn. Full instructions were available for participants to read and were read aloud prior to the experiment. These instructions are presented in Appendix B.

4.1 Task

We sought to devise an experimental game that could approximate the feeling of an actual work environment, leading us to use a real-effort task in continuous time. Our design attempts to capture the process of specialization in our model, treating distinct complementary tasks under “minimal effort” production. However, because the division of labor can be driven by heterogenous skills among a group, as well as beliefs about such skills, it was important to use a design in which individuals have similar levels of potential productivity while allowing for different levels of actual productivity within the game. That is to say, we did not want individuals switching to a different task simply because they thought they would be more skilled at it. To avoid these pitfalls, our design uses the same simple task for all subjects. The interdependence of the tasks comes from the payoff structure and we model specialization by imposing costs of switching between tasks (so $\alpha > 1$).

The task is to clear blocks in a 20x20 grid (see Figure 3 for a screenshot) via simple clicking, with a 9 second enforced delay between clicks. We expect that all students should have a similar ability in clicking. However, they may have a different utilities of effort as is considered in our model.

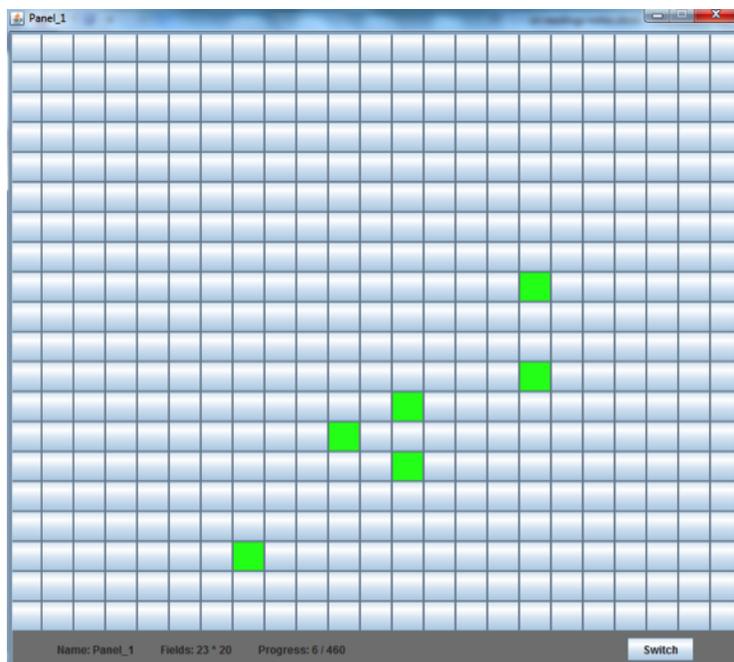


Figure 3: Clicking Task

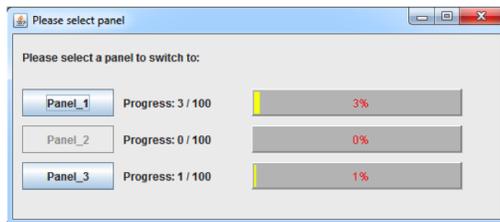


Figure 4: Switching Screen

Holding the actual tasks constant, we then specialize the participants by dividing the field up into thirds, with each individual only able to work in one-third of the field at a time. Each individual has a specialized unique third of the field, and the game begins with them viewing this portion of the field. To work in a different (non-specialized) portion of the field an individual must click “switch” and pay a switching cost equivalent to 18 seconds of effort. Upon clicking the switch button (observable in the bottom right corner of Figure 3), subjects are presented with a switching screen (see Figure 4 for a screenshot). In this screen they can observe the progress made in the other subfields and the participant can choose to switch and then work in the respective subfield.²²

Subjects in our experiment were also permitted to browse the internet during the experiment, acting as the outside option. And the imposed 9 second delay between clicks served to make the option more enticing. A browser window displaying Google.com was open on their desktop at the time of the experiment and, informally, we observed about half of the participants using the internet. In each of 2 experimental rounds, participants had 13 minutes time to work on their subfield and/or switch to another subfield and work there. Thus if every individual fully specialized the maximum production within a subfield would be 13 minutes times 60 seconds divided by 9 seconds waiting time per click, or 86. An individual in group j 's payoff is determined by

$$\$5 + \frac{\$20 * \min(\sum_i y_{ij1}) + \$20 * \min(\sum_i y_{ij2})}{3 * 86}$$

²²Subjects must pay the switching cost before observing this screen.

This payoff includes a \$5 show-up fee plus \$20 times the minimum production y within a subfield i in both round 1 and round 2. These round-specific payoffs are then split evenly among the group (there are 3 people per group and thus they are divided by 3) as well as normalized by the maximum possible production (divided by 86). Thus the maximum payoff within this game is just over \$18 for each individual.

