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Diagnosing the Italian Disease

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Abstract

We try to explain why Italy's labor productivity stopped growing in the mid-1990s. We find no evidence that this slowdown is due to trade dynamics, Italy's inefficient governmental apparatus, or excessively protective labor regulations. By contrast, the data suggest that Italy's slowdown was more likely caused by the failure of its firms to take full advantage of the ICT revolution. While many institutional features can account for this failure, a prominent one is the lack of meritocracy in the selection and rewarding of managers. Familyism and cronyism are the ultimate causes of the Italian disease.

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After 2008 (and even more so after 2010) Italy faced a major fiscal and economic crisis that impacted employment and productivity. However, Italy's economic problems predate this crisis. For decades, Italy has stood out among developed economies for its abysmal performance on labor productivity, with growth in output per hour worked from 1996 to 2006 standing at just 0.5%, compared to 1.7% in Germany, 1.9% in France, and 2% in both the United States and Japan. During the period 1996–2006, Italy fell behind a sample of other advanced nations in labor productivity terms by a cumulative 17.4% (figure 1). Even accounting for lower capital accumulation, Italy's total factor productivity cumulative growth gap ranges from 17.3% (figure 2) to 20.1% (figure 3), depending on how TFP growth is averaged across sectors. Following the global financial crisis of the late 2000s, Italy did even worse. What could possibly have caused a slowdown of such magnitude?

From 1996 to 2006 Italy did not suffer any major financial crises, did not face persistent deflation (the average increase in the consumer price index during this period is 2.7%), and benefited from low and stable interest rates. In fact, it benefited from a monetary policy loose enough to fuel an overheated economy in Spain, Greece, and Ireland. The fiscal policy was not that restrictive, either, with an average fiscal deficit of 3.7% per year. Finally, during this period, Italy did not face any major political instability: It enjoyed the longest-lasting governments of all its post-WWII history. What, then, is the cause of this Italian disease?

Italy lags behind other developed countries on many institutional dimensions. While these deficiencies might be able to explain why Italy is less productive overall, they cannot easily account for the sudden stop in productivity growth; these deficiencies were present in the 1950s and 1960s when Italy was considered an economic miracle, and persisted in the 1970s and 1980s, when Italy continued to have GDP and productivity growth above the European average. For these deficiencies to explain the sudden stop in productivity growth, it is necessary to identify a shock that, at the turn of the 20th century, made productivity growth more highly dependent on an institutional dimension along which Italy was particularly lacking.

The first of such possible shocks is an unfavorable demand shock resulting from China's entry to the WTO (see Pierce and Schott 2016). Italy might have been affected more significantly than other countries by its own entry to the eurozone, which prevented it from engaging in competitive devaluation as it did in the 1970s and 1980s. We know from Frankel and Romer (1999) and Alcalá and Ciccone (2004) that a country's exposure to international markets has a strong causal effect on the productivity of its firms. It is therefore conceivable that a significant loss of market shares by Italian firms might have produced the productivity slowdown.

A second (related) shock is the increased need for flexibility of the labor force, induced by a combination of technology and globalization (Dorn and Hanson, 2015). Italy's historically rigid labor market, which has been the target of policy recommendations by the IMF and the OECD, might have prevented the reallocation of labor units, adversely affecting its productivity (see Calligaris et al. 2016).

The third potential explanation is a country-specific shock. While Italy has long been known to lag behind other developed countries in terms of the quality of its institutions, some observers (see Gros 2011) have noted that, starting from the mid-1990s, Italy experienced a sharp decline in government quality as measured by the World Bank's Worldwide Governance Indicators. This decline might have caused Italy to fall further behind on the technological frontier. A recent IMF study (Giordano et al. 2015), for example, using a measure we developed for this paper, found a link between public sector efficiency in Italian provinces and firm-level labor productivity.

Finally, the mid-1990s marks the beginning of what is known as the information and communication technology (ICT) revolution. As shown, among others, by Bresnahan et al. (2002), Brynjolfsson et al. (2002), and Garicano and Heaton (2010), the impact of ICT capital on productivity exhibits strong complementarity with meritocratic managerial practices. As noted by Bandiera et al. (2008) (and confirmed in our sample), Italy is severely deficient across this dimension, too: A majority of Italian firms select, promote, and reward people based on loyalty rather than merit. Therefore, it is possible that non-meritocratic managerial practices might have severely hindered Italy's ability to exploit the benefits of the ICT revolution. Bloom et al. (2012) find that a similar mechanism caused the US and EU's aggregate productivities to diverge around the same period. Thus, the Italian disease could be a more extreme form of the European disease.

We begin investigating these hypotheses using sector-level growth accounting data from the EU KLEMS dataset. We find no evidence that sectors that became more exposed to Chinese imports lagged behind in TFP growth.

We also find no evidence of the labor misallocation hypothesis: Productivity in sectors where labor turnover has been disproportionately large in the United States (which has some of the laxest labor regulations among developed countries) did not grow disproportionately less in countries with less flexible labor markets. Similarly, sectors that are more government-dependent do not exhibit disproportionately lower productivity growth in countries, like Italy, that experienced deterioration on indicators of quality of government.

By contrast, we do find that TFP in more ICT-intensive sectors grew faster in countries where firms are more likely to select, promote, and reward people based on merit, as measured by the World Economic Forum expert survey.

Since a country's propensity for meritocracy in the business sector is correlated with many other institutional characteristics (quality of government, ICT infrastructure, size of the shadow economy), by using aggregate data alone it is hard to be sure that lack of meritocracy is the main cause for Italy's productivity slump. For this reason, we probe deeper with a firm-level dataset (the Bruegel-Unicredit EFIGE dataset). Using answers to five EFIGE survey questions regarding the use of incentives and the selection of managers, we construct a firm-level measure of meritocratic management. While there are only seven countries covered in the EFIGE dataset, the country-level averages of this variable correlate strongly with the WEF measure of meritocracy.

The firm-level data exhibit the same patterns as the KLEMS sectoral data: TFP grows faster in more meritocratic firms in sectors where the ICT contribution is larger. This result holds after controlling for country and sector fixed effects. The EFIGE dataset also contains a firm-level indicator (based on the firms' responses) of how labor regulation constrains growth. Therefore, we can test with micro data the effect of labor rigidity on TFP growth. We find this effect to be economically and statistically indistinguishable from zero.

Most of Italy's productivity growth gap, we find, is not due to slower ICT capital accumulation, but rather to a worse utilization of ICT investments. Again, using EFIGE survey data, we can investigate this channel directly by constructing an indicator of ICT usage. Consistent with Garicano and Heaton (2010), we find that more meritocratic firms exploit computing power more effectively. This effect is also stronger in sectors where ICT is more relevant.

All these findings raise a further question: Why does Italy lag behind in the adoption of meritocratic management practices? The most obvious explanation is that non-meritocratic (i.e., loyalty-based) management has greater benefits in Italy than in other developed countries. The main advantage of a loyalty-based management is its ability to function in environments where legal enforcement is either inefficient or unavailable. Among developed countries, Italy stands out both for its inefficient legal system and for the diffusion of tax evasion and bribes. Thus, a reasonable explanation is that, at the onset of the ICT revolution, Italy found itself with the wrong type of management system to take advantage of these newly available technologies.

To test this hypothesis, we exploit another feature of the EFIGE survey: Firms are asked to indicate the main impediments to their growth. We look at three major sources of external constraints: access to finance, labor market regulation, and bureaucracy. We find that, while in our sample meritocratic firms are less likely to experience any of these constraints, this effect is significantly weaker for Italian firms. Thus, it appears that in Italy, loyalty-based management has a relative advantage in overcoming financial and bureaucratic constraints.

We are certainly not the first to point out Italy's productivity slowdown. In fact, it is so well known as to have become an international problem in the aftermath of the eurozone crisis (see, for example, the 2017 IMF Country Reports on Italy). Yet, there is a dearth of data-based explanations.

The most prominent contribution is from Daveri and Parisi (2010). They attribute Italy's productivity slowdown to the old age of Italian CEOs and to a 1997 labor market reform that liberalized temporary employment contracts, which reduced firms' incentives to invest in human capital. Consistent with this hypothesis, they find that between 2001 and 2003 the productivity growth of Italian firms correlated negatively with the share of temporary workers employed. In our seven-country sample of manufacturing firms (2001–07), we find that these findings do not generalize. Controlling for the share of temporary workers in our specification does not change any of our results.

We are also not the first ones to point to Italy's delay in the adoption of ICT: Bugamelli and Pagano (2004) use micro data from the mid- to late 1990s to show that, in Italy, firms need to undergo major reorganization in order to adopt ICT. Milana and Zeli (2004) were the first to correlate these delays with sluggish aggregate productivity growth in the years 1996–99. Their channel is the lower level of ICT investment. Hassan and Ottaviano (2013) use the same channel to explain the slowdown in Italian TFP growth. In our analysis, while we confirm that lower investment is part of the problem, we show that the reduced productivity of such investments is indeed even more important. Schivardi and Schmitz (2017) build on our findings to construct a model that explains productivity differences between Germany and Italy.

The rest of the paper proceeds as follows. Section 1 describes our data. In section 2 we explore the possible structural causes for the lack of productivity growth using sector-level data. In section 3 we conduct deeper analysis using firm-level data. In section 4, we provide suggestive evidence of why, in Italy, loyalty prevails over merit in the selection and rewarding of managers. In section 5, we conclude.

1. Datasets description

1.A Sector-level data

Our main data source is the EU-KLEMS structural database (O'Mahony and Timmer, 2009). This dataset, first made available in 2007, contains measures of value added, output, inputs, total factor productivity, and input compensation shares at the three-digit ISIC level for 25 European countries, Australia, South Korea, Japan, and the United States since 1970. This level of disaggregation makes it possible to focus on inter-sectoral variations in productivity growth, by controlling for country-level determinants with country fixed effects. It also allows us to study the interaction between country-specific factors and industry-specific factors. We end our sample in 2007 to avoid mixing the structural problems of Italy before the two crises with the effect of the two crises.

The dataset also provides industry-level growth accounting (value added growth at constant prices is broken down into a TFP component, an ICT capital component, a non-ICT capital component, an hours worked component, and a human capital component).

