

Institutions and the Sectoral Organization of Production

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Abstract

The impact of economic institutions on development is presently taken for granted but there is surprisingly scarce evidence on the channels through which institutions affect the organization of output. Imperfections in contractual enforcement, for example, could lead firms to adopt technologies that inefficiently minimize dependence on other sectors, thus going hand in hand with a reduction in productivity. Another channel would be the concentration of economic activity in sectors that have fewer interactions with other sectors. Using a dataset on manufacturing, this paper presents empirical evidence supporting both effects: better contractual enforcement raises relatively more the labor share of sectors that interact more with other sectors; further, good governance also boosts relatively more labor productivity in more complex subsectors of manufacturing. Both effects are strongest among countries whose labor productivity ranks in the second and third quartiles of the world productivity distribution and they are mute for the two extreme groups of poor and developed economies.

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1 Introduction

The impact of economic institutions on development is presently taken for granted (for landmark references see e.g. Knack and Keefer (1995), Hall and Jones (1999), Acemoglu, Johnson and Robinson (2001), and Acemoglu and Robinson (2012) and references therein for a detailed and comprehensive literature overview) but there is surprisingly scarce evidence on the channels through which institutions affect the organization of output. In this paper, we examine the implications of poor contractual enforcement for the organization of output across sectors.

Imperfections in contract enforcement raise the cost of interacting with others. This suggests that, in environments where such frictions are important, firms would economize on interactions with other firms or economic agents. Conditional on the production of a given good, they would have incentives to adopt more in-house production and avoid acquiring inputs and services from outside the boundaries of the firm (this would be the case provided the contracting costs internal to the firm were less severe than those associated with outside parties). Thus, the quality of contractual enforcement would determine the choice of technology, with less efficient technologies going together with poorer institutions. We label this effect the “productivity effect.”

Another way in which contractual enforcement could affect the organization of output, a consequence of the former effect, is by shifting resources toward sectors that interact less with others. This would follow from the fact that costly contractual enforcement would lower input productivity relatively more in sectors where the interaction with other sectors is important and thus reduce labor demand in those sectors. We label this effect the “allocation effect.” The change in the allocation of labor across sectors could take place despite the choice of technology not suffering significant reductions in *measured* productivity: it could simply be the case that firms only produce when they can use an efficient technology and, whenever contractual imperfections impose too high a cost on a given sector, there is simply no output there. In this scenario, we would see important shifts in the way labor is allocated across sectors (better contractual enforcement raising the labor shares of more complex sectors) but with productivity not being systematically affected by enforcement quality. Of course both effects on the organization of output could take place simultaneously.

The idea that technology choice is influenced by the institutional environment has received some attention in the literature. In the context of a Ricardian trade model, Costinot (2009) offers microfoundations for ways in which contractual imperfections may affect the productivity of firms and comparative advantage. In his model, better institutional quality and higher human per worker capital are complementary sources of comparative advantage. Acemoglu, Antràs and Helpman (2007) build on the ideas of Costinot to propose a tractable general equilibrium model showing that contractual imperfections (contractual incompleteness) leads to the adoption of less advanced technologies, and that the impact of contractual incompleteness is more pronounced when there is greater complementarity among the intermediate inputs. They further argue (by resorting to a stylized simulation) that the frictions they consider are a quantitatively important source of productivity differences across countries. As in Costinot, they make the case that institutions are a source of comparative advantage.

On the empirical side, Nunn (2007) and Levchenko (2007) show that institutions are an important determinant of the direction of trade flows and, as such, of comparative advantage. Nunn shows that countries with good contract enforcement specialize in the production of goods for which relationship-specific investments are most important. According to his estimates, contract enforcement would explain more of the pattern of trade than physical capital and skilled labor combined. Levchenko extends a Heckscher-Ohlin model to incorporate institutional quality and shows that only the country with better institutions will produce the good where more than one input is required. He finds wide empirical support for the positive effect of institutional quality on comparative advantage.

On a different but related front, Koren and Tenreyro (2007) show that developing countries have disproportionately large labor shares in sectors with high volatility, both idiosyncratic as well as global sectoral risk. Their variance decomposition indicates that more than half the differential in output volatility between the top 5% and the bottom 5% countries in terms of GDP per capita is due to differences in the sectoral allocation of output. This evidence poses a big question mark on the reasons behind such apparently suboptimal allocation of labor to sectors.¹ Our results indicate that institutional quality

¹We label this pattern suboptimal because it differs from that of developed countries as documented in Koren and Tenreyro. Presumably, more developed economies face less restrictions in the choice of

is an important part of the answer.

Estimates of the sectoral impact of institutions on trade patterns bundle together productivity and allocation effects. Comparative advantage in institutionally dependent sectors is interpreted as resulting from the impact of institutions on technology which could then raise labor demand and the labor share and output of those sectors relative to others. The goal of this paper is to examine the impact of institutions on the organization of domestic output by separating the productivity and labor allocation channels and without confining it to the relevance of a country's openness to trade. We will do so by focussing on the decomposition of output per worker in a country as the product of the share of workers in a given sector times the labor productivity of that sector. By regressing the sectoral labor share on the product of institutional quality and an index of the complexity of a sector's interactions with other sectors (together with country and sector dummies), we will be able to assess whether or not institutions disproportionately shift production toward sectors whose complexity necessarily requires greater institutional quality. This is the first attempt we are aware of of empirically isolating the impact of institutions on the allocation effect explicitly and beyond the impact of trade. Further, we will try to answer the question of whether institutional quality also affects the choice of technology by regressing the second factor, labor productivity, on the same product of institutional quality and sectoral complexity. In this endeavour, we second Cowan and Neut (2007) who carry out a direct test of the productivity effect for a broad cross-section of countries, focussing on the manufacturing industry.

Using a dataset on manufacturing, this paper presents empirical evidence supporting both effects: better contractual enforcement raises relatively more the labor share of sectors that interact more with other sectors; further, good governance also boosts relatively more labor productivity in more complex subsectors of manufacturing.² Both effects are strongest among countries whose labor productivity ranks in the second and third quartiles of the world productivity distribution and they vanish among developed technology and in the sectoral allocation of output.