After Period 1, i.e. the first 13 minutes, subjects were given information on the performance of their group. Subjects observed their group production for the round— $\min(\sum_i y_{ij1})$ —and were reminded of the maximum number of clicks (86) for context. They then repeated the task again in period 2 with the same group.

4.2 Trust Manipulation

In order to manipulate different trust environments, we use a method that is similar to the one proposed by Bartling et al. (2013). We prime the trust of individuals by presenting them with actual examples of past performance in this task, taken from a pilot study. We present this information neutrally, describing it as “an actual example of a subject’s performance in a game played previously”.²³ While the text is the same for all subjects, the examples are different. The primes are included in Figure 5: Panel (a) for the “Low Trust” treatment and Panel (b) for the “High Trust” treatment. Subjects were told that “The Red Line shows the total number of clicks possible” and “The Blue Bars show the actual (cumulative) number of clicks.”²⁴

Because subjects read the instructions and learned about the task beforehand, we expect that this prime affects their beliefs about others’ perception of the task. Bénabou & Tirole (2003) refer to this as the “trust effect” which is the belief about another’s “cost or pleasure of accomplishing the task” (p. 494). They contrast this with a “profitability effect” which comes from receiving information about another person’s ability. Differing beliefs about

²³It was made clear to the participants beforehand that the experiment would involve no deception.

²⁴The data was taken from a pilot experiment using the same game, but in which there was a longer delay imposed between clicks and thus the maximum was lower than 86.

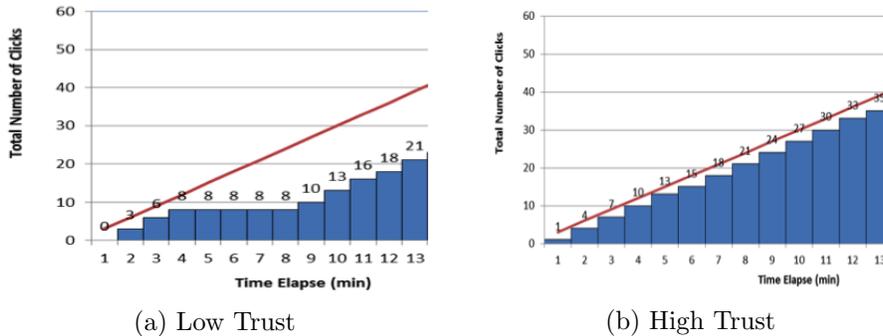


Figure 5: Trust Manipulation

ability are unlikely in our experiment, since the task is simply clicking a mouse every nine seconds. To further ensure that we were manipulating trust, we asked subjects in a post-experimental survey to recall how trustworthy they believed their team was (on a scale of 1-7) “as they began the task” and “at the end of the task.”²⁵ Among the subjects who responded we find a significant difference in how trustworthy they thought their team was at the end of the experiment, as well as how likely they were to experience a decline in trust. Subjects in the “Low Trust” condition are significantly more likely ($p < 0.05$)²⁶ to report a lower “trustworthy” rating after the experiment than those in the “High Trust” condition. Subjects in “Low Trust” were also significantly more likely to exhibit an overall decrease in trust (“trust after” minus “trust before”), and the mean change in trust was negative in low trust groups (-0.285).

4.3 Procedure

We conducted the experiment at the Columbia Experimental Laboratory for the Social Sciences (CELSS), using 63 Columbia University undergraduates who were recruited via ORSEE (Greiner, 2004). There were 3 sessions lasting approximately 45 minutes apiece. A show up fee of \$5 combined with

²⁵This survey was voluntary and there was some observed attrition (10 of the 63 subjects did not complete the survey) which reduces our number of observations somewhat.

²⁶All reported p values are from OLS regressions clustered at the group level unless otherwise noted.

the incentivized earnings produced an average payoff of \$15 per subject. Participants were unaware of the nature of the experiment before entering the laboratory.

5 Experimental Results

In the following, we treat the number of task switches as examples of generalist behavior and we measure the effect of trust on generalist behavior on the intensive and extensive margins. We define a task switch as occurring when one subject switches to another’s field and then proceeds to click one or more times on this non-specialized field, switching back to the specialized task is costless and not counted as a task switch. Monitoring switches—in which one switches to another field but then (costlessly) switches back without working—were possible in this game but somewhat uncommon. Of the 131 acts of switching we observe, only 14 (10.6 percent) were monitoring switches. We test whether there is a significant effect of trust on a pure monitoring switch, and the results are insignificant ($p=0.86$) with a coefficient of .01. While the inclusion of these monitoring switches does not substantively impact our results (see Appendix C), we exclude them for our main analysis and focus on task switching, in which subjects actually work on non-specialized tasks.