Capital formation and growth accounting series are unavailable for 11 countries for the main period of interest (1995–2006). This leaves 18 countries. We use this data at the finest sectorial decomposition for which growth accounting series are made available, with the following three exceptions: 1) we aggregate sectors 50 to 52 (wholesale and retail trade) in order to merge to the dataset some explanatory variables that are available at industry level; 2) we use the aggregate sector 70t74 instead of 70 (real estate) and 71t74 (other business services) because Italian data presents some specific issues regarding the attribution of real estate assets between sectors 70 and 71t74[1]; and 3) we drop, as customary, public sector and compulsory social services (sectors 75-99) from the analysis altogether, due to the well-known issues related to the measurement of public sector productivity.[2]

This leaves 23 sectors in total. Apart from growth accounting series, we also use sector-level price deflators for output, intermediate inputs, and labor, as well as capital compensation and real capital stock indices. These variables are used in conjunction with firm-level data to produce TFP growth series at the firm level.

Multiple releases of this dataset are available. We use the March 2011 update[3] of this dataset because it covers all sectors, it offers the largest sample size in terms of country/sector/year and has a sector definition that is compatible with trade and layoff series, allowing us to merge the series. In the appendix, we also use an earlier release of the dataset (using the same sector definition) for robustness.

1.B Country-level variables

To construct a proxy variable for meritocratic management at the country level, we use a measure of the extent to which firms select, promote, and reward people based on merit, starting from the Global Competitiveness Report Expert Opinion Surveys (2012). We compute the variable *Country Meritocracy* as the average numerical answer to the following three questions: 1) "In your country, who holds senior management positions?" [1 = usually relatives or friends without regard to merit; 7 = mostly professional managers chosen for merit and qualifications]; 2) "In your country, how do you assess the willingness to delegate authority to subordinates?" [1 = not willing at all – senior management makes all important decisions; 7 = very willing – authority is mostly delegated to business unit heads and other lower-level managers]; and 3) "In your country, to what extent is pay related to employee productivity?" [1 = not at all; 7 = to a great extent].

To gauge time-variation in the quality of a country's institutions, we use two indicators from the World Bank's Worldwide Governance Indicators (WGI): Rule of Law, and (in the appendix) Control of Corruption. It is important to note that these indicators are standardized within years: they do not, therefore, carry cardinal meaning, but only ordinal meaning. We believe they are nonetheless suitable for our analysis, since a country's distance from the technological frontier has more to do with the relative rather than

[1] See the EU KLEMS Methodology document and our data appendix
[2] See http://www.euklems.net/data/EUKLEMS_Growth_and_Productivity_Accounts_Part_I_Methodology.pdf
[3] www.euklems.net/data/09ii/sources/March_2011_update.pdf

absolute value of the quality of its institutions. Also, we use different variables based on hard data, and expressed in levels, to perform robustness tests in our appendix.

To evaluate the ICT infrastructures that different countries have in place, we use a sub-index of the Networked Readiness Index, published yearly by the World Economic Forum (we use the 2012 wave). This index is constructed by combining country-level data on mobile network coverage, the number of secure internet servers, internet bandwidth, and electricity production.

To control for country-level differences in the quality of managers' training, we use answers to another question from the WEF executive opinion survey: "In your country, how do you assess the quality of business schools?" [1 = extremely poor – among the worst in the world; 7 = excellent – among the best in the world].

Finally, we also use, as a control variable, the size of the shadow economy as a percentage of the total economy, as computed by Schneider (2012).

1.C Sectoral exposure to shocks

We measure how much each sector is dependent on the government, by counting news in major economics and financial news outlets from the Factiva News Search database over the period 2000–2012. Government dependence is defined, for each sector, as the ratio of total news having "government" as topic (see table 1 for details) to total news for that sector. We identify government-related news using the subject tags in the Factiva news search engine.

To capture variation in the need for labor force mobility across sectors, we use mass layoff rates in US industries as computed by Bassanini and Garnero (2013), which are based on information from the CPS displaced workers supplements relevant to the 2000–2006 period.[4]

To compute a measure of the change in exposure to Chinese imports across countries and sectors over the period of interest, we use data from the OECD-WTO Trade in Value Added (TiVA) dataset. The variable of interest, *ΔChina Exposure*, is defined as the yearly change in sector-level of imports from China as a percent of domestic demand (output + imports - exports), all measured in US dollars, between 1996 and 2005. We can only look at the 1996–2005 period because sector-level trade data is reported in TiVA at five-year intervals starting from 1995 (no data is available before that period).

To gauge the importance of ICT capital at the country/sector level, we use the EU KLEMS series for the yearly contribution of ICT capital to output growth over the 1985–1995 and 1996–2006 periods. In any given year, the contribution of ICT capital to growth is defined as the current one-year percentage

[4] Because our sector definitions are coarser than the one by Bassanini and Garnero (2013), we adapt their layoff rates to our sector definitions by taking simple averages where needed.

increase in the real ICT capital stock, times the two-period moving average of the ICT capital share of value added.[5]

1.D Firm-level dataset

For the firm-level analysis of section 3, we use the EFIGE (European Firms in a Global Environment) dataset, developed by Altomonte and Aquilante (2012). The dataset covers 14,000 manufacturing firms from seven European countries (Austria, France, Germany, Hungary, Italy, Spain, and the United Kingdom).

In addition to balance sheet information obtained from the Amadeus-BvD databank, this dataset contains response data from a survey undertaken in 2010 that covers a wide range of topics related to the firms' operations. In particular, this survey contains questions about managerial practices that allow us to compute a measure of firm-level meritocracy. Specifically, the questions are: 1) "Can managers make autonomous decisions in some business areas?" 2) "Are managers incentivized with financial benefits?" 3) "Has any of your executives worked abroad for at least one year?" 4) "Is the firm not directly or indirectly controlled by an individual or family-owned entity? If it is, was the CEO recruited from outside the firm?" 5) "Is the share of managers related to the controlling family lower than 50%?"[6] . We construct our meritocracy index by summing the number of affirmative answers to the above questions.

Similarly, the survey asks whether a firm's management uses: 1) IT systems for internal information management; 2) IT systems for e-commerce; and 3) IT systems for management of the sales/purchase network. We construct our ICT usage index as the sum of the affirmative answers to these questions.

The survey also provides information on the constraints faced by firms by asking managers which of the following (non-mutually exclusive) factors prevent the growth of their firms: 1) financial constraints, 2) labor market regulation, 3) legislative or bureaucratic restrictions, 4) lack of management and/or organizational resources, 5) lack of demand, and 6) other. Firms are also offered the option to say that they face no constraints. To measure these constraints, we create three dummy variables that represent, respectively, whether the firm chooses the first, second, or third option.

[5] This is computed by the authors by applying a perpetual inventory model to country/-/sector/-/asset-level capital investment series.

[6] The original question asks firms to report the number of managers that are and are not related to the controlling family, either in levels or a percentage of the workforce. We transform this information into a choice of whether the share of managers related to the controlling family is above or equal to 50% because the resulting percentagesanswers are highly clustered around this threshold. If the 0%, 50% and 100% valuespercentage of managers affiliated with the controlling family is not reported, we use 1 minus the percentage of managers not affiliated with the controlling family (if this is reported). If this is also missing, but the absolute levels are reported, we compute the percentage ourselves from the absolute figures.

Finally, the EFIGE dataset contains several questions about workforce characteristics. We use the percentage of the firm's workforce that has a college degree, as well as the percentage that, in 2008, was employed on a fixed-term contract.[7]

1.E Additional remarks

All the variables used are defined in table 1. Table 2 provides the summary statistics. Additional variables used for robustness are presented in the appendix.

2. Sector-level analysis

2.A Decomposing output growth

The first basic fact we want to pin down is that the Italian growth problem is fundamentally a productivity one. Figure 1 graphically decomposes GDP per capita growth at constant prices in a cross-section of 18 countries in the period 1996–2006, according to the following formula:

$$\Delta \log \frac{GDP}{Population} = \Delta \log \frac{GDP}{Hours} + \Delta \log \frac{Hours}{Employment} + \Delta \log \frac{Employment}{Population} \qquad (2.1)$$

where Δ represents the first difference operator with respect to time. The first term on the right-hand side is the labor productivity growth, the second is the growth in the number of hours worked per employee (intensive margin), and the last one is the growth in the employment ratio (extensive margin). This decomposition shows that Italy lags behind in labor productivity growth (only 7.5% over the period against an average of 25.6% for the other countries). It also shows that Italy's lower GDP per capita growth is not due to a reduction in the extensive or the intensive margin of its workforce. To the contrary, an increase in the participation rate appears to have been masking a labor productivity growth rate that is much smaller than that of any other country except Spain.

To further decompose GDP per hour worked, we use sector-level growth accounting series from the EU KLEMS dataset. This dataset constitutes the strongest effort, to date, to produce sector-level growth figures that are comparable across countries. The EU KLEMS consortium does so by consolidating and harmonizing sector-level output, input, and price statistics from national statistic agencies. One key advantage of this dataset is that it accounts separately for ICT capital (computers, communication equipment, software) and non-ICT capital. Additionally, EU KLEMS measures labor input as "labor services," a composite index that weighs the number of hours worked by the compensation shares of each

[7] If the percentage of employees with a college degree is not reported, but the absolute level is reported, we compute the percentage ourselves from the absolute figures by dividing the number of employees with degrees by the total number of employees.

worker category (in terms of age, gender, and educational attainment). Since in a competitive market, each hour is paid its marginal revenue product, this measure allows us to account for changes in quality composition of the workforce.