²Here, we replicate the findings of Cowan and Neut, also performed on manufacturing subsectors. Our quantitative estimates are similar to theirs (see, e.g., on Table 3, the columns for "Rule of Law" and "Efficiency of the Judiciary"). We also examine a different dataset of developed economies but with more sectors, and find no evidence of institutional impact on the organization of output in relation to the complexity of a sector's interactions with other sectors.

economies. Overall, the evidence strongly supports the effect of governance on the way labor is allocated across sectors, with those that are more complex and thus more contract dependent receiving disproportionate shares of labor when good law enforcement is present.

Our paper is also related to recent work by Herrendorf and Valentinyi (2012) and Hsieh and Klenow (2009) among others. Relative to the literature, Herrendorf *et al.* propose a finer, five-sector decomposition of aggregate output to identify which sectors contribute the most to the lower total factor productivity (TFP) of developing countries. They find that, in equipment, construction, and food the sectoral TFP differences between developing countries and the United States are much larger than in the aggregate. However, in manufactured consumption the sectoral TFP differences are about equal to the aggregate TFP differences, and in services they are much smaller. Our results on the productivity effect are complementary to these.

Hsieh and Klenow (2009) find sizeable differences in the productivity of both labor and capital across firms within a given industry in both India and China, as compared to the United States. Were capital and labor reallocated to equalize marginal products to the extent observed in the United States, they estimate manufacturing TFP gains of 30%–50% in China and 40%–60% in India would materialize. This resonates with our findings, though our data only allows us to analyze productivity effects at the sectoral level.

We believe our results are one more piece in the puzzle of understanding aggregate productivity. Institutions have implication that are deeper than their direct effects on productivity alone and this paper follows up on the most logical and immediate consequence of institutionally impacted productivity differentials, the effect of productivity on labor shares.

2 Model and Estimation Procedure

2.1 Model

We begin with the following decomposition of value added per worker in a given country:

$$\frac{Y_c}{L_c} = \sum_{i=1}^N \underbrace{\frac{Y_{ic}}{L_{ic}}}_{\text{Labor productivity in sector } i} \underbrace{\frac{L_{ic}}{L_c}}_{\text{Share of sector } i \text{ in total employment}} \quad (1)$$

where c denotes country and i is for sector. Y_c is value added in country c and L_c the number of workers engaged in the production of Y_c . Y_{ic} and L_{ic} are value added and employment at the sector level, and there are N sectors of activity in the economy. Equation (1) shows that output per worker can be split into a sum of a product of two factors, namely labor productivity in a given sector and that sector's share of total employment.

We think of output in sector i being generated by a production function $A_i(\mathcal{C}_c) F\left(K_i, L_i, \sum_{j=1}^{J_i} X_j; \mathcal{C}_c\right)$ where \mathcal{C}_c is a measure of the quality of contractual enforcement in country c , A_i a measure of total factor productivity in sector i possibly affected by the quality of contractual enforcement, K_i and L_i inputs of capital and labor employed in this sector and X_j the amount of intermediate inputs acquired by sector i from sector j , out of J_i sectors with whom sector i transacts:

$$Y_{ic} = A_i(\mathcal{C}_c) F\left(K_{ic}, L_{ic}, \sum_{j=1}^{J_i} X_j; \mathcal{C}_c\right). \quad (2)$$

We choose to condition the $F(\cdot)$ part of the production function on \mathcal{C}_c to allow for the possibility that the effect of contractual enforcement, if any, affects output beyond its potential impact on TFP. We come back later to this issue.

In line with the literature (see references above), we postulate that lower quality of contract enforcement is harmful for production processes that have many interactions with other parties. If, say, a company has to hire many workers, acquires many inputs from other sectors (and thus from outside sources) and engages a variety of different types of capital, it becomes heavily dependent on these transactions and, as such, on the quality of contractual enforcement to make them happen (and to provide incentives to its business parties toward good outcomes). By comparison, a good that can be produced

using only a few intermediate inputs and which does not require specific capital nor engaging many laborers will be much more insulated from variations in the quality of contractual enforcement. We conclude from here that good contractual enforcement is especially beneficial for sectors that rely heavily on interactions with others.

More formally, we assume that, for two values of contractual quality \mathcal{C}_1 and \mathcal{C}_2 , with $\mathcal{C}_2 > \mathcal{C}_1$,

$$A_i(\mathcal{C}_2) F\left(K_i, L_i, \sum_{j=1}^{J_i} X_j; \mathcal{C}_2\right) > A_i(\mathcal{C}_1) F\left(K_i, L_i, \sum_{j=1}^{J_i} X_j; \mathcal{C}_1\right), \quad (3)$$

$$A_i(\mathcal{C}_2) \frac{\partial F\left(K_i, L_i, \sum_{j=1}^{J_i} X_j; \mathcal{C}_2\right)}{\partial K_i} > A_i(\mathcal{C}_1) \frac{\partial F\left(K_i, L_i, \sum_{j=1}^{J_i} X_j; \mathcal{C}_1\right)}{\partial K_i}, \quad (4)$$

$$A_i(\mathcal{C}_2) \frac{\partial F\left(K_i, L_i, \sum_{j=1}^{J_i} X_j; \mathcal{C}_2\right)}{\partial L_i} > A_i(\mathcal{C}_1) \frac{\partial F\left(K_i, L_i, \sum_{j=1}^{J_i} X_j; \mathcal{C}_1\right)}{\partial L_i}. \quad (5)$$

Equation (3) says that better contractual enforcement will raise output, while equations (4) and (5) indicate that this effect will carry over to the marginal products of labor and capital.

Consider now the effects of reducing contractual quality from \mathcal{C}_2 to \mathcal{C}_1 in a given country, a reduction taking place for exogenous reasons that remain otherwise orthogonal to the functioning of the economy.³ Firms operating competitively equate the marginal product of inputs to their opportunity costs, respectively wages and the interest rate. Since, by assumption, lower contracting quality lowers the marginal product of inputs, it follows that sectors where the reduction in productivity due to lower contracting quality is the greatest would suffer the largest reduction in their optimally chosen input levels. If there is no international factor mobility (closed economy), then full employment of all inputs would require wages and interest rates to decline. If there is factor mobility and the country in question is a small open economy, then factors would migrate. Either way, there would be a shift in input usage toward industries where the productivity effects of lower contractual quality were felt the least and away from those production processes that are contract intensive.

³The effects of institutions on the overall functioning of the economy are empirically captured through country fixed effects.