Figure 6 presents the number of switches in a cumulative distribution function (CDF) for both treatments. The figure shows clearly the difference between the treatments in specialized behavior. In the High Trust treatment, 66 percent of the participants fully specialize, i.e. they never switched to another field. In stark contrast, only 28 percent of participants in the Low Trust treatment never switched, i.e. fully specialized on their field. The figure shows not only that there are differences on the extensive margin but also that the number of switches are higher in the Low Trust treatment (on average, subjects in this treatment switched 0.92 times) compared to the High Trust treatment (0.5 switches).

While Figure 6 pools our observations across both periods, Figure 7 shows the trend in specialist behavior across periods. While we observe posi-

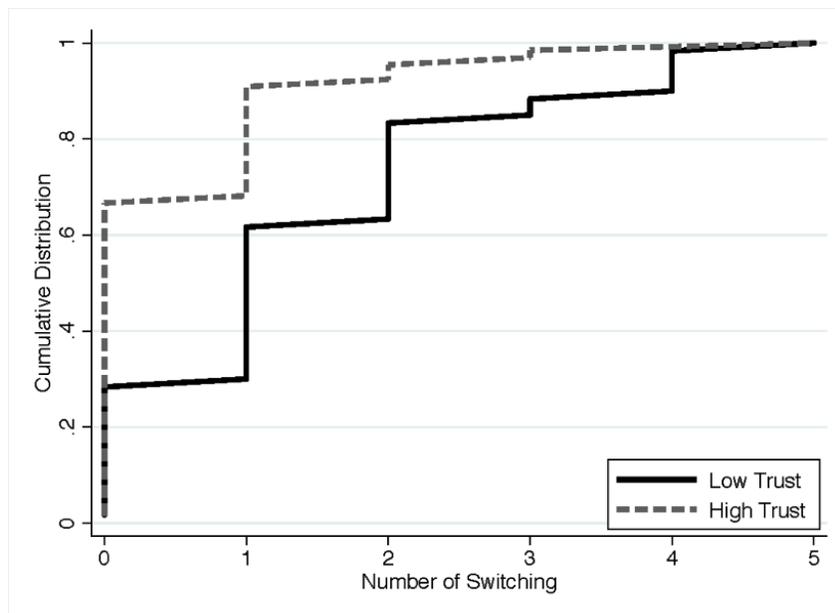


Figure 6: A CDF Representation of Specialist Behavior by Condition

tive trends in specialization across both conditions, the increase in specialist behavior is only significantly different in the High Trust treatment. Using a logit regression on specialization and clustering at the group level, the high trust groups demonstrably improve from Period 1 to Period 2 ($p < .05$), while the change for the low trust groups is not significant ($p = .26$). The differences between the two treatments in the time trend is, however, not significant on any conventional level. But the point estimate indicates that the difference in division of labor in the two environments intensifies over time.

Table 2 shows the results of the Figure 6 and Figure 7 in a regression framework in which the dependent variable in column (1) is a dummy variable that is 1 if a participants fully specialized, i.e. never switching, and 0 otherwise. In model (2), the dependent variable is a count measure on the number of switches. Standard errors are clustered on the group level.

The table confirms the results from the figures: the High Trust treatment increases the probability of fully specializing behavior by 34.3 percent ($p <$

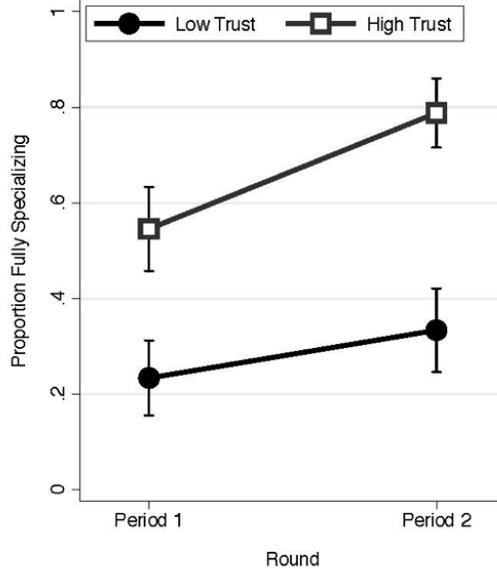


Figure 7: Division of Labor over Time

0.05). The High Trust treatment also decreases the number of switches (Column 2). Participants in the High Trust treatment exhibit 1.036 fewer switches than participants in the Low Trust treatment. The coefficients on “Round” show that for participants in the Low Trust treatment, the incidence of fully specializing increases somewhat but this increase is not statistically significant ($p = 0.25$). The interaction “High Trust x Round” indicates that for the High Trust treatment specialized behavior increase further ($p = 0.327$). While the difference in the time trend between the treatments is not statistically significant, the increase in specialized behavior is statistically significant for the High Trust treatment ($p < 0.05$).