Assume that there is a representative firm at the country/sector-level, which uses the following Cobb-Douglas production function:

$$VA_{cst} = TFP_{cst} \cdot I_{cst}^{\left(\alpha_{cst}^{I}\right)} K_{cst}^{\left(\alpha_{cst}^{K}\right)} L_{cst}^{\left(\alpha_{cst}^{L}\right)} \tag{2.2}$$

where VA_{cst} is value added (at constant prices) in country *c*, sector *s* at time *t*. Similarly, TFP_{cst} is total factor productivity, I_{cst} is the ICT capital employed in production, K_{cst} is the non-ICT capital, and L_{cst} is the labor input in country *c*, sector *s* at time *t*. We have constant returns to scale, therefore the elasticities $\left(\alpha^I \ \alpha^K \ \alpha^L\right)$ sum to one. Then we decompose value added growth of sector *s* in country *c* at time *t* as

$$\Delta \log VA_{cst} = \Delta \log TFP_{cst} + \alpha_{cst}^{I} \Delta \log I_{cst} + \alpha_{cst}^{K} \Delta \log K_{cst} + \alpha_{cst}^{L} \left(\Delta \log H_{cst} + \Delta \log \frac{L_{cst}}{H_{cst}} \right) \tag{2.3}$$

where Δ represents the first difference operator with respect to time and H_{cst} is the total number of hours worked. Notice how we have separated the growth of hours worked ($\Delta \log H$) from that of labor services per hour worked $\left(\Delta \log \frac{L}{H}\right)$. Subtracting $\Delta \log H_{cst}$ from both sides of the equation and using the constant returns to scale assumption, we can rewrite (2.3) as:

$$\Delta \log \frac{VA_{cst}}{H_{cst}} = \Delta \log TFP_{cst} + \alpha_{cst}^{I} \Delta \log \frac{I_{cst}}{H_{cst}} + \alpha_{cst}^{K} \Delta \log \frac{K_{cst}}{H_{cst}} + \alpha_{cst}^{L} \Delta \log \frac{L_{cst}}{H_{cst}} \tag{2.4}$$

At the sector level, the production function elasticities $\left(\alpha^I \ \alpha^K \ \alpha^L\right)$ can be recovered from the relative factor compensation shares of output.[8]

In this way, we have broken down labor productivity growth, at the sector level, into its four components. The first one $\left(\Delta \log TFP_{cst}\right)$ is total factor productivity growth. The second $\left(\alpha_{cst}^{I} \Delta \log \frac{I_{cst}}{H_{cst}}\right)$ is the contribution of ICT capital accumulation, given by the product of factor elasticity $\left(\alpha_{cst}^{I}\right)$ and the log-

[8] See EU KLEMS Methodology document for a description of the computation of factor compensation shares... www.euklems.net/data/09ii/sources/March_2011_update.pdf.

growth of ICT capital per hour worked $\left(\Delta \log \frac{I_{cst}}{H_{cst}}\right)$. The third $\left(\alpha_{cst}^{K} \Delta \log \frac{K_{cst}}{H_{cst}}\right)$ is the contribution of non-ICT capital, given by the product of factor elasticity $\left(\alpha_{cst}^{K}\right)$ and the log-growth of non-ICT capital per hour worked $\left(\Delta \log \frac{K_{cst}}{H_{cst}}\right)$. The fourth $\left(\alpha_{cst}^{L} \Delta \log \frac{L_{cst}}{H_{cst}}\right)$ is the contribution of the varying composition of labor. An increase (or a decrease) in the relative share of hours worked by skilled workers would be captured by this variable. The EU KLEMS dataset provides sector-level time series for each of these four components at the level of broad (two-digit) ISICv3 sectors.[9] It is natural at this point to ask whether Italy does significantly worse on any of these components.

Figure 2 graphically shows this decomposition of labor productivity growth for the cross-section of the 18 countries in our sample for the period 1996–2006. We find that an overwhelming fraction of Italy's lower labor productivity growth (-23%) is due to a lower TFP growth (-17.3%). All other factors play a very limited role: labor composition (-0.6%), ICT capital (-2.8%), and non-ICT capital (-2.1%). In particular, Italy's lower contribution of ICT capital is due partly to lower investment (9.6% compared to a cross-country average of 12.4%) and partly to a lower estimated elasticity of value added with respect to ICT capital (2.4% compared to a cross-country average of 4.3%).

In figure 2, the sectors are weighted by their importance in GDP. As a result, this analysis might mask the effect of a different sectoral composition of the Italian economy. For this reason, in figure 3 we weight all the sectors equally. As one can see, the results are broadly unchanged. In fact, the gap in Italian labor productivity growth appears even bigger (-28%), as does the gap in TFP growth (-21.1%). The main difference between the two figures is the performance of Spain. As Garcia-Santana et al. (2016) show, the slowdown in Spanish productivity growth is partially due to a large increase in construction during this decade. With regard to Spain's remaining TFP growth gap, Gopinath et al. (2017) showed that it can be

[9] We are well aware of the drawbacks of using aggregate input expenditures to compute production function elasticities. The recent literature has focused on estimating sector-level production functions using firm-level data, correcting for sample selection and simultaneity in the production function deriving from the semi-fixedness of capital input (see for example Olley and Pakes (1996),, Levinsohn and Petrin (2003),, and Wooldridge (2009)).). This is obviously impossible to attain with both our sector-level data (because we cannot model sample selection) and our firm-level data (because we do not have the firm-level input of ICT capital). Nevertheless, we trust the validity of our key econometric results for three reasons. First, because the elasticity estimates are not based on a regression. Second, while the EU KLEMS framework treats capital as a variable input, it does not use actual capital compensation to compute the elasticity of output with respect to capital; hence there is no clear indication of how α^{K} would be affected by sample selection either. Finally, even if there is measurement error in α^{K}, it would likely result in the error term of our regression being correlated with *ICT Contribution*. Hence its coefficient would be biased. However, we have no reason to suspect that it might be correlated with its interaction with *Country Meritocracy*, conditional on *ICT Contribution* (which is also the reason we insist that *ICT Contribution* be included as well). Our computation of the "Explained TFP growth gap" does not rely on the estimated baseline coefficient of *ICT Capital Contribution.*

largely explained by a significant increase in capital misallocation following Spain's entry into the eurozone. But what explains Italy's slowdown?

Overall, this analysis suggests that very little of Italy's labor productivity gap can be explained by a failure to accumulate capital or to improve the skill mix of the labor force, or by the sectoral composition of its economy. Italy's slowdown appears to be overwhelmingly driven by its lag in total factor productivity growth, which is what we will try to explain next.

2.B Discussion of plausible shocks

Italy lags behind other countries in our sample on many institutional dimensions: During this period, it ranks low for control of corruption (0.49 against an average of 1.56), rule of law (0.66 against an average of 1.43) human capital (2.79 against an average of 3.20), and high in regulatory protection of labor (0.65 against an average of 0.53)[10]. For any of these deficiencies to be able to explain the sudden stop in Italian TFP growth, however, we need a post-1995 shock that makes these deficiencies more important than before for productivity growth.

The first such shock we consider is trade integration. China's entry in the WTO threatened Italy's market share in global manufactures (Tiffin 2014), precisely at the time when Italy had given up exchange rate flexibility by joining the euro. Several European economists (Bagnai 2016; Soukiazis, Cerqueira, and Antunes 2014) have claimed that the reduced foreign demand has hampered the ability of Italian firms to exploit economies of scale and learning by doing, consequently slowing down TFP growth. To test this hypothesis, we cannot simply estimate a regression of TFP changes on changes in exports, since the direction of causality might be the opposite. Thus, we need an exogenous measure of exposure to international trade that is not directly affected by the lack of productivity growth; we use the change in imports from China, as a percentage of total domestic demand, in each country/sector, from 1996 to 2005. If the trade hypothesis is correct, we would expect countries/sectors that experienced a greater increase in Chinese imports to also have experienced lower TFP growth.

It has been shown that globalization and technology created a need for reallocation of labor across firms (see, e.g., Dorn and Hanson 2015). The rigidity of Italy's labor market might have played a role in delaying this reallocation and reducing TFP growth. If this hypothesis is correct, we should expect that sectors more affected by this reallocation shock should exhibit lower TFP growth in countries with greater labor protection.

[10] "Rule of Law" and "Control of Corruption" are from the Worldwide Governance Indicators of the World Bank; Human Capital is measured by the Barro-Lee index; regulatory protection of labor is measured by the composite index of Botero et al. (2004). For variables that change over time, we compute the average over 1996-2006.

The other shock we investigate is a change in the quality of Italian institutions. Italy appears to have experienced, at least in relative terms, a deterioration across this dimension: it recorded the sharpest decline in Rule of Law (one of the Worldwide Governance Indicators) within our sample. Another possibility is that the importance of government inputs in production has increased as the economy became more complex. If Italy's government is the real culprit of its slowdown, we should observe that the sectors most dependent on regulations and government inputs should experience a sharper TFP slowdown.

Last but not least, the mid-1990s also marked the beginning of the ICT revolution (Bloom et al., 2012). The impact of ICT investments on productivity growth, however, is not necessarily the same across countries. We know from Bresnahan et al. (2002) and Brynjolfsson et al. (2002) that ICT capital exhibits strong complementarity with management practices, quality of human capital, and quality of a country's institutions. In particular, Garicano and Heaton (2010) show that, to reap the productivity benefits of the ICT revolution, firms must have performance-based, meritocratic management. Thus, the Italian TFP growth gap could be the result of a lower impact of its ICT investments due to its low level of meritocracy in the business sector.

For any of these conjectures to be a convincing explanation, it cannot hold just for Italy: it must explain total factor productivity growth across all other countries in our sample, as well. For this reason we use sector-level data, so we can exploit both the cross-sectoral and cross-country variation for identification.

2.C A panel analysis of TFP growth across sectors

Our objective is to explain cross-sectional variation across countries and sectors in TFP growth in the period 1996–2006. Our first specification is:

$$\Delta \log TFP_{cs} = \gamma_c + \varsigma_s + \beta X_{cs} + \varepsilon_{cs} \tag{2.5}$$

where $\Delta \log TFP_{cs}$ is the log change in TFP in sector *s* country *c* in the period 1996–2006, γ_c is a country fixed effect, ς_s is a sector fixed effect, and X_{cs} is an explanatory variable that should vary across countries and sectors. The first such variable is $\Delta \mathit{China\ Exposure}$, which is the change in Chinese imports as a percent of domestic demand (output + imports - exports), all measured in US dollars, in sector *s* of country *c* between 1996 and 2005. We show the results of the OLS estimation of this specification in table 3, panel A, column 1. We find that, if anything, exposure to Chinese imports had a positive (not negative) effect on TFP growth, although this effect is not statistically significant.