In terms of the decomposition of sectoral output in (1), we would expect to see lower enforcement quality negatively affect the productivity term. This is the productivity effect. Further, the reallocation of inputs (labor in particular) toward sectors whose productivity is less institution sensitive would raise the labor shares of those sectors. This is the allocation effect. This would mean that an economy with poor institutions could look rather different from an economy with good enforcement quality at the level of sectoral composition. An interesting possibility is that these effects take place in an extreme form: in the presence of fixed costs or other nonconvexities, it could be that firms suffering a reduction in productivity would simply stop producing in those sectors. What we would then observe would be a large shift in labor shares toward institution-independent sectors but without productivity losses. Of course this would still be a manifestation of the productivity effect: it is precisely because of the reduction in productivity that labor is reallocated across sectors. But firms minimize out their losses and so avoid producing in sectors in which they are no longer efficient, causing the productivity reduction not to show.

2.2 Estimation Procedure

From the previous discussion, we set out to estimate the following equations:

$$\frac{L_{ict}}{L_{ct}} = \alpha_1 + \beta_1 \text{enforcement}_{ct} \cdot \text{complexity}_{i,US,t} + \mu_{1i} + \mu_{1c} + \mu_{1t} + \varepsilon_{1ict}, \quad (6)$$

$$\ln \left(\frac{Y_{ict}}{L_{ict}} \right) = \alpha_2 + \beta_2 \text{enforcement}_{ct} \cdot \text{complexity}_{i,US,t} + \mu_{2i} + \mu_{2c} + \mu_{2t} + \varepsilon_{2ict}. \quad (7)$$

with i denoting sector, c country and t time. The interaction terms on the right-hand side cross measures of the quality of contract enforcement with measures of sector complexity given by US sectoral allocations. The terms μ_{1i} and μ_{1c} are sector and country dummies, whereas μ_{1t} is a time dummy. Similar notation applies for equation (7). This regression format was first made popular in the work of Rajan and Zingales (1998). In the present framework, it captures the notion that contractual enforcement is relatively more beneficial for sectors which have more complex productive structures. Because of the cross-country nature of our data, likely to contain a very nonlinear series of productivity values as we go from poorer to richer countries, we chose to perform the productivity regression in logs.

Following the discussion above, we think of contracting costs to be positively related to the intensity of exchanges that a sector has to carry out with other sectors. We label this variable “complexity.” In line with the literature (see e.g. Blanchard and Kremer (1997), Levchenko (2007), Nunn (2007)), we resort to the Input-Output matrix of the United States to measure the degree of concentration of exchanges carried out by each sector. The Herfindahl index is calculated for each sector as follows. First, the column data is transformed into shares (the initial column magnitude is divided by the sum of that column’s total). The Herfindahl index is computed out of these shares for each column, giving a sectoral measure of concentration. The larger the concentration, the least the interaction with other sectors (the Herfindahl index takes the maximum value of unity in the case that a sector’s inputs all come from a single sector). In order to correctly measure complexity, we need its reciprocal and so use $1/\text{Herfindahl}$ as our measure of complexity. As in Rajan and Zingales, we use a measure of complexity from the United States (US) for all countries. The idea is that the productive structure of that country would face the least contracting constraints of all, thus reflecting a kind of “ideal” measure of sectoral complexity.

From the model presented in section 2.1, we expect β_1 to be positive and significant reflecting the allocation effect of contracting quality. To the extent that the productivity effect does not take place in an extreme form, estimates of β_2 should be positive and significant. Insignificant estimates of β_2 would mean that firms opt for dropping production when they face contract-induced productivity losses, in fact an extreme manifestation of the productivity effect.

3 Data and Estimation

3.1 Data

Industrial Statistics We use two main datasets regarding employment, wages and productivity measures. One is INDSTAT2 2012, the Industrial Statistics Database in 2012 (2-digit level of ISIC code, revision 3) from the United Nations Industrial Development Organization (henceforth referred to as the UNIDO dataset). The other is the Organization for Economic Cooperation and Development STAN database for Structural Analysis (henceforth STAN dataset). We collect sectoral employment and productivity

measures (based on value added) from both sources. UNIDO contains only data on manufacturing sectors whereas STAN has a more general sectoral coverage but it only covers developed economies. We find this diversity useful in interpreting the results.⁴

Complexity The measure of complexity comes from the Input-Output US matrix provided in the STAN database and thus the Herfindahl measure computed is also used with the UNIDO dataset. Input-Output data for the US in STAN is only available for the years 1995, 2000 and 2005. For this reason, we can only compute the interaction term for these three years.

Governance Indicators We use the *Worldwide Governance Indicators* (2011) provided by the World Bank. Our preferred measure of the quality of contractual enforcement is the “Rule of Law.” According to the source, Rule of Law “reflects perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.” Thus, the Rule of Law indicator measures instances of the quality of contractual enforcement, as intended. The earliest datapoint for this indicator is 1996 and, as a result, we construct the product of the 1995 complexity measure times the 1996 rule of law. The variables used in the interaction terms for the other years (2000 and 2005) are each measure in the corresponding years.⁵ We also report the results obtained using the other five governance indicators provided by the same source (“voice and accountability,” “political stability,” “government effectiveness,” “regulatory quality,” and “control of corruption”). The results are reassuringly similar across indicators.

3.2 Results

All results are presented in tables placed at the end of the paper. Tables labeled “A” were computed using the UNIDO dataset whereas those labeled “B” come from STAN data. Our preferred functional form for estimation is that described in equations (6)

⁴Tables 9 through 11 at the end contain the list of countries included in each dataset as well as the sectors.

⁵E.g. “rule of law” measured in 2000 times “1/Herfindahl” measured in 2000.

and (7), where the data for all three available years is used. We have also performed individual-year regressions (not shown) and will discuss how the results compare across both alternatives.

3.2.1 Allocation Effect

Baseline Table 1 presents the estimates of equation (6) (only estimates of β_1 are shown). Rule of Law and other measures of governance do influence relatively more the share of labor employed in more complex sectors. The effect is strongest under UNIDO data. Recall that the UNIDO dataset covers many countries but only the manufacturing sector, whereas STAN is not restrictive in terms of activity sectors but, instead, focusses only on OECD countries. Coefficients in UNIDO are very significant (always at the 0.1% level) whereas with STAN statistical significance is not always attained. In fact, for our preferred indicator of contracting quality, “Rule of Law,” the estimate of β_1 is only significant at the 5% level. For other governance indicators, however, such as “Governmental Effectiveness,” “Regulatory Quality” and the “Control of Corruption,” we get significance at the 1% level. Given STAN’s focus on developed economies which have a much lower variance in the governance indicators, the finding of an effect in this restrictive country sample is, in itself, noteworthy.