The results so far show that creating a high trust environment endogenously leads to more specialization and less switching tasks. One possible explanation for increased specialized behavior in the high trust groups is that the high trust manipulation might have induced more effort, perhaps because the prime functions as an anchor. However, our prime does not specify that the clicks were made in a specialist field, and thus it is not triv-

Table 2: The Causal Impact of Trust on Division of Labor

Dependent Variable	(1) Specialize Dummy	(2) # of Switches
High Trust (=1)	1.372** (0.623) [0.343]	-1.036** (0.473)
Round	0.496 (0.434) [0.124]	-0.667** (0.293)
High Trust \times Round	0.633 (0.646) [0.158]	0.273 (0.331)
Constant	-1.190** (0.472)	1.733*** (0.381)
R-squared		0.190
N	126	126

Note: Results from a logit (1) and an OLS (2) regression, robust errors clustered at the group level and reported in parentheses. Marginal effects reported in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

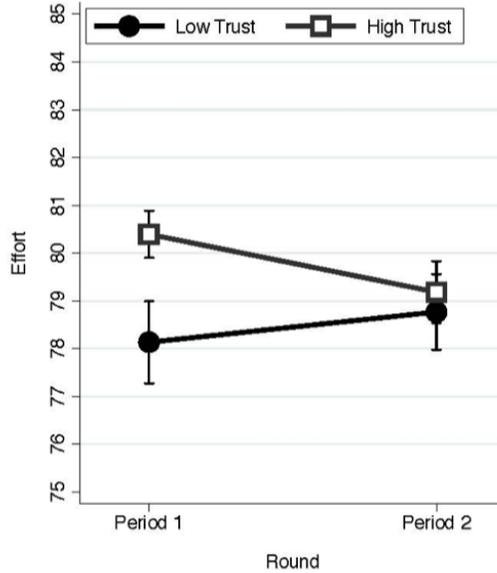


Figure 8: Effort across Periods and Treatments

ial that specializing would be a straightforward result from a “high effort” anchor. Figure 8 plots effort levels in the two treatment for the two periods together. There are no significant differences in effort overall ($p=.13$). Splitting the sample by round, round 1 effort is higher in the High Trust treatment compared to the Low Trust treatment ($p < 0.05$), and there is no difference in effort in round 2. Thus, even with indistinguishable effort in round 2, the Low Trust groups exhibit significantly less specialization.

In sum, the experimental evidence shows that exogenously changed trust levels affect how specialized members of a group work together. In a high trust environment, we observe more division of labor, i.e. individuals work on their specialized task and do not switch as often to the task of others. As a result, they also earn more. Payoffs are \$15.10 in High Trust groups versus \$14.56 in Low Trust groups ($p < 0.01$). Trust makes groups more specialized and more productive, with level of specialization seem to increase over time. The experimental approach allows us to provide internally valid effects of our manipulation (trust) on our outcome measure (division of labor), which

complements the results from the cross-country analysis (section 3).

6 Conclusion

This paper investigates whether differences in corporate culture can explain the emergence of different organizational structure, especially different degrees of division of labor. We begin our study with a model of the effect of trust on organization form, and then provide evidence on the cross-country correlation between trust and the division of labor. We then experimentally evaluate a productive group that can attain different levels of productivity depending on its level of division of labor. This provides causal evidence on the question of trust and division of labor by showing in an experiment that exogenously ‘shocking’ an organization with high or low trust levels leads to the emergence of different degrees of division of labor. This evidence suggests that one aspect of corporate culture—trust—can have an effect on corporate performance through organizational structure. Demonstrating that trust affects organizational structure is important both because it sheds light on the nature of firms—an age-old puzzle in economics and strategy—and also because it represents a plausible mechanism which could drive the relationship between trust and economic growth.

While the experimental evidence provides high internal validity, the cross-country evidence is high on external validity. Taken together, these two pieces of empirical evidence provide a solid foundation to study further the effect of trust on division of labor.

While demonstrating the causal impact of trust on specialization, this paper raises several important questions and points to areas where further research is needed. Of major interest is how easy it is to change an existing culture of trust, since levels of trust can have long-lasting effects on organizations. To that end it would be useful to document how start-ups confront this problem by establishing strong cultures. Additional field evidence in this vein would be of significant value. There is also the matter of trust as only one component of corporate culture, but of course culture extends far beyond this and it thought to determine orientations toward innovation,

fairness, experimentation and more (O'Reilly et al., 1991). Finally, it could be very useful to analyze the effect of trust on the span of control, including task division as well as task allocation. The relationships among organizational form and these other aspects of culture should prove to be a fruitful avenue of exploration.