To estimate the impact of labor market rigidities on aggregate TFP growth, we need a variable that changes both across sectors and across countries. As a measure of the sectorial need for reallocation we use the mass layoff rates in US industries computed by Bassanini and Garnero (2013) using data from the CPS biennial displaced workers supplement. As a measure of country-level labor market rigidity, we use a composite index of employment law strictness from Botero et al. (2004). We use the interaction of these two variables as an explanatory variable in table 3, panel A, column 2: the interaction coefficient between $US\ Layoff\ \ Rate$ and $Employment\ Laws$ is indeed negative, but not statistically different from zero. In the online appendix, we show that results do not change significantly by using the OECD's measure of employment protection laws instead, or by interacting $Employment\ Laws$ with $\Delta China\ Exposure$.

We face a similar problem in estimating the effect of government effectiveness: we don't lack country-level indicators of government effectiveness (e.g., La Porta et al. 1999), but we do lack a measure of sectoral dependency on government inputs. As a source of country-level variation, we use the change in the World Bank's Rule of Law score. To measure how much each sector is dependent on the government, we compute our own measure of sectoral government dependence. Specifically, we count news articles using the Factiva news search engine. The variable $Government\ Dependence$ is defined, for each sector, as the ratio of total news counts having "government" as the topic to total news for that sector (see table 1 for details). Figure 4 shows how this variable varies across EU KLEMS sectors. This measure has been validated by Giordano et al. (2015), who find a positive correlation between the variation in public sector efficiency across Italian provinces and firm productivity.

We find that the interaction between $Government\ Dependence$ and $\Delta Rule\ of\ Law$ has no significant effect on TFP growth (table 3, panel A, column 3). In the online appendix, we show there is no substantial difference in the results whether using, instead of $\Delta Rule\ of\ Law$, the change in "Control of corruption" or alternative measures of government efficiency (Chong et al., 2014, Djankov et al. 2003) that are expressed in levels.

To analyze the differential impact of ICT investments, we need to explain why this impact is not already included in the growth accounting exercise of section 2. First of all, it is important to note that the measure of TFP growth that we use as a dependent variable is the residual growth after the impact of all investments, including ICT investments, has been accounted for. The validity of this growth accounting exercise relies on the assumption that firms equalize the marginal revenue product of each input to its marginal cost. However, as shown by Bresnahan et al. (2012), there is a great level of uncertainty in the estimates of productivity of ICT investments. Thus, it is reasonable that firms lacking an appropriate organizational structure will systematically overinvest in ICT, as shown by Garicano and Heaton (2010) in the case of police departments. Furthermore, because ICT investments are characterized by strong externalities and network effects (Stiroh 2002), it has been hypothesized that the aggregate returns on ICT investment might deviate substantially from the firm-level returns.

If the determinants of ICT absorption differ across countries, this effect might vary across countries. If that is the case, then the EU KLEMS estimate of TFP growth is not a "true" residual, because it embeds a component that is directly related to ICT investments. To see how this could be reflected in our growth accounting framework, consider the following amendment to equation (2.4):

$$\Delta \log VA_{cst} = \Delta \log TFP^{*}_{cst} + (1+\delta_c)\alpha^{I}_{cst}\Delta \log I_{cst} + \alpha^{K}_{cst}\Delta \log K_{cst} + \alpha^{L}_{cst}\Delta \log L_{cst} \tag{2.6}$$

where δ_c is a country-level parameter that can either amplify or dampen on aggregate value added. Given the findings of Bresnahan et al. (2002), Brynjolfsson et al. (2002), and Garicano and Heaton (2010), we assume the aggregate impact of ICT capital accumulation is affected by the country level of meritocracy in managerial choices ($Meritocracy_c$). Because total factor productivity growth is defined implicitly as the residual of the growth accounting equation, by accounting for country-specific returns to ICT adoption (through δ_c) we obtain a different residual, which we denote as $\Delta \log TFP^{*}_{cst}$. Subtracting (2.3) from (2.6) and assuming a linear functional relationship between $Meritocracy_c$ and δ_c, we obtain the following relationship between the EU KLEMS residual TFP and the "true residual" TFP^{*}:

$$\Delta \log TFP_{cst} = \Delta \log TFP^{*}_{cst} + (a + b \cdot Meritocracy_c) \times \alpha^{I}_{cst}\Delta \log I_{cst} \tag{2.7}$$

In other words, if the returns to adopting ICT vary systematically across countries, the EU KLEMS total factor productivity growth rate should be positively correlated with an interaction term, which is equal to the product of a country-level measure of meritocratic management and the contribution of ICT.

We test this relationship in table 3, panel A, column 4. We compute the variable $Country\ Meritocracy$ as the average of three World Economic Forum executive opinion surveys previously described. We find that the interaction between $ICT\ contribution$ and $Country\ Meritocracy$ is positive and statistically significant at the 5% level. In order to allow the minimum effect of the ICT contribution to be different from zero, we also insert, in the specification the level of ICT contribution by itself. The coefficient of this variable is negative. This means that, at a low level of meritocracy, the impact of ICT investments captured by TFP is negative, and as a consequence the marginal product of ICT capital on aggregate value added is overestimated in KLEMS growth accounts.

In table 3, panel A, column 5 we combine all these interaction variables in one specification. The results do not change. The only interaction that is statistically different from zero is the one between ICT contribution and meritocracy.

2.D Robustness

Because meritocracy correlates at the country level with many other institutional variables, we want to make sure that the observed effect is really due to meritocracy and not to other factors. For this purpose, in table 3, panel B we include other controls for country characteristics, interacted with ICT capital contribution. In particular, we use a measure of ICT infrastructure computed by the World Economic Forum, a measure of the quality of management schools from World Economic Forum, and a measure of the size of the shadow economy by Schneider (2012), all interacted with the ICT capital contribution. None of these variables has a statistically significant impact on TFP growth. We find that the estimated impact of the interaction of *ICT contribution* and *Country Meritocracy* tends to increase by adding these controls; it remains statistically significant.

Another way to check that the effect of the interaction between ICT capital contribution and meritocracy is not spurious is to test whether this variable has an effect before the beginning of the ICT revolution. For this reason, in table 3, panel C, we repeat the same estimations of table 3A for the sample period 1985–1995. Consistent with our conjecture, the effect of ICT capital contribution is not significant. In fact, it even has the opposite sign of the one obtained in the last specification.

In figure 5 we show the impact of the ICT revolution graphically. We divide the countries and the sectors in three groups each. We classify as "high ICT" the eight sectors at the top for average ICT contribution across all countries, while we label as "low ICT" the bottom eight. We do the same for countries, with the top six for meritocracy labelled as "high merit" and the bottom six as "low merit." For each of these groups we compute the cross-country, median TFP growth during the period 1985–2006. For convenience, the TFP level of these four groups is set to 100 in 1995. While before 1995 TFP growth was fairly similar across all four groups, after 1995 there is a clear pecking order. High-ICT sectors in high-meritocracy countries grow the fastest (19.4% cumulatively). Then, low-ICT sectors in low-meritocracy countries (12.3%). Third comes the low-ICT sectors in high-meritocracy countries (9.8%) and last the high ICT sectors in low-meritocracy, with only just positive growth (5.3%). This picture confirms the results obtained in table 3, panels A and C. It also suggests that, in low-ICT sectors, low-meritocracy countries can grow faster than high meritocratic ones.[11]

3. Firm-level analysis

3.1 Productivity regressions

An even better way to ensure that our findings from the previous section are not spurious is to try to corroborate them using firm-level data, such as EFIGE. A distinct advantage of this dataset is that it combines financial information from the Amadeus-BvD dataset[12] with an extensive survey containing information about firms' organizational practices, IT usage, and workforce composition.

[11] This last effect is the only one that is not robust to excluding the three eastern European countries (Czech Republic, Hungary, and Slovenia), for which we do not have data before 1995.

[12] In firm-level regressions, we use the inverse probability weighting scheme devised by Pellegrino and Zheng (2017)

On the downside, it is not possible to reproduce EU KLEMS' growth accounting series exactly using firm-level data. This is because we do not have a breakdown of capital at the firm level, and it is therefore impossible to distinguish ICT capital from other types of capital. Also, at the firm level, value added has a different definition than at the sector level, which does not map onto sector-level accounts. Consequently, the production function must be redefined in terms of gross output. With these caveats in mind, we obtain TFP growth, for a generic firm *i* from country *c* in sector *s*, from the following formula:

$$\Delta \log TFP_{it} = \Delta \log Y_{it} - \alpha^{K}_{cst} \Delta \log K^{*}_{it} - \alpha^{L}_{cst} \Delta \log L_{it} - \alpha^{X}_{cst} \Delta \log X_{it} \tag{3.1}$$

where Y_{it} is real output, K^{*}_{it} is the (total) capital input, L_{it} is the labor input as before, and X_{it} is intermediate inputs. At the firm level, these four variables are mapped, respectively, to revenues, fixed assets, labor costs, and residual costs (all costs other than capital and labor).[13] For each of these variables we can obtain a deflator as well as a sector-level compensation counterpart in the EU KLEMS dataset. Moreover, there is a 1:1 mapping of EU KLEMS sectors to EFIGE sectors. This allows us to merge sector-level expenditures and deflators into the EFIGE dataset and to convert firm-level revenues and inputs series from current-prices series to volume indices.

In table 4, we reproduce a similar specification as in table 3, panel A at the firm level. The main difference with respect to the sector-level analysis is that $\mathit{Country\ Meritocracy}$ is now replaced by $\mathit{Firm\ Meritocracy}$ (we explain its construction in section 1 and table 1). Apart from the fact that this variable varies at the firm level, a distinct advantage of it is that it reflects factual information about firm characteristics, as opposed to perceptions. As figure 6 shows, Italy exhibits a distribution of this firm-level meritocracy that is much more left-skewed than the other countries in our sample. Notably, almost half of the Italian firms in our sample score zero. The firm-level meritocracy is highly correlated with the country-level one (see figure 7).