The magnitude of the effects is not trivial, and this is also the case for the STAN sample. We provide a “back-of-the-envelope” calculation to gauge the magnitude of the effects. Because the dependent variable is in logs, the coefficients are to be interpreted as the percentage change in the labor share of a given sector whenever the interaction variable changes by unity. Thus, in the UNIDO sample, a one unit change in the right-hand side product of enforcement times complexity in a given sector will deliver a 3.7% increase in the labor share of that sector. To put things in perspective, one standard deviation in the Rule of Law indicator is 0.99 and the least complex sector has a complexity index of 1.97. For this sector, a one standard deviation improvement in the Rule of Law would lead to a 7% increase in its labor share. In STAN, our estimate indicates a change of 1.1% in the labor share whenever the right-hand side interaction value changes by unity. In this sample, the standard variation of the Rule of Law indicator is about half of that in UNIDO, 0.55. For the least complex sector (which

happens to be the same as in the UNIDO sample), the percentage change in its labor share that goes together with a one standard deviation improvement in the Rule of Law would be 1.2%.

Time Sensitivity To the extent that the indicators of governance are contemporaneously correlated with the labor share, it would be desirable to use lagged values of those indicators. While the data used to compute the complexity indicator is only available for the three years mentioned above, labor share data is readily available for all years from 1996 till 2007 (and beyond). We thus perform two additional regressions to address endogeneity concerns. We use leading values of the dependent variable, dated one and two years ahead of the interaction term. For example, we construct a series with the 2006, 2001 and 1996 values of the labor share which we regress on the interaction of the complexity and governance indicators measured in 2005, 2000 and 1995. We label this the “one lead” regression. We do the same for the labor share measure two years ahead of the interaction terms (thus regressing labor shares in 2007, 2002 and 1997 on the available interaction years). This is the “two lead” regression. Results are presented in Table 2. Estimates of β_1 are remarkably stable there, for both samples. Because other governance variables had appeared to have greater significance on the labor share in STAN, we extended this dynamic comparison also to “Regulatory Quality” and “Control of Corruption” (not shown). Similar patterns emerged. The stability of the coefficients in the regressions with leading labor shares suggests that endogeneity is not a serious concern for our results.

Additional Controls Next, we include additional controls to check for the possibility that omitted variables might be biasing the results despite our inclusion of country, sector and time dummies. We add sectoral log wages and log value added. Our motivation to include these two additional variables is rooted on the theoretical examination of a firm operating in a competitive environment with a Constant Elasticity of Substitution (CES) production function using capital and labor. The CES technology safeguards the possibility that institutions may affect the productivity of labor and capital in a differentiated manner, an outcome ruled out by the Cobb-Douglas technology. Once we solve for the labor share of such a firm, we find that it depends on the sector’s aggregate

value added and wages, and some other terms. The results are displayed in Table 3 for our preferred indicator, the Rule of Law. In addition to the baseline case in column 1, column 2 adds log wages and column three additionally includes value added. Columns 4 and 5 interact the variable log wages with a sectoral dummy, allowing the effect of wages to be sector specific. This would capture technological differences across sectors in terms of their human capital requirements.

Concerning UNIDO, Table 3A shows that the inclusion of the wages does not reduce the significance of the interaction institutions times complexity term, and the size of the coefficient is only slightly reduced. Because the log of value added is never significant but including it leads to omission of observations due to missing data, we prefer the specifications that do not include it. Comparing columns (2) and (4), we see that the inclusion of log wages with an interaction effect improves the overall fit of the regression (the adjusted R^2 goes up by about 5 percentage points). Thus, our preferred specification is that of column (4).

For STAN, Table 3B portrays a different story. The already marginally significant coefficient of the baseline regression is rendered insignificant once log wages are included, in any of the alternatives described above. We thus conclude that, among developed economies, good contracting quality is not associated with the way in which output is organized across sectors. Here, looking at another governance indicator does not rescue the significance of estimates of β_1 .

Splitting the UNIDO Sample Since the UNIDO sample covers all countries (up to availability of data), we next try to break it into tiers reflecting percentiles of the world’s productivity distribution. The question we want to address is whether the allocation and productivity effects manifest themselves differently in different parts of that distribution. Because we only have value added in manufacturing in the UNIDO sample, we took a measure of output per worker from the Penn World Tables (PWT 7.1). We used the variable “rgdpwok:” PPP converted GDP chain per worker at 2005 constant prices. Year 1995 was chosen since it is the earliest date in our sample. The correlation of rgdpwok with other per person and per worker variables was very close to unity. Countries were then ranked according to this variable and categorized into several groups: 10 or 20% poorest economies, above or below median income, middle 50% (above the 25% poorest

and below the 75% poorest) and, finally, restricted to be also represented in the STAN sample.

Results are displayed in Table 4. Because of attrition in sectoral data, the regressions covering the poorest groups often have significantly fewer observations than those covering wealthier economies. With this caveat in mind, examination of the regressions performed for the 10 and 20% poorest countries finds no trace of a disproportionate effect of institutional quality on complex sectors. There is a strong and very significant effect for economies above median income and the strongest effect (in terms of the β_1 estimate) is found in the economies ranking in the lowest 25%-75% income group. Here, the estimate of β_1 , 0.03722, even exceeds slightly the baseline estimate, 0.03671. Finally, we restrict the sample to countries that are present in the STAN database as well. Though we only have manufacturing subsectors in UNIDO (and STAN contains a much larger sector exposure), the findings are the same as those in the STAN sample in that the effect of interest is not found.

3.2.2 Productivity Effect

Baseline Tables 5A and 5B present estimates of equation (7). Here, there are important differences depending on the sample considered. With UNIDO data, estimates are significant at the 0.1% level for all but one governance indicator. The effects are quantitatively important. As before, because the dependent variable is in logs, estimates of β_2 indicate the percentual change in productivity in a given sector following a unitary change in the interaction term on the right-hand side. Thus, a unitary increment of the product of institutional quality and complexity in a given sector would result in an increase of 1.3% in the productivity of that sector. Using the numbers above, it follows that the productivity of the least complex sector would increase by 2.6% following a one standard deviation increment in that governance indicator (and by 21% in the most complex). Under STAN data, however, involving only OECD countries, estimates are not statistically different from zero.