References

- Akerlof, G. A. (1982). Labor contracts as partial gift exchange. *The Quarterly Journal of Economics*, 97(4), 543–569.
- Alchian, A. A. & Demsetz, H. (1972). Production, information costs, and economic organization. *The American Economic Review*, (pp. 777–795).
- Algan, Y. & Cahuc, P. (2010). Inherited trust and growth. *The American Economic Review*, 100(5), 2060–2092.
- Almazan, A. & Molina, C. A. (2005). Intra-industry capital structure dispersion. *Journal of Economics & Management Strategy*, 14(2), 263–297.
- Arrow, K. J. (1962). The economic implications of learning by doing. *The Review of Economic Studies*, 29(3), 155–173.
- Bartling, B., Fehr, E., & Huffman, D. (2013). Institutions and the causal effect of trust. *Working Paper*.
- Becker, G. S. & Murphy, K. M. (1992). The division of labor, coordination costs, and knowledge. *The Quarterly Journal of Economics*, 107(4), 1137–1160.
- Bénabou, R. & Tirole, J. (2003). Intrinsic and extrinsic motivation. *The Review of Economic Studies*, 70(3), 489–520.
- Bloom, N., Sadun, R., & Van Reenen, J. (2012). The organization of firms across countries*. *The Quarterly Journal of Economics*, 127(4), 1663–1705.
- Bohnet, I., Greig, F., Herrmann, B., & Zeckhauser, R. (2008). Betrayal aversion: Evidence from brazil, china, oman, switzerland, turkey, and the united states. *The American Economic Review*, 98(1), 294–310.

- Camerer, C. & Weber, R. (2013). Experimental organizational economics. *The Handbook of Organizational Economics*, (pp. 213).
- Chandler, A. D. (1990). *Strategy and structure: chapters in the history of the industrial enterprise*, volume 120. MIT press.
- Chatterji, A., Findley, M., Jensen, N. M., Meier, S., & Nielson, D. L. (2015). Field experiments in strategy research. *Strategic Management Journal*, forthcoming.
- Covey, S. M. (2006). *The speed of trust: The one thing that changes everything*. Simon and Schuster.
- Crockett, S., Smith, V. L., & Wilson, B. J. (2009). Exchange and specialisation as a discovery process*. *The Economic Journal*, 119(539), 1162–1188.
- Croson, R., Anand, J., & Agarwal, R. (2007). Using experiments in corporate strategy research. *European Management Review*, 4(3), 173–181.
- Falk, A. & Zehnder, C. (2013). A city-wide experiment on trust discrimination. *Journal of Public Economics*, 100(C), 15–27.
- Feenstra, R. C., Inklaar, R., & Timmer, M. (2013). *The next generation of the Penn World Table*. Technical report, National Bureau of Economic Research.
- Fehr, E. (2009). On the economics and biology of trust. *Journal of the European Economic Association*, 7(2-3), 235–266.
- Fehr, E., Kirchsteiger, G., & Riedl, A. (1998). Gift exchange and reciprocity in competitive experimental markets. *European Economic Review*, 42(1), 1–34.
- Fehr, E. & List, J. A. (2004). The hidden costs and returns of incentives, trust, and trustworthiness among ceos. *Journal of the European Economic Association*, 2(5), 743–771.
- Fershtman, C. & Gneezy, U. (2001). Discrimination in a segmented society: An experimental approach. *Quarterly Journal of Economics*, 116(1), 351–377.
- Gambetta, D. (2000). Can we trust trust. *Trust: Making and breaking cooperative relations*, 2000, 213–237.

- Gibbs, J. P. & Poston, D. L. (1975). The division of labor: Conceptualization and related measures. *Social Forces*, 53(3), 468–476.
- Girmscheid, G. & Brockmann, C. (2009). Inter-and intraorganizational trust in international construction joint ventures. *Journal of Construction Engineering and Management*, 136(3), 353–360.
- Glaeser, E. L., Laibson, D. I., Scheinkman, J. A., & Soutter, C. L. (2000). Measuring trust. *Quarterly Journal of Economics*, 115(3), 811–846.
- Greiner, B. (2004). An online recruitment system for economic experiments. *Forschung und wissenschaftliches Rechnen*.
- Guiso, L., Sapienza, P., & Zingales, L. (2008). Long term persistence. *NBER Working Paper*, 14.
- Guiso, L., Sapienza, P., & Zingales, L. (2014). The value of corporate culture. *Journal of Financial Economics*.
- Kimbrough, E. O., Smith, V. L., & Wilson, B. J. (2008). Historical property rights, sociality, and the emergence of impersonal exchange in long-distance trade. *American Economic Review*, 98(3), 1009–1039.
- Kimbrough, E. O., Smith, V. L., & Wilson, B. J. (2010). Exchange, theft, and the social formation of property. *Journal of Economic Behavior & Organization*, 74(3), 206–229.
- Knack, S. & Keefer, P. (1997). Does social capital have an economic payoff? a cross-country investigation. *The Quarterly Journal of Economics*, 112(4), 1251–1288.
- Kogut, B. & Zander, U. (1996). What do firms do? coordination, identity, and learning. *Organization Science*, 7(5), 502–518.
- Kreps, D. M. (1990). Corporate culture and economic theory. *Perspectives on Positive Political Economy*, (pp. 109–110).
- Larkin, I., Pierce, L., & Gino, F. (2012). The psychological costs of pay-for-performance: Implications for the strategic compensation of employees. *Strategic Management Journal*, 33(10), 1194–1214.
- Lawrence, P. R. & Lorsch, J. W. (1967). Differentiation and integration in complex organizations. *Administrative Science Quarterly*, 12(1), 1–47.