The estimates obtained from the EFIGE firm-level regressions are very similar to the ones obtained in the KLEMS sector-level regressions. In particular, the ICT contribution by itself has a negative and statistically significant effect on TFP growth while the interaction effect is positive and significant. In the most loyalty-oriented firms, the effect of the ICT contribution on TFP growth is -1.61, while in the most meritocratic ones it can be as high as 1.89. Consistent with the KLEMS regression, the estimated impact of ICT for Italy is negative. As a result, the marginal impact of ICT capital on output is overestimated.

In the EFIGE dataset, we can also estimate the effect of labor market frictions on growth. As in the KLEMS sample, the effect is economically and statistically insignificant.

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to correct for sample selection of German and British firms. They find no evidence of selection into the sample for firms from the other countries of the EFIGE dataset. The methodology is described in their appendix.

[13] More specifically, residual costs are equal to Revenues - (EBITDA + Labor Costs).

At the firm level, one important confounder for the absorption of ICT is the amount of human capital per employee. We can control for this factor because EFIGE provides the share of employees who are college graduates. Unsurprisingly, this variable has a positive and statistically significant effect on TFP growth. However, when interacted with ICT contribution, it has a negative, statistically significant coefficient. Most importantly, inserting this variable does not change the effect of the interaction term between firm meritocracy and $ICT\ Contribution$.

Daveri and Parisi (2010) attribute Italy's productivity slowdown to a decrease in innovation, which is in turn caused by diffusion of temporary jobs and the preponderance of older CEOs. We test this hypothesis by inserting, in the previous specification, the percentage of temporary workers and the age of the firm's CEO (which EFIGE measures in decades), both in levels and interacted with $ICT\ Contribution$. None of these variables has a statistically significant effect.

3.2 ICT usage regressions

Our results rely on the assumption of a complementarity between the style of management selection and incentives and the use of technology. Using firm-level data, we can test this hypothesis directly. We do this by computing the variable $ICT\ Usage$, a firm-level score (ranging from 0 to 3) of the extent to which ICT technologies are utilized by the firm's management. If $Firm\ Meritocracy$ affects TFP through the effective utilization of ICT investments, it should have a significant explanatory variable over this variable. In table 5, column 1, we estimate an ordered probit regression of $ICT\ Usage$ on our firm-level measure of meritocracy and country and sector fixed effects. Since one would expect that firms that invest more in ICT would also use more ICT, we control for the level of $ICT\ Contribution$ at the country/sector level and we also interact this with $Firm\ Meritocracy$. We find that more meritocratic firms tend to use ICT, the more so in sectors where $ICT\ Contribution$ was larger. $Firm\ Meritocracy$, as well as its interaction with $ICT\ Contribution$, has a positive and statistically significant effect on $ICT\ Usage$. Based on these estimates, when a typical firm increases its level of meritocracy from 0 to 5, it doubles its probability of attaining a high level of $ICT\ Usage$ (2 or 3), from 26.6% to 52%.

In table 5, column 2, we add, as a control variable, the percentage of employees with a college degree. This variable has a positive and statistically significant effect on $ICT\ Usage$, but its interaction with $ICT\ Contribution$ does not. The coefficient of $Firm\ Meritocracy$ remains substantially unchanged.

Finally, in table 5, column 3, we add CEO age and the percentage of temporary workers as additional controls. In contrast with the findings of Daveri and Parisi (2010), these additional variables have no effect on $ICT\ Usage$. The impact of meritocracy remains broadly unchanged.

3.3 Magnitude of the Effect

How much of the Italian TFP gap can be explained by the inability of loyalty-based management to fully exploit the ICT revolution? To obtain this estimate we need to adjust the TFP growth of all countries in the sample. To obtain the "adjusted" TFP growth we subtract the effect of meritocracy, interacted with ICT from TFP growth, as in equation (2.7).

First, note that equation (2.7) makes the implicit assumption that meritocracy has no effect on TFP growth in sectors that did not accumulate ICT capital. If that effect exists, it is captured, in our regression, by the country fixed effects. To be conservative, we do not account for such a direct effect of meritocracy on TFP growth in the calculations that follow.

Second, because the baseline (non-interaction) coefficient of $ICT\ Contribution$ is not identified (the coefficient *a* in [2.7]), we need to make assumptions about it. Specifically, we need to make an assumption about the baseline effect of $ICT\ Contribution$ on TFP growth in the lowest-meritocracy country in our sample, which is Italy. We consider three possibilities.

We start from the assumption that the baseline effect of $ICT\ Contribution$ is zero. If the baseline effect is zero, it means that $ICT\ Contribution$ in Italy is correctly estimated in KLEMS (and is underestimated for all other countries in our sample), and ICT capital has no indirect effect on aggregate output that is captured by TFP. Second, we consider a baseline effect of -0.5. Under this assumption, the "true" contribution of ICT in Italy is only half as large as the one estimated by KLEMS. Third, we consider a baseline effect of -1. This level implies that the indirect effect of ICT on *Value added* (which is captured by TFP) completely offsets the contribution of ICT capital computed in KLEMS, hence the accumulation of ICT capital has no effect on aggregate value added growth in Italy.

If we assume that the variable *Meritocracy* is perfectly observed, under the conservative assumption of a baseline effect of zero, Italy's TFP gap drops from 21.1% to 12.5%; in other words, the "meritocracy" effect explains 41% of the Italian gap. With a baseline of -1, the "meritocracy" effect explains 55% of the Italian gap.

Most likely, country-level meritocracy is measured with some noise. To correct for the attenuation bias of the standard errors-in-variable problem, we need to make an assumption on the reliability of the measurement of the variable $Country\ Meritocracy$. Since the squared correlation between the country-level meritocracy and firm-level meritocracy is about 50%, we assume this reliability to be 50%. When we factor in the correction for the errors-in-variable problem, the TFP gap of Italy drops to 8.2 percentage points when the baseline is 0 and to 3.7 percentage points when the baseline is -1. Thus, the "meritocracy" effect explains between 61% and 83% of the Italian gap. In sum, the failure of Italian firms to take full advantage of the ICT revolution can explain at least half of the Italian TFP gap during this period.

4. Distortions to competition and meritocracy in the firm

When we look at the decade ending in 1995, it appears that this loyalty-based management style had no negative consequences on Italy's TFP growth. By contrast, with the advent of the ICT revolution, the lower ability of the loyalty-based system to translate ICT investments into productivity seems to have cost Italy between 13 and 17 percentage points of TFP growth.

If this is the case, why did Italian firms fail to adopt superior managerial techniques? To be more specific, how can we explain the persistence of the loyalty model of management in Italy, given its cost in terms of lack of TFP growth?

One explanation could be hysteresis. In the 1980s, the management style was simply a neutral mutation. When the advantages of meritocracy came about, Italian firms were slow to adapt. This explanation has the advantage of containing the hope that, in the long run, the adaptation will take place, even absent policy interventions.

A more rational (but less optimistic) interpretation is that in Italy, even today, there are some advantages to adopting the loyalty-based management system which offset (or partially offset) the inability to fully exploit the ICT revolution. If this were the case, then convergence in the long run will not occur without a policy intervention.

But what are the advantages of a loyalty-based management? The most obvious one is that loyalty-based management can function better in environments where legal enforcement is either inefficient or unavailable. Among developed countries, Italy stands out both for its inefficient legal system (the average time to enforce a contract, as measured by Djankov et al. [2003] is 638 days, nearly 2.5 times the cross-country average) and for the diffusion of tax evasion and bribes (in 2017, it ranked 60th in Transparency International's Corruption Perceptions Index, behind every other country in our sample). Thus, a reasonable hypothesis is that at the onset of the ICT revolution Italy found itself with the optimal level of management for its institutions, but the worst possible type for taking advantage of this revolution.

To corroborate this hypothesis, we need to find a way to measure the differential benefit of being loyalty-based in Italy. To this end, we use another set of variables from the EFIGE survey. Specifically, we use the firms' answers to a multiple-choice question in which they were asked to identify the main factors preventing the growth of their firm.

We focus on three external constraints, namely: financial constraints, labor regulation, and bureaucracy. In table 6, we estimate, using a probit model, the conditional probability that the firm encounters each of these constraints. Beside sector fixed effects, the key explanatory variables are the firm level of meritocracy, and its interaction with a dummy for Italy.

As expected, more meritocratic firms face fewer constraints (of any kind). However, this effect is not present in Italy. The interaction between the meritocracy index and the Italy dummy is very similar in magnitude, but opposite in sign, to the baseline coefficient of meritocracy. Interestingly, this interaction effect for Italy is significant for financial constraints and bureaucratic constraints, but not for labor market constraints. This difference makes a lot of sense. Loyal management can exchange favors with banks and bypass bureaucracy through political connections or bribes, but finds it more difficult to overcome the constraints that labor regulation puts on growth.

These results are hardly proof that loyalty-based management is advantageous in Italy, but they are consistent with this assumption.

5. Conclusions

In this paper we try to explain why 20 years ago Italian productivity stopped growing. We find no evidence that this slowdown is due to international trade developments. We also do not find any evidence supporting the claim that excessive protection of employees is the cause. By contrast, we find evidence that the slowdown is associated with Italy's inability to take full advantage of the ICT revolution. In this sense, the Italian disease is an extreme form of the European disease identified by Bloom et al. (2012). We find evidence for this hypothesis using both country/sector-level data and firm-level data. In addition, at the firm level we can show that ICT usage is less pronounced in less meritocratic firms.

Italy loyalty-based management is not necessarily a leftover of the past. Our evidence suggests that even today un-meritocratic managerial practices provide a comparative advantage in the Italian institutional environment.

In sum, the explanation for the Italian disease most consistent with the data is that Italy suffers from an extreme form of the European disease identified by Bloom et al. (2012): inability to exploit fully the ICT revolution. In particular, we show that Italian firms' proclivity to select, promote, and reward people based on loyalty rather than merit is a major cause of the low productivity of Italian ICT investments. In other words, familyism and cronyism are the ultimate cause of the Italian disease.