Time Sensitivity In Table 6, regressions of leading series of productivity values on past complexity and governance interactions are shown, replicating those performed for the allocation effect. The stability of the coefficients and of their significance once again

suggest that endogeneity is not a serious concern.

Additional Regressors We proceed by including additional regressors. Based on the same framework as above (firms operating in a competitive environment under a CES technology), we additionally include log wages, with and without interacting them with sectoral dummies. As in all previous regressions, country, sector and time dummies are included. Results are presented in Table 7. In the UNIDO sample, the size and significance of β_2 estimates are affected by the inclusion of the wage variable. Still significance is always in excess of 5% and the estimate increases slightly in the specification with sectoral interactions, our preferred one. Table 7B reinforces the fact that the productivity effect is not present in STAN.

Splitting the UNIDO Sample We perform additional regressions by splitting the sample in income groups, as above. Results are presented in Table 8. The flavor of the results is the same as above. Attrition makes sample size smaller for poorer economy groups. The effect of interest is not present among poor economies. Once again, evidence supporting a disproportionate impact of contracting quality in complex activity sectors is found in the subsample of economies whose income ranks among the 25%-75% poorest. Estimates of β_2 are more than twice as large in this subsample compared to the benchmark case. Among STAN economies, there is no effect.

Overall, we see the evidence supporting the allocation and productivity effects among mid-income economies but not so among the wealthy or the very poor.

3.2.3 Simulation Exercise

The UNIDO data suggests that both productivity and allocation effects are at work in the organization of production. It might be tempting to ask the question of which of the two effects is the most relevant. One could, for example, compute the effects of raising the Rule of Law indicator by one standard deviation, calculate the resulting new labor shares and productivities and find out which of the two effects – allocation or productivity – independently contributed to the growth of output per worker. However, because sectoral productivity and complexity are *negatively* correlated, assigning larger labor

shares to complex sectors without simultaneously raising their productivities necessarily results in a reduction of output per worker.

Despite the negative correlation between productivity and complexity, the *change* in sectoral productivity and the change in sectoral labor shares are positively correlated with complexity. If we split the sample in two according to compute the average sectoral productivity across wealth

The following “back-of-the-envelope” calculations suggest that they happen in a coordinated fashion as follows. In the UNIDO sample, sectoral productivity and complexity are negatively correlated. Thus, the thought expe

In order to prod deeper into the relationship between these two effects and output per worker, we perform a simple simulation exercise with the 1995 subsample. We consider a one standard deviation improvement of the Rule of Law indicator and compute the implied changes in sectoral labor shares as well as productivity levels.⁶ We then compute new values of aggregate output per worker by adding up the products of the modified productivity and labor shares. We then see how they compare to the original values of aggregate value added per worker. Because of the need to reshuffle labor across sectors as given by the modified labor shares, in this exercise we restrict the observations to include only countries that have a complete range of sectoral data. This leaves us with 23 countries (out of 145 in the full sample) and 18 sectors. This restriction may not be without consequences for it biases the sample toward wealthier countries. Indeed, 12 out of the 23 countries considered have incomes per worker ranking in the top 25% of the UNIDO sample and only 1 country’s income per worker is in the bottom 25%. Further, only 10 countries have income per worker in excess of the 25% poorest but below the 75% wealthiest. Recall that the middle income range includes the countries where the allocation and productivity effects were significant in our sample. In this restricted sample, there is thus overrepresentation of the wealthy and underrepresentation of the poor.

⁶Because labor shares must add to unity, we perform the following normalization. We first compute the new sectoral labor shares by multiplying one standard deviation in the Rule of Law indicator times the sectoral complexity index and times the estimate of β_1 . We add these new labor shares across all 18 subsectors of manufacturing available in the UNIDO data. Because we are facing an improvement in the Rule of Law, the sum exceeds unity. We compute the average new labor share and subtract the difference of this average to unity from all sectoral labor shares, which then add to one.

We compute first the average growth rate of GDP per worker when both labor shares and productivity are modified as above. Then we compute two other counterfactuals: the average growth rate of GDP per worker (1) with the new labor shares but the initial sectoral productivities and (2) with the original sectoral labor shares but with the new productivity. The results are striking. We find that average GDP per worker increases on average 15.4% as a result of the combined changes in productivity and labor shares; but that it *decreases* on average by 5.04% if we give economies the new labor shares but keep the original productivity. Further, maintaining the initial labor shares but allowing for sectoral productivity to change yields the largest increase in GDP on average, 20.22%.

Table A

	Average Growth Rate of GDP per Worker (%)
New labor share and productivity	15.4
New labor share, initial productivity	−5.04
Initial labor share, new productivity	20.22

Note that, by construction, the computed growth rates of labor shares and productivity are perfectly correlated across countries (because they are the multiple of an estimate of β_1 or β_2 times a sector complexity measure – given by the US measure for that sector – and the common standard deviation of the Rule of Law for the sample). The latter two factors in the product are common across countries for a given sector. Thus, by design, the changes in labor shares put more weight in sectors whose productivity is also being enlarged. How then do we interpret these findings?⁷

They strongly suggest that labor was efficiently allocated to the most productive sectors in its original allocation. Further, they tell us that the gradient of change of the labor shares, given by the product of institutional quality and sectoral complexity, is not in line with the initial configuration of sectoral productivities. If indeed institutions modified labor shares in a direction that were strongly correlated with the original distribution of sectoral productivities, then our exercise would have delivered a positive number also for the second row of Table A. In the limit, this could suggest that, while

⁷Restricting the sample even further to the set of countries to the middle 50% range in terms of GDP per worker does not overturn the results above.

contracting quality affects disproportionately more the productivity of complex sectors, this is not the main determinant of productivity overall; and, should labor shares follow productivity as theory would predict, then labor shares appear not to mimic the product of institutions times complexity because other factors would have greater importance. Before taking on this line of reasoning, we point out that the analysis in UNIDO is confined to subsectors of manufacturing and not to the economy as a whole. It could well be the case that an overall shift of labor away from manufacturing and toward other sectors might lead to an overall enhancement of output per worker.