- McEvily, B., Radzevick, J. R., & Weber, R. A. (2012). Whom do you distrust and how much does it cost? an experiment on the measurement of trust. *Games and Economic Behavior*, 74(1), 285–298.
- Nelson, R. R. (1991). Why do firms differ, and how does it matter? *Strategic Management Journal*, 12(S2), 61–74.
- Nickerson, J. A. & Zenger, T. R. (2008). Envy, comparison costs, and the economic theory of the firm. *Strategic Management Journal*, 29(13), 1429–1449.
- Oliver, D. (2004). *Basketball on paper: rules and tools for performance analysis*. Potomac Books, Inc.
- O'Reilly, C. A., Chatman, J., & Caldwell, D. F. (1991). People and organizational culture: A profile comparison approach to assessing person-organization fit. *Academy of Management Journal*, 34(3), 487–516.
- Palan, N. (2010). Measurement of specialization—the choice of indices. *FIW Working Paper Series*, 062.
- Porter, M. E. (1979). The structure within industries and companies' performance. *The Review of Economics and Statistics*, 61(2), 214–227.
- Puranam, P., Alexy, O., & Reitzig, M. (2014). What's "new" about new forms of organizing? *Academy of Management Review*, 39(2), 162–180.
- Puranam, P., Powell, B. C., & Singh, H. (2006). Due diligence failure as a signal detection problem. *Strategic Organization*, 4(4), 319–348.
- Raveendran, M., Puranam, P., & Warglien, M. (2015). Emergence and stability of the division of labor: Experimental evidence. *Management Science*, forthcoming.
- Ross, E. A. (1896). Social control. *The American Journal of Sociology*, 1(5), 513–535.
- Santos, F. M. & Eisenhardt, K. M. (2005). Organizational boundaries and theories of organization. *Organization Science*, 16(5), 491–508.
- Sapienza, P., Toldra-Simats, A., & Zingales, L. (2013). Understanding trust. *The Economic Journal*, 123(573), 1313–1332.
- Schein, E. H. (2010). *Organizational culture and leadership*, volume 2. John Wiley & Sons.

- Smith, A. & Nicholson, J. S. (1887). *An Inquiry Into the Nature and Causes of the Wealth of Nations...* T. Nelson and Sons.
- Sørensen, J. B. (2002). The strength of corporate culture and the reliability of firm performance. *Administrative Science Quarterly*, 47(1), 70–91.
- Tabellini, G. (2008). Presidential address: Institutions and culture. *Journal of the European Economic Association*, 8(4), 255–294.
- Vanneste, B., Puranam, P., & Kretschmer, T. (2013). Trust over time in exchange relationships: Meta-analysis and theory. *Strategic Management Journal*, forthcoming.
- Wan, W. P. & Hoskisson, R. E. (2003). Home country environments, corporate diversification strategies, and firm performance. *Academy of Management Journal*, 46(1), 27–45.
- Woodward, J. (1965). *Industrial organization: theory and practice*. Oxford University Press.
- Zanini, M. T. (2007). *Trust Within Organizations of the New Economy: A Cross-industrial Study*. Springer-Verlag.

For Online Publication Only

Appendix

A Construction of a measure for the division of labor

Existing measures of specialization, such as the Krugman Specialization Index, are suited to analyzing a country's level of industrial specialization. Though there are several of these measures (an overview of which is provided in Palan (2010)) they focus on the extent to which an industry dominates the output of a country. Our model offers no clear prediction for a relationship between industrial concentration and trust, thus we constructed a measure based on Gibbs & Poston (1975). Recall from the main text that an industry j 's d -score is calculated as follows:

$$d_j = \frac{\sum_{i=1}^n x_{ij}^2}{(\sum_{i=1}^n x_{ij})^2}$$

Where n is the number of possible occupations and x is the number of individuals in that occupation. The matrix in Table A1 (adapted from Gibbs & Poston) provides some intuition about how this measure changes with the distribution of individuals within occupations and industries.