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Figure 1: Decomposition of GDP/capita growth (1996–2006)

This chart shows the breakdown of log growth in GDP per capita at constant prices between 1996 and 2006 into its three components: hours worked per employee, employment to population, and GDP per hour worked. For this chart we use country-level data for the whole economy.

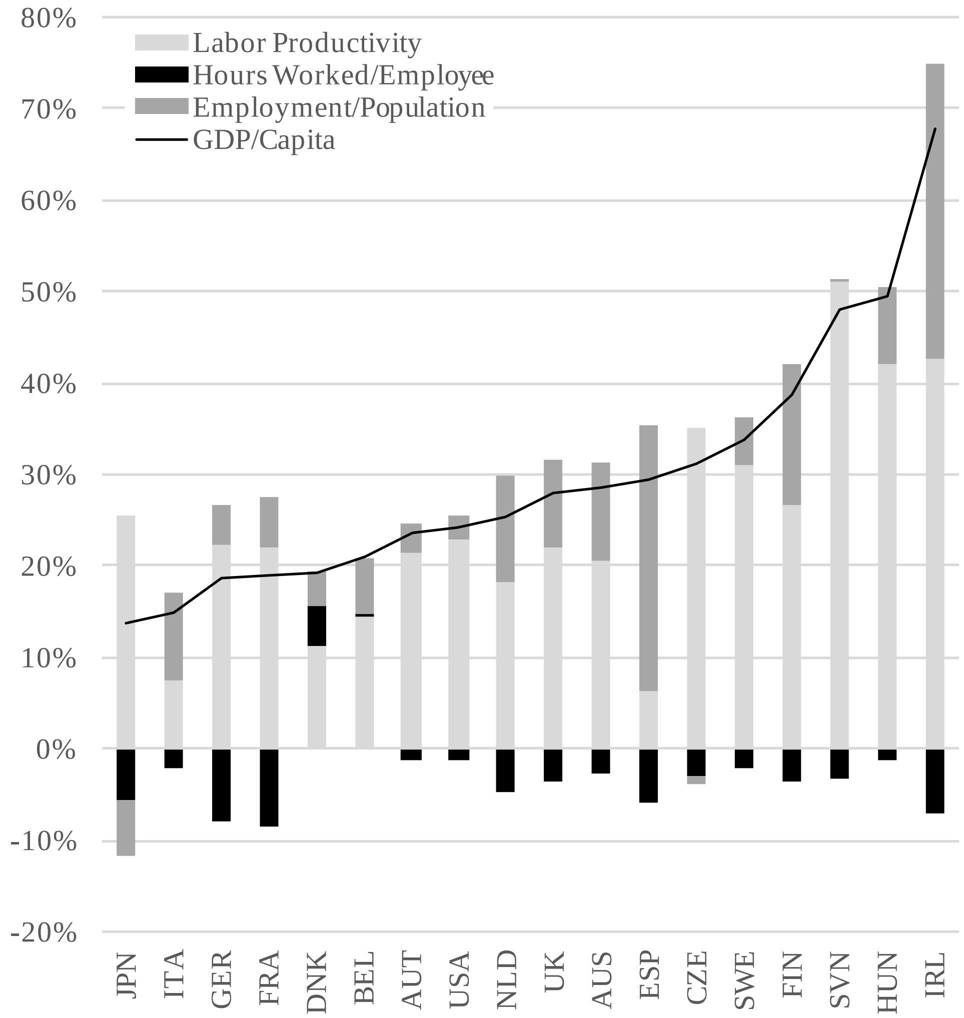

Figure 2: Decomposition of labor productivity growth (weighted, 1996–2006)

This chart shows the breakdown of log growth in GDP per hour worked at constant prices between 1996 and 2006 into its four components: TFP growth and the contributions of ICT capital, non-ICT capital and labor composition. For this chart we use industry-level data in the business sector. Industry growth rates are weighted at the country level using hours worked in the initial year.

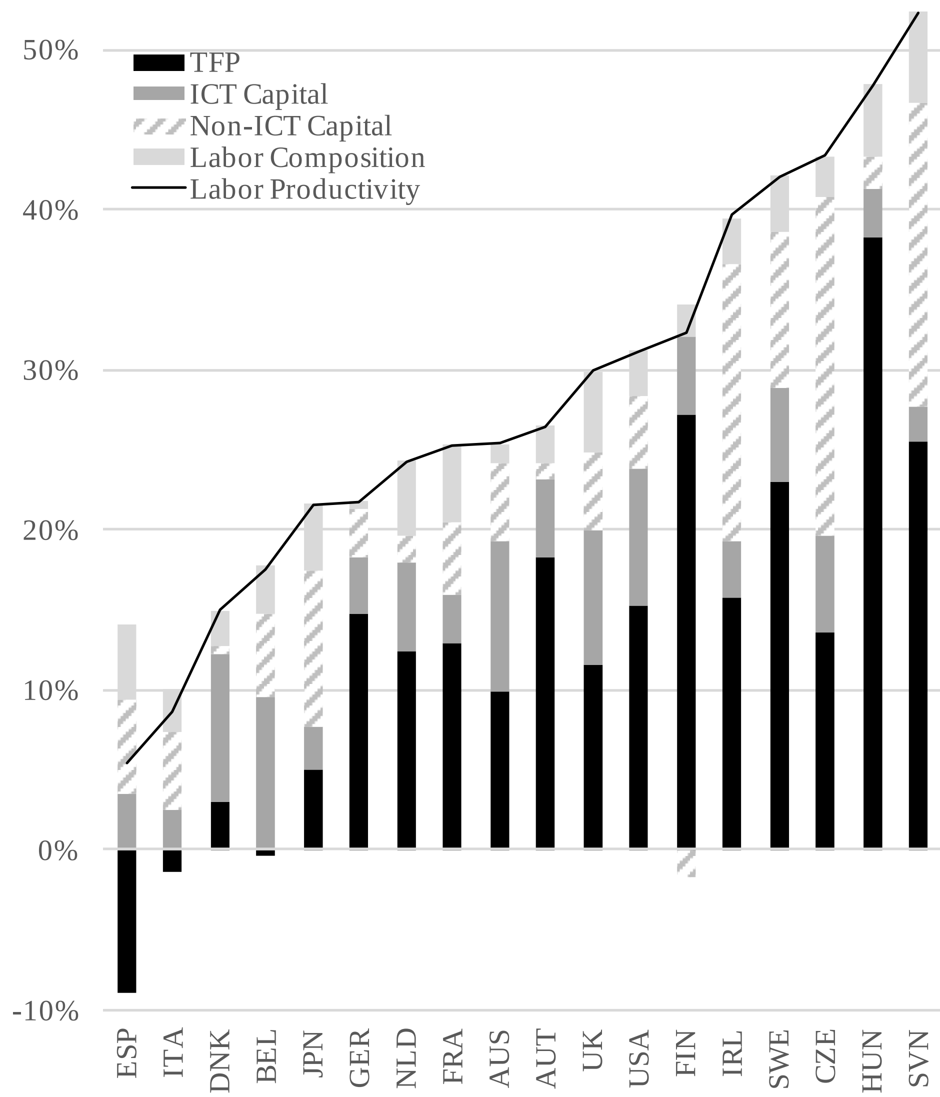

Figure 3: Decomposition of labor productivity growth (unweighted, 1996–2006)

This chart shows the breakdown of log growth in GDP per hour worked at constant prices between 1996 and 2006 into its four components: TFP growth and the contributions of ICT capital, non-ICT capital and labor composition. For this chart we use industry-level data in the business sector. Growth across sectors is unweighted, in order to factor out the sectoral composition of the economy.

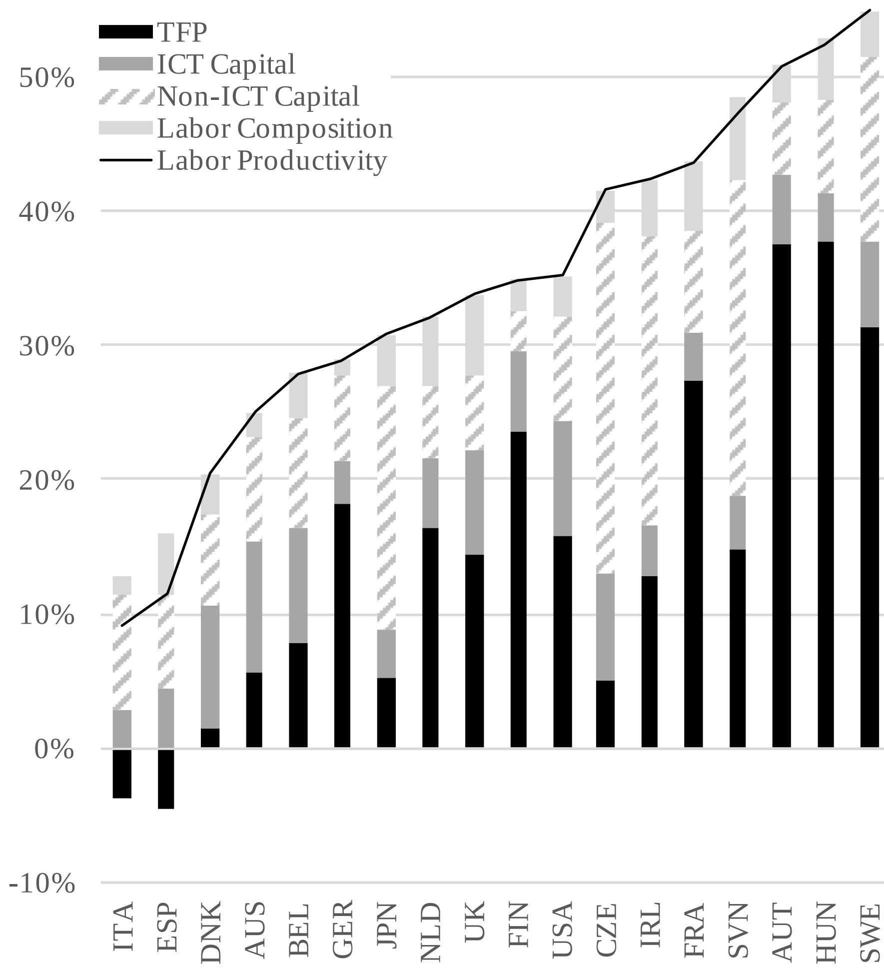

Figure 4: Public sector dependence scores

This chart shows public sector dependence scores, defined as the ratio of government-related news to total sector news. We use articles from the years 2000–2012 from Bloomberg, Dow Jones, Financial Times, Reuters, Thomson Financial, and the Wall Street Journal sourced from the Factiva news search database.