But let us now suppose that that is not the case: the change in sectoral labor shares is not positively correlated with the existing productivity differentials across sectors. Is this a concern for the quantitative relevance of institutions and contracting quality in the organization of sectoral output? We think not. Factors such as intrinsic technological differences across sectors should definitely have a first-order role in how labor is organized across sectors. In the regressions, they were captured by the fixed effects. What our numbers showed was that, once those are held fixed, contracting quality and other institutional measures of governance still affect in a very large quantitative fashion how labor is allocated across sectors, relatively more so the more complex the sector.

Caselli (2005) performed an accounting exercise similar to the present one in spirit though our results are not directly comparable in a number of dimensions. He noticed that the labor share of agriculture in poor countries is disproportionately large relative to developed economies, and that agriculture is also a very low productivity sector in those countries. He then computed several counterfactuals to assess the impact of this situation: he considered giving poor countries the same labor share in agriculture as developed economies, or to give them the productivity in agriculture attained in the US (and other cases). Giving developing economies the same labor share in agriculture as the US and keeping other things the same (namely productivity in agriculture and in the remaining sectors) reduces cross-country income inequality by about two-thirds. Caselli is effectively taking workers from a low productivity sector and moving them towards other more productive areas of the economy. Thus, output per person can but increase in that case. However, unlike in our case, in this particular simulation he was not trying to address what part of these effects was accountable for by institutions.

4 Conclusion

The evidence put forth in this paper suggests that institutions may play an important role in the allocation of labor across sectors, a new idea in the literature, beyond their direct impact on productivity, which was also documented. These effects were found to take place for economies in an intermediate range of the worldwide distribution of output per worker and to be mute among two extreme groups in that distribution: poor and developed economies. We see our findings as one more piece in the complex puzzle of the determinants of living standards.

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5 Tables

Table 1A – UNIDO data
 Dependent Variable is Log[Labor Share] – cluster(sector,country)

VARIABLES	(1) rule law	(2) voice	(3) polstab	(4) gov effect	(5) reg quality	(6) contr corcpt
herfruleoflaw	0.03671*** (0.006)					
herfvoiceaccount		0.0326*** (0.007)				
herfpolstab			0.0311*** (0.006)			
herfgeffect				0.0366*** (0.006)		
herfregqual					0.0394*** (0.007)	
herfcontcorrupt						0.0289*** (0.005)
Constant	0.77214*** (0.206)	0.5396* (0.228)	1.4905*** (0.315)	0.8173*** (0.201)	0.6720** (0.207)	0.7495*** (0.211)
Observations	4,312	4,321	4,303	4,312	4,312	4,312
Adjusted R-squared	0.507	0.505	0.504	0.507	0.507	0.505

Robust standard errors in parentheses, sector, country and time dummies

*** p<0.001, ** p<0.01, * p<0.05

Table 1B – STAN data
 Dependent Variable is Log[Labor Share] – cluster(sector,country)

VARIABLES	(1) rule law	(2) voice	(3) polstab	(4) gov effect	(5) reg quality	(6) contr corrpt
herfruleoflaw	0.01138* (0.005)					
herfvoiceaccount		0.0098 (0.005)				
herfpolstab			0.0048 (0.004)			
herfgeffect				0.0120** (0.004)		
herfregqual					0.0115** (0.004)	
herfcontcorrupt						0.0114** (0.004)
Constant	-0.65297** (0.251)	-0.7232** (0.237)	-0.5457*** (0.160)	-0.7213** (0.234)	-0.6783** (0.238)	-0.6785** (0.238)
Observations	2,885	2,885	2,885	2,885	2,885	2,885
Adjusted R-squared	0.845	0.845	0.845	0.846	0.846	0.846

Robust standard errors in parentheses, sector, country and time dummies

*** p<0.001, ** p<0.01, * p<0.05

Table 2A – UNIDO data
 Dependent Variable is Log[Labor Share] –
 time sensitivity

VARIABLES	(1) coincident	(2) one lead	(3) two leads
herfruleoflaw	0.03671*** (0.006)	0.03531*** (0.006)	0.03720*** (0.006)
Constant	0.77214*** (0.206)	1.40713*** (0.217)	-0.46103 (0.660)
Observations	4,312	4,389	3,930
Adjusted R-squared	0.507	0.508	0.515

Robust standard errors in parentheses, sector, country and time dummies
 *** p<0.001, ** p<0.01, * p<0.05

Table 2B – STAN data
 Dependent Variable is Log[Labor Share] –
 time sensitivity

VARIABLES	(1) coincident	(2) one lead	(3) two leads
herfruleoflaw	0.01138* (0.005)	0.01189* (0.005)	0.01268** (0.005)
Constant	-0.65297** (0.251)	-0.59559* (0.242)	-0.89269*** (0.239)
Observations	2,885	2,887	2,815
Adjusted R-squared	0.845	0.848	0.850

Robust standard errors in parentheses, sector, country and time dummies
 *** p<0.001, ** p<0.01, * p<0.05

Table 3A – UNIDO data
 Dependent Variable is Log[Labor Share] – cluster(sector,country)

VARIABLES	(1) baseline, rule law	(2) Logw	(3) Logw, v.added	(4) Logw w sect inter	(5) Logw, v.added w sect inter
herfruleoflaw	0.03671*** (0.006)	0.03364*** (0.006)	0.03560*** (0.007)	0.03109*** (0.007)	0.03147*** (0.008)
lwages		0.17240*** (0.065)	0.17650* (0.094)		
lvaproductivity			-0.01264 (0.061)		0.00393 (0.061)
Constant	-2.89917*** (0.618)	-3.71751*** (0.868)	-3.46961*** (0.865)	-6.37771*** (1.318)	-8.02431*** (1.198)
Observations	4,312	3,893	3,436	3,893	3,436
Adjusted R-squared	0.507	0.512	0.512	0.564	0.574

Robust standard errors in parentheses, sector, country and time dummies

*** p<0.001, ** p<0.01, * p<0.05

Table 3B – STAN data
 Dependent Variable is Log[Labor Share] – cluster(sector,country)