To further establish the suitability of the d -score as measure of the division of labor we consider it in well-established theoretical contexts. A regression of GDP on d provides evidence that the division of labor is, in fact, associated with the wealth of nations ($p < 0.01$). Industries with the highest observed d -score include "public administration" (judiciary and police force, etc.) and "specialized construction activities". Industries that receive the lowest d -scores include fishing and ore mining. The mean country-industry d -score we observe in the sample is 0.72 with a standard deviation of 0.24.

Table A1: Simulated d -scores

	Ind 1	Ind 2	Ind 3	Ind 4	Ind 5	Ind 6	Ind 7	Ind 8
occup.								
x_1	0	1	20	20	1	1	20	1
x_2	0	1	5	0	3	0	20	1
x_3	0	1	0	0	2	1	20	1
x_4	0	1	0	0	0	1	20	1
x_5	200	1	50	20	3	1	20	1
x_6	0	1	0	20	0	1	20	1
x_7	0	1	40	0	2	1	20	1
x_8	0	1	60	20	2	1	20	1
x_9	0	1	0	0	2	1	20	1
x_{10}	0	191	25	20	2	1	20	1
d	0	0.09	0.78	0.8	0.87	0.89	0.9	0.9

B Experimental Instructions

Instructions for Participants

Welcome and thank you for participating in our economic decision-making study. If you read and follow these instructions carefully, you can, depending on your decisions and the decisions made by other participants, earn a considerable amount of money. It is therefore important that you take the time to understand the instructions. **IMPORTANTLY:** All the information provided here is correct, and all the payments will be made as promised. So there is **NO DECEPTION** involved. Also, all participants read the exact same instructions for each treatment.

After the experiment your earnings will be paid to you privately, including your show up fee of \$5 and any additional money you have earned.

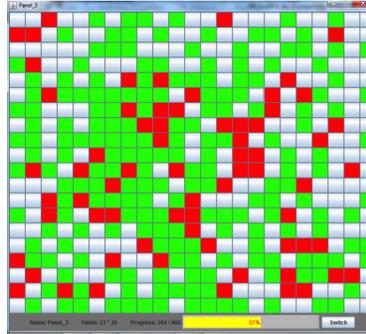
Overview of the experiment

Each and every participant in this experiment is assigned to the same “worker” role. You will be paired with other participants in groups of three to work on a task.

The experiment has 2 periods each lasting 13 minutes. In each period you will be assigned to a group with two others to work on a task. At the outset, participants will be matched randomly. **Details of the experiment**

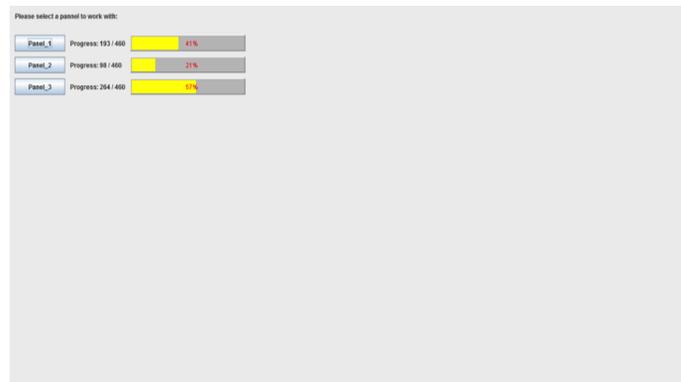
- In the group of three, each worker will click to de-mine a portion of a larger minefield. The field is divided into thirds: Portion A, Portion B, and Portion C.
- Initially, each worker is placed into a different portion. Workers can choose to work on the same portions of the larger field or different portions.
- Workers de-mine a field by clicking one square in it. After each click there is a 9 second re-charge required before another square can be de-mined.
- Participants are free to use the internet as they please during this experiment. Details of your usage will not be tracked by the experimenters.
- After beginning work on one portion of the larger field, a worker can switch to another portion at a cost.

Screenshot for de-mining



Details of switching To switch to a different portion than the one they started in, a worker must pay a cost of 2 clicked squares. So if a worker has 30 squares clicked prior to switching, that player’s progress will be reduced to 28 upon the switch. If a worker opts to switch, they will then observe the progress made in each of the other portions of the field and they will be given the opportunity to work on one of those fields if they so choose. At any point during their work on the other field a worker can return to the field they started from without paying a cost by clicking “switch back.” **Note that the “switch” button incurs a cost while the “switch back” button does not.**

Example of a screenshot after switching



Procedure

Once a period begins groups are free to begin de-mining fields as they see fit. Each period will last approximately 13 minutes, at which point group

and individual payoffs will be computed for that period. Players will be able to observe their group's output and then the second round will begin, with the rules remaining the exact same as in the first period.