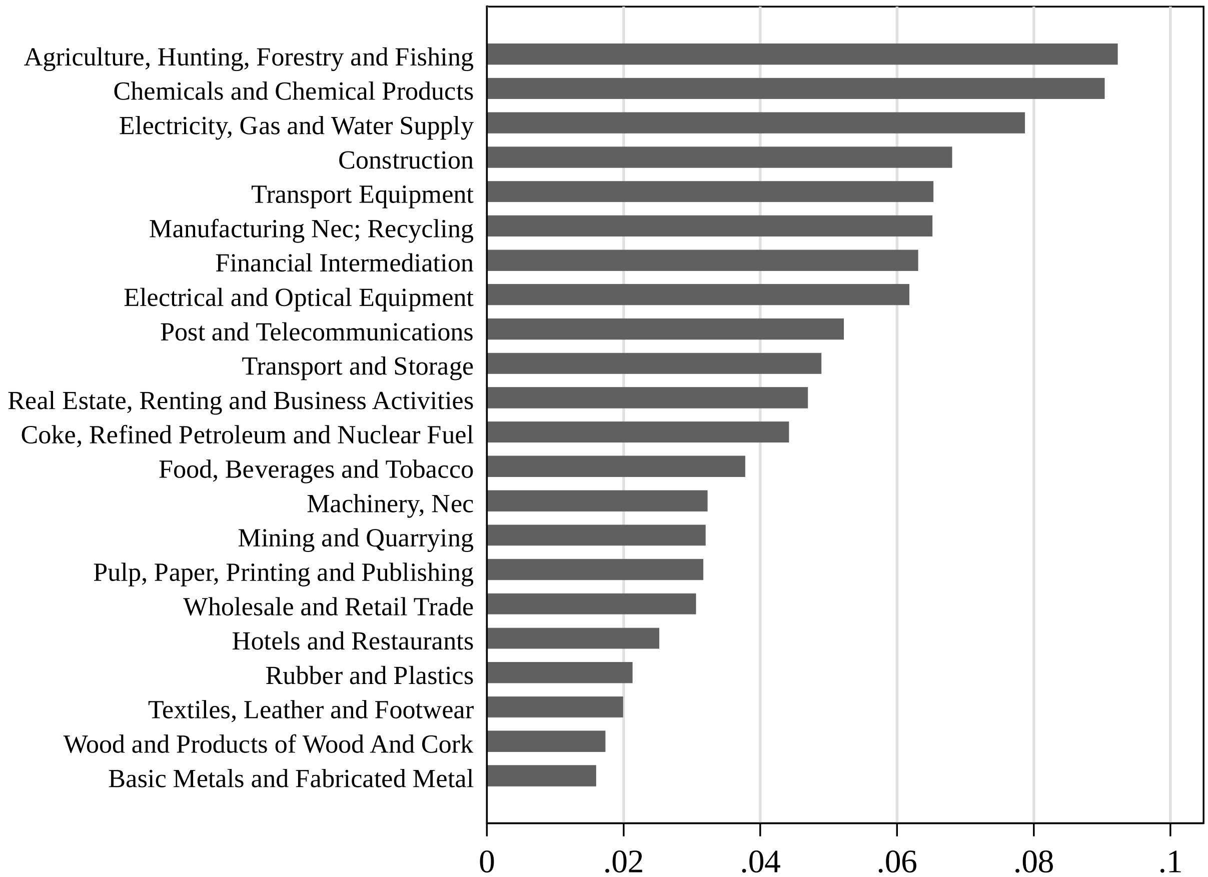

Figure 5: Sector-level productivity growth around the ICT revolution

This figure displays the evolution of TFP estimates, indexed at 1995, from the EU KLEMS database for different country/sector groups. We sort high-Meritocracy versus low-Meritocracy countries (top tercile versus bottom tercile based on our country-level measure of meritocracy) and high ICT intensiveness versus low ICT intensiveness sectors (top eight versus bottom eight sectors based on the sector-level, cross-country average contribution of ICT capital to output growth in 1995–2006). We take the median TFP growth rate for each group/year, giving equal weight to all country/sectors.

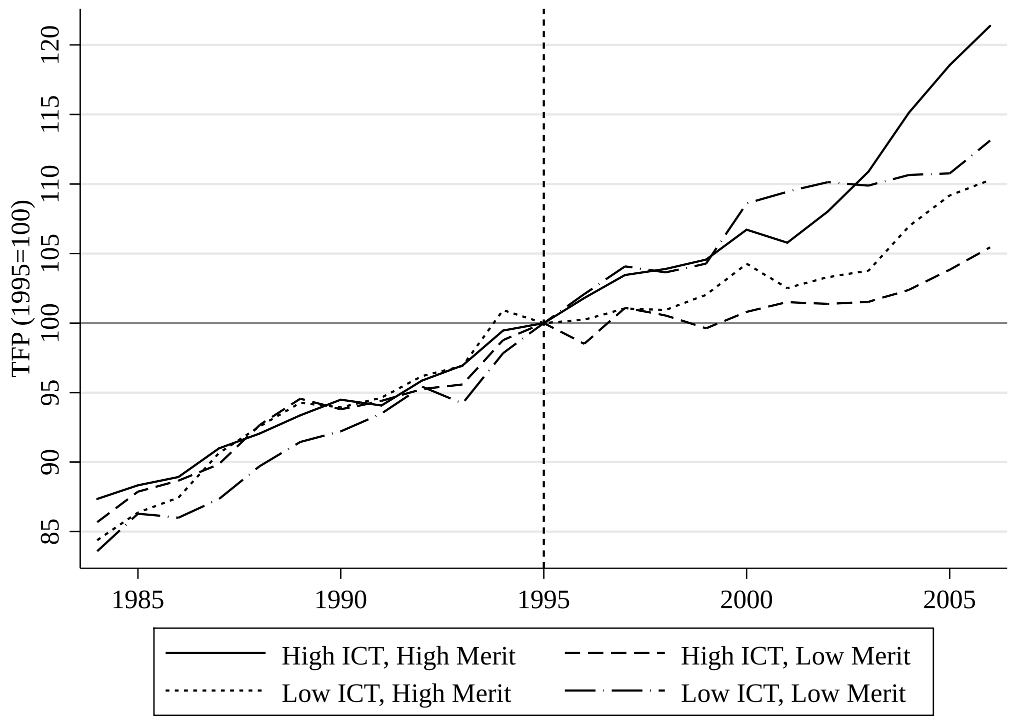

Figure 6: Distribution of firm-level Meritocracy

The figure below displays histograms, by countries and for the whole sample, of firm-level meritocracy. Observations are weighted using the sampling weights of the EFIGE survey in order to obtain consistent population estimates of the distribution of the Meritocracy index.

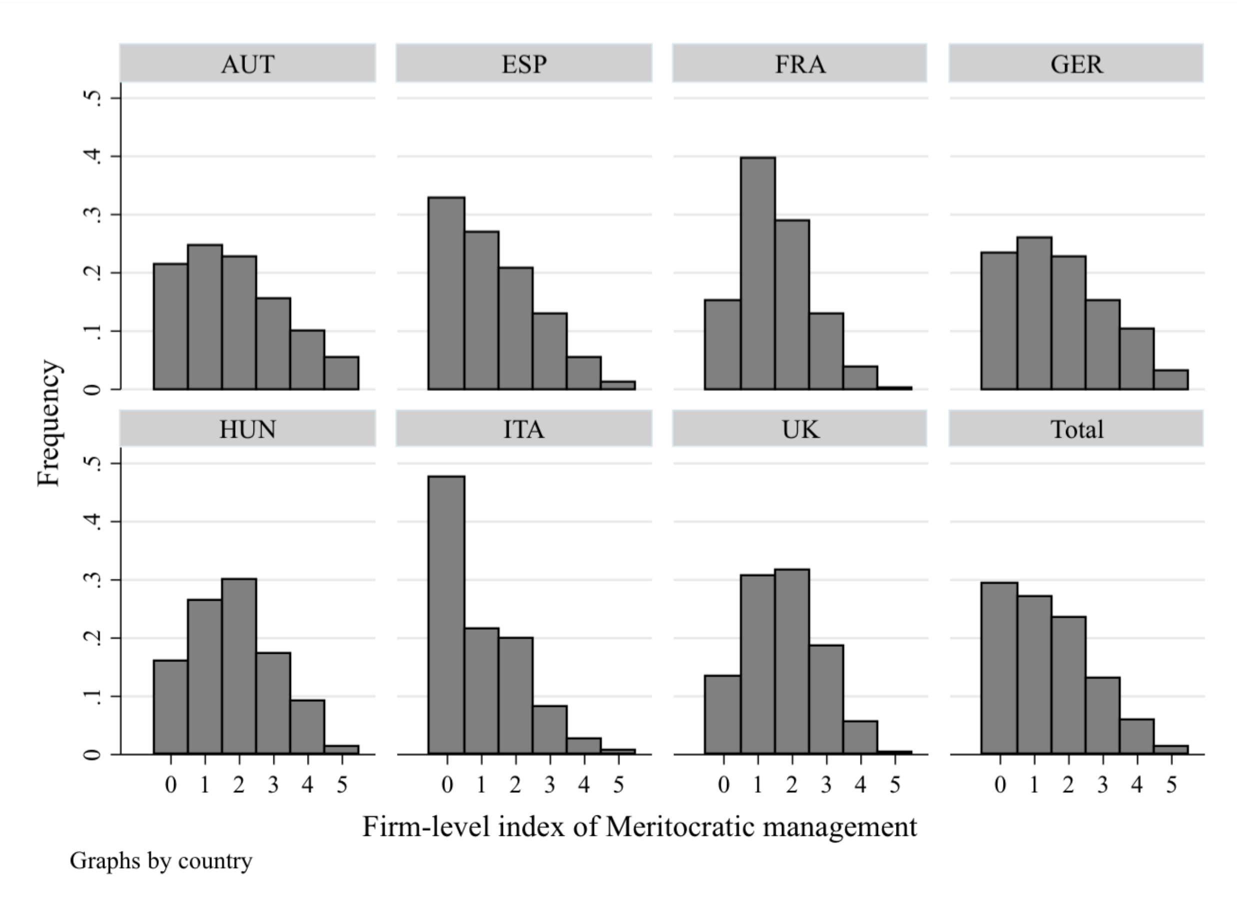

Figure 7: Firm-level and country-level Meritocracy

The figure is a scatter plot of our country-level measure of meritocratic management, derived from WEF surveys, against country-level averages of the firm-level meritocracy, constructed from firm-level EFIGE survey data. Only domestically owned firms are included. Firm-level figures are weighted using the sampling weights of the EFIGE survey in order to obtain consistent population estimates of the distribution of the Meritocracy index.