VARIABLES	(1) baseline, rule of law	(2) Logw	(3) Logw, v.added	(4) Logw w sect inter	(5) Logw, v.added w sect inter
herfruleoflaw	0.01138* (0.005)	0.00165 (0.002)	0.00291 (0.002)	0.00029 (0.002)	0.00230 (0.002)
lwages_ppp		0.82957*** (0.023)	0.84367*** (0.026)		
lvaproductivity_ppp			-0.25809*** (0.038)		-0.25596*** (0.036)
Constant	-1.79067*** (0.427)	-13.90843*** (0.395)	-18.21151*** (0.781)	-11.66254*** (0.488)	-18.86126*** (0.811)
Observations	2,885	2,050	1,937	2,050	1,937
Adjusted R-squared	0.845	0.968	0.973	0.969	0.974

Robust standard errors in parentheses, sector, country and time dummies

*** p<0.001, ** p<0.01, * p<0.05

Table 4 – UNIDO data
 Dependent Variable is Log[Labor Share], cluster(sector,country)

VARIABLES	(1) Baseline	(2) 10% Richest	(3) 10% Poorest	(4) 20% Poorest	(5) >= Median	(6) < Median	(7) Middle 50%	(8) STAN
herfruleoflaw	0.03671*** (0.006)	0.01105 (0.019)	0.01908 (0.055)	-0.01502 (0.033)	0.03117*** (0.007)	0.02151 (0.017)	0.03722*** (0.010)	0.0135 (0.016)
Constant	-2.89917*** (0.618)	-1.85575 (1.813)	-8.41246 (5.512)	-0.72162 (3.226)	-2.72314** (0.837)	-4.73189** (1.779)	-4.42218*** (0.978)	0.3929 (2.058)
Observations	4,312	669	257	493	2,615	1,697	2,276	1,025
Adjusted R ²	0.507	0.430	0.738	0.586	0.518	0.553	0.578	0.412

Robust standard errors in parentheses, sector, country and time dummies

*** p<0.051, ** p<0.01, * p<0.05

Table 5A – UNIDO data
 Dependent Variable is Log[Productivity] – cluster(sector,country)

VARIABLES	(1) rule law	(2) voice	(3) polstab	(4) gov effect	(5) reg quality	(6) contr corprt
herfruleoflaw	0.01334*** (0.004)					
herfvoiceaccount		0.0182*** (0.004)				
herfpolstab			0.0110** (0.004)			
herfgeffect				0.0160*** (0.004)		
herfregqual					0.0172*** (0.004)	
herfcontcorrupt						0.0118*** (0.003)
Constant	7.51510*** (0.605)	7.5455*** (0.602)	7.5185*** (0.607)	7.5616*** (0.600)	7.5235*** (0.602)	7.5309*** (0.604)
Observations	3,643	3,643	3,643	3,643	3,643	3,643
Adjusted R-squared	0.807	0.808	0.807	0.807	0.808	0.807

Robust standard errors in parentheses, sector, country and time dummies

*** p<0.001, ** p<0.01, * p<0.05

Table 5B – STAN data
 Dependent Variable is Log[Productivity] – cluster(country,sector)

VARIABLES	(1) rule law	(2) voice	(3) polstab	(4) gov effect	(5) reg quality	(6) contr corprt
herfruleoflaw_2	0.00420 (0.004)					
herfvoiceaccount_2		0.0078 (0.006)				
herfpolstab_2			0.0043 (0.004)			
herfgeffect_2				0.0028 (0.004)		
herfregqual_2					0.0022 (0.003)	
herfcontcorrupt_2						0.0020 (0.003)
Constant	10.10037*** (0.391)	10.0070*** (0.607)	10.4256*** (0.342)	10.5005*** (0.425)	10.5669*** (0.339)	10.5861*** (0.338)
Observations	2,543	2,543	2,543	2,543	2,543	2,543
Adjusted R-squared	0.847	0.847	0.847	0.847	0.847	0.847

Robust standard errors in parentheses, sector, country and time dummies

*** p<0.001, ** p<0.01, * p<0.05

Table 6A – UNIDO data
 Dependent Variable is Log[Productivity] – cluster(sector,country)
 time sensitivity

VARIABLES	(1) coincident	(2) one lead	(3) two leads
herfruleoflaw	0.01334*** (0.004)	0.01599*** (0.004)	0.01123** (0.004)
Constant	7.51510*** (0.605)	8.41854*** (0.182)	9.93828*** (0.922)
Observations	3,643	3,782	3,399
Adjusted R-squared	0.807	0.814	0.813

Robust standard errors in parentheses, sector, country and time dummies
 *** p<0.001, ** p<0.01, * p<0.05

Table 6B – STAN data
 Dependent Variable is Log[Productivity] – cluster(sector,country)
 time sensitivity

VARIABLES	(1) coincident	(2) one lead	(3) two leads
herfruleoflaw	0.00420 (0.004)	0.00117 (0.004)	-0.00158 (0.004)
Constant	10.52075*** (0.239)	10.25078*** (0.224)	11.43959*** (0.142)
Observations	2,543	2,548	2,525
Adjusted R-squared	0.847	0.849	0.849

Robust standard errors in parentheses, sector, country and time dummies
 *** p<0.001, ** p<0.01, * p<0.05

Table 7A – UNIDO data
 Dependent Variable is Log[Productivity], cluster(country, sector)

	(1)	(2)	(3)
VARIABLES	Baseline	Log w	Log w w/ sect inter
herfruleoflaw_2	0.01334*** (0.004)	0.00765* (0.003)	0.01457** (0.006)
lwages		0.87176*** (0.045)	
Constant	6.18099*** (0.728)	3.65278*** (1.020)	3.21493*** (1.095)
Observations	3,643	3,473	3,473
Adjusted R-squared	0.807	0.868	0.870

Robust standard errors in parentheses, sector, country and time dummies
 *** p<0.001, ** p<0.01, * p<0.05

Table 7B – STAN data
 Dependent Variable is Log[Productivity], cluster(country,sector)

	(1)	(2)	(3)
VARIABLES	Baseline	Log w	Log w w/ sect inter
herfruleoflaw	0.00420 (0.004)	0.00272 (0.005)	0.00679 (0.005)
lwages_ppp		0.05079 (0.056)	
Constant	10.10037*** (0.391)	9.41174*** (1.442)	9.26696*** (1.311)
Observations	2,543	1,937	1,937
Adjusted R-squared	0.847	0.845	0.856