The calculation of payoffs will be as follows: each group will be paid according to the progress made in the least complete portion only. The amount completed in the least-complete portion will be multiplied against \$20 (the value of a 100% completed field.) This amount will then be divided equally among the group members. The experiment consists of two such periods, with payments made for both.

At the end of the experiment, after both periods are over, you will be asked to complete a short survey. After a short time we will call you up to receive your payments.

Here are some examples:

- At the end of a period a group has de-mined portions as follows: Portion A 40% complete, Portion B 40% complete and Portion C 30% complete. In this case, the group will receive \$20 times .30, the amount completed of the least-complete field. Each participant will receive one third of this amount for this period.
- At the end of a period a group has de-mined portions as follows: Portion A 60% complete, Portion B 50% complete and Portion C 0% complete. In this case the group (and each participant) will receive 0 for this period.
- At the end of a period a group has de-mined portions as follows: Portion A 50% complete, Portion B 50% complete and Portion C 50% complete. In this case, the group will receive \$20 times .50, the amount completed of the least-complete field(s). Each participant will receive one third of this amount for this period.

Once you have completed reading the instructions please click continue in order to proceed.

C Supplementary experimental analysis

In the main text we exclude “monitoring switches” from our analysis because we believe they are less relevant to the functional division of labor in groups. These are switches in which individuals click “switch” but then do not work on another’s field, and thus there is no actual task overlap. Nevertheless we include these switches in table A2 to show that our results are robust to them.

Table A2: Including “Monitoring Switches”

Dependent Variable	(1) # of ALL Switches
High Trust (=1)	1.08** (0.478)
Round	-0.766** (0.434)
High Trust \times Round	0.342 (0.323)
Constant	1.9*** (0.381)
R-squared	0.190
N	126

Note: Results from an OLS regression, robust errors clustered at the group level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

D Extensions of the Trust and Division of Labor model

Our assumption about constant effort from types is fairly strong since we are implicitly assuming that an agent's incentive problem is either satisfied or not satisfied at all regardless of organizational form. Our conclusions are not impacted substantially when relaxing this assumption. Suppose $\exists \hat{\theta} \in [0,1)$, with $\theta + \hat{\theta} + (1-\theta-\hat{\theta})=1$. $\hat{\theta}$ is the portion of the population for which the participation constraint is only met under full specialization and not under generalization. If no specializing equilibrium exists then this type is indistinguishable from $\underline{\theta}$ as they simply set effort to zero in all cases. This type also has no incentive to unilaterally deviate from generalization so that equilibrium still exists. However, where specialization is an equilibrium, including this type does allow specialization to payoff dominate at a lower level of trust, since $(\theta + \hat{\theta})e > \theta e$.

We also have ignored the task-coordination problem inherent in the specializing equilibrium. That is, we have assumed that if both workers specialize then they specialize in different tasks. Note that the generalizing equilibrium has no such task-coordination problem. Assuming that no task coordinating device exists then the conditions on the existence of the specializing equilibrium become more stringent, $\frac{\theta e}{2} \geq \frac{e}{2\alpha}$, and trust and/or gains from specialization must be higher than in the baseline to ensure the equilibrium. The same is true for the conditions on payoff dominance and risk dominance. See Figure A1 for the model's results including task-coordination problems.

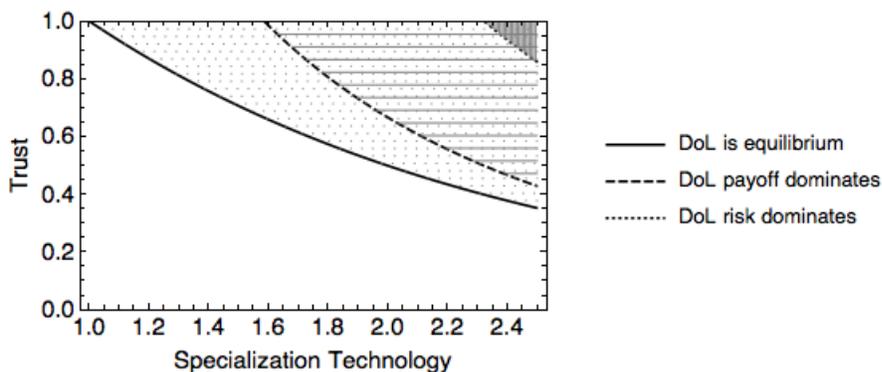


Figure A1: Specialization under Task Miscoordination