Robust standard errors in parentheses, sector, country and time dummies
 *** p<0.001, ** p<0.01, * p<0.05

Table 8 – UNIDO data
 Dependent Variable is Log[Productivity], cluster (country,sector)

VARIABLES	(1) Baseline	(2) 10% Richest	(3) 10% Poorest	(4) 20% Poorest	(5) >= Median	(6) < Median	(7) Midle 50%	(8) STAN
herfruleoflaw	0.01334*** (0.004)	-0.00079 (0.011)	0.09587 (0.048)	0.05464 (0.033)	0.01137* (0.005)	0.01717 (0.011)	0.03046*** (0.008)	-0.000 (0.009)
Constant	6.18099*** (0.728)	9.31899*** (1.166)	-3.74708 (4.890)	4.15491 (3.287)	8.42484*** (1.116)	6.08730*** (1.243)	6.46214*** (0.810)	9.85153 (0.896)
Observations	3,643	596	203	340	2,351	1,292	1,880	965
Adjusted R ²	0.807	0.703	0.523	0.553	0.775	0.634	0.696	0.692

Robust standard errors in parentheses; sector, country and time dummies

*** p<0.001, ** p<0.01, * p<0.05

Table 9 – List of sectors (UNIDO: only sectors 3 through 20)

Number in Dataset	Sector Name
1	C01T05 Agriculture, hunting, forestry and fishing
2	C10T14 Mining and quarrying
3	C15T16 Food products, beverages and tobacco
4	C17T19 Textiles, textile products, leather and footwear
5	C20 Wood and products of wood and cork
6	C21T22 Pulp, paper, paper products, printing and publishing
7	C23 Coke, refined petroleum products and nuclear fuel
8	C24 Chemicals and chemical products
9	C25 Rubber and plastics products
10	C26 Other non-metallic mineral products
11	C27 Basic metals
12	C28 Fabricated metal products except machinery and equipment
13	C29 Machinery and equipment n.e.c
14	C30 Office, accounting and computing machinery
15	C31 Electrical machinery and apparatus n.e.c
16	C32 Radio, television and communication equipment
17	C33 Medical, precision and optical instruments
18	C34 Motor vehicles, trailers and semi-trailers
19	C35 Other transport equipment
20	C36T37 Manufacturing n.e.c; recycling
21	C40t41 Electricity, gas and water supply
22	C45 Construction
23	C50T52 Wholesale and retail trade; repairs
24	C55 Hotels and restaurants
25	C60T63 Transport and storage
26	C64 Post and telecommunications
27	C65T67 Finance and insurance
28	C70 Real estate activities
29	C71 Renting of machinery and equipment

- 30 C72 Computer and related activities
- 31 C73 Research and development
- 32 C74 Other Business Activities
- 33 C75 Public admin. and defence; compulsory social security
- 34 C80 Education
- 35 C85 Health and social work
- 36 C90T93 Other community, social and personal services
- 37 C95 Private households with employed persons

Table 10 – Countries in UNIDO dataset

Country number in dataset	Country name
4	Afghanistan
8	Albania
12	Algeria
31	Azerbaijan
32	Argentina
36	Australia
40	Austria
44	Bahamas
50	Bangladesh
51	Armenia
52	Barbados
56	Belgium
60	Bermuda
68	Bolivia (Plurinational State of)
70	Bosnia and Herzegovina
72	Botswana
76	Brazil
100	Bulgaria
104	Myanmar
112	Belarus
116	Cambodia
120	Cameroon
124	Canada
144	Sri Lanka
152	Chile
156	China
158	China, Taiwan Province
170	Colombia
184	Cook Islands

188	Costa Rica
191	Croatia
196	Cyprus
203	Czech Republic
208	Denmark
214	Dominican Republic
218	Ecuador
222	El Salvador
231	Ethiopia
232	Eritrea
233	Estonia
242	Fiji
246	Finland
250	France
266	Gabon
268	Georgia
270	Gambia
275	Palestinian Territories
276	Germany
288	Ghana
300	Greece
320	Guatemala
332	Haiti
340	Honduras
344	China, Hong Kong SAR
348	Hungary
352	Iceland
356	India
360	Indonesia
364	Iran (Islamic Republic of)
372	Ireland

376	Israel
380	Italy
384	Côte d'Ivoire
388	Jamaica
392	Japan
398	Kazakhstan
400	Jordan
404	Kenya
410	Republic of Korea
414	Kuwait
417	Kyrgyzstan
418	Lao People's Dem Rep
422	Lebanon
426	Lesotho
428	Latvia
438	Liechtenstein
440	Lithuania
442	Luxembourg
446	China, Macao SAR
450	Madagascar
454	Malawi
458	Malaysia
470	Malta
480	Mauritius
484	Mexico
496	Mongolia
498	Republic of Moldova
504	Morocco
508	Mozambique
512	Oman
524	Nepal

528	Netherlands
530	Netherlands
531	Curaçao
533	Aruba
554	New Zealand
562	Niger
566	Nigeria
578	Norway
586	Pakistan
590	Panama
598	Papua New Guinea
600	Paraguay
604	Peru
608	Philippines
616	Poland
620	Portugal
630	Puerto Rico
634	Qatar
642	Romania
643	Russian Federation
646	Rwanda
682	Saudi Arabia
686	Senegal
702	Singapore
703	Slovakia
704	Viet Nam
705	Slovenia
710	South Africa
716	Zimbabwe
724	Spain
736	Sudan (including South Sudan)

740	Suriname
748	Swaziland
752	Sweden
756	Switzerland
760	Syrian Arab Republic
762	Tajikistan
764	Thailand
776	Tonga
780	Trinidad and Tobago
788	Tunisia
792	Turkey
800	Uganda
804	Ukraine
807	The f. Yugosl. Rep. of Macedonia
818	Egypt
826	United Kingdom
834	United Republic of Tanzania
840	United States of America
854	Burkina Faso
858	Uruguay
862	Venezuela (Bolivarian Republic of)
887	Yemen
891	Serbia and Montenegro

Table 11 – Countries in STAN Database

Australia
Austria
Belgium
Canada
Chile
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Iceland
Ireland
Israel
Italy
Japan
Korea
Luxembourg
Mexico
Netherlands
New Zealand
Norway
Poland
Portugal
Slovak Republic
Slovenia
Spain
Sweden

Switzerland

United Kingdom

United States

West Germany