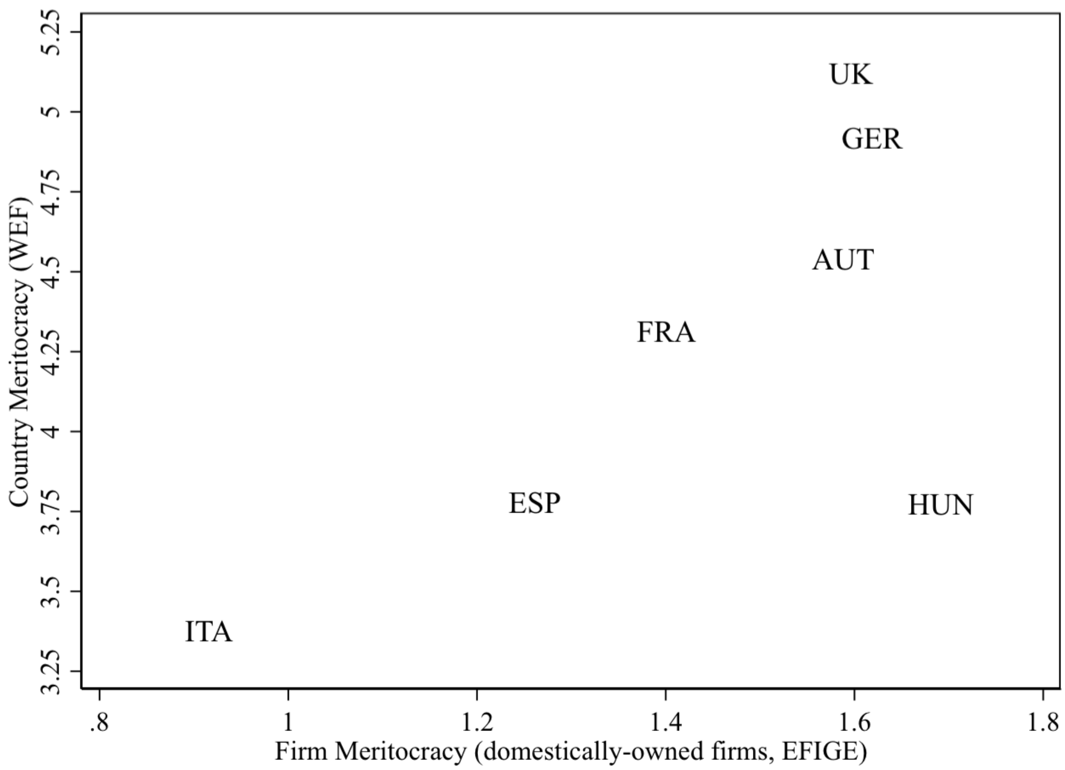

Table 1: Variable descriptions

<table>
<tr><th>Variable</th><th>Description</th><th>Source</th></tr>
<tr><td>Bureaucratic Frictions</td><td>Dummy equal to one if the firm selects “Bureaucracy/Government Regulation” when prompted to “indicate the main factors that hamper the growth of your firm.”</td><td>Bruegel-Unicredit EU-EFIGE Dataset</td></tr>
<tr><td>CEO Age</td><td>Age of current CEO/company head in years, grouped into seven categories: <25, 26-35, 36-45, 46-55, 56-65, 66-75, >75.</td><td>Bruegel-Unicredit EU-EFIGE Dataset</td></tr>
<tr><td>Country Meritocracy</td><td>Average of three Global Competitiveness Report Expert Surveys (2012):
“In your country, to what extent is pay related to employee productivity? [1 = not at all; 7 = to a great extent]”
“In your country, who holds senior management positions? [1 = usually relatives or friends without regard to merit; 7 = mostly professional managers chosen for merit and qualifications]”
“In your country, how do you assess the willingness to delegate authority to subordinates? [1 = not willing at all – senior management takes all important decisions; 7 = very willing – authority is mostly delegated to business unit heads and other lower-level managers]”</td><td>World Economic Forum, 2012</td></tr>
<tr><td>Employees with degree</td><td>(Firm-reported) Share of the firm’s workforce that are university graduates. If the percentage of employees with a college degree is not reported, but the absolute level is reported, we compute the percentage ourselves from the absolute figures, dividing the number of employees with degree by the total number of employees.</td><td>Bruegel-Unicredit EU-EFIGE Dataset</td></tr>
<tr><td>Employment Laws</td><td>Composite Index of Strictness of Employment Laws. Obtained by Botero et al. (2004) combining measures of difficulty of hiring, rigidity of hours, difficulty of redundancy, and redundancy costs (in weeks of salary).</td><td>Botero et al. (2004)</td></tr>
<tr><td>Financial Constraints</td><td>Dummy equal to one if the firm selects “Financial Constraints” when prompted to “indicate the main factors that hamper the growth of your firm.”</td><td>Bruegel-Unicredit EU-EFIGE Dataset</td></tr>
<tr><td>Firm Meritocracy</td><td>Takes on integers 0–5. It is the sum of the affirmative answers to the following questions:
Managers can make autonomous decisions in some business areas?
Managers are incentivized with financial benefits?
Have any of your executives worked abroad for at least one year?
Is the firm not directly or indirectly controlled by an individual or family-owned entity? If it is, was the CEO recruited from outside the firm?
Is the share of managers related to the controlling family lower than 50%?
If the percentage of managers affiliated with the controlling family is not reported, we use 1 minus the percentage of managers not affiliated with the controlling family (if this is reported). If this is also missing, but the absolute levels are reported, we compute the percentage ourselves from the absolute figures.</td><td>Bruegel-Unicredit EU-EFIGE Dataset</td></tr>
<tr><td>Government Dependence</td><td>Ratio of government-related news to total sector news in a pool of articles from Bloomberg, Dow Jones, Financial Times, Reuters, Thomson Financial, and the Wall Street Journal from the period 2000–2012. We define as government-related news items that have at least one of the following subject tags in the Factiva news database: 1) government policy/regulation, 2) government aid, 3) government contracts.</td><td>Factiva News Search</td></tr>
</table>

ICT Capital Contribution	Average yearly contribution of ICT capital to value added growth in 1996–2006. It is defined as the two-period average compensation share of capital in value added (estimated by subtracting labor compensation from value added) times the ICT assets share of capital compensation (estimated using current rental prices), times the rate of growth in ICT capital (estimated through a perpetual inventory model).	EU KLEMS
ICT Infrastructure	Infrastructure component of the 2012 Networked Readiness Index. It is computed by the World Economic Forum using country data on mobile network coverage, the number of secure internet servers, internet bandwidth, and electricity production.	World Economic Forum, 2012
ICT Usage	Sum of "YES" answers to the following three EFIGE survey questions on whether the firm has access to/uses: 1) IT systems for internal information management; 2) IT systems for e-commerce; 3) IT systems for management of the sales/purchase network	Bruegel-Unicredit EU-EFIGE Dataset
Labor Frictions	Dummy equal to one if the firm selects "Labor Market Regulation" when prompted to "indicate the main factors that hamper the growth of your firm."	Bruegel-Unicredit EU-EFIGE Dataset
US Layoff Rate	Mass layoff rates for US sector. Computed by Bassanini and Garnero (2013) using various waves of the CPS biennial Displaced Workers Supplement (2000–2006, even years).	Bassanini & Garnero (2013)
Management Schools	Average of Global Competitiveness Report Expert Survey (2012): • "In your country, how do you assess the quality of business schools? [1 = extremely poor – among the worst in the world; 7 = excellent – among the best in the world]"	World Economic Forum, 2012
Shadow Economy	Shadow Economy, percent of GDP (average in 1999–2006)	Schneider, 2012
Temporary Employees	(Firm-reported) Percentage of employees which, in 2008, have worked for the firm with a fixed-term contract.	Bruegel-Unicredit EU-EFIGE Dataset
ΔChina Exposure	Average yearly change in "China Exposure" in 1996–2005. We define "China Exposure" as sector-level imports from China as a percentage of sector-level domestic demand (= output + imports - exports). Imports, exports and output are measured in current US$ and are sourced from the TiVA dataset, which contains trade data that can be merged to EU KLEMS for the years 1995, 2000, and 2005.	OECD/WTO Trade in Value Added (TiVA) Database
ΔlogTFP	Average total factor productivity growth in 1996–2006 at the sector level, in 2001–2006 at the firm level. At the sector level, it is computed by the authors of the EU KLEMS database as the residual growth in sector-level value added after subtracting the contributions of ICT and non-ICT capital and of the labor services (see EU KLEMS methodology for more information). At the firm level, it is computed by us as the residual growth in output (revenues at constant prices) after deducting the contributions of capital (measured as fixed assets at constant prices), labor (measured as labor expenditure at constant prices), and other inputs (measured as the residual costs at constant prices). Deflators and compensation shares are from EU KLEMS.	*sector-level:* EU KLEMS *firm-level:* Bruegel-Unicredit EU-EFIGE Dataset and EU KLEMS
ΔRule of Law	Average yearly change in Rule of Law Index, from the Worldwide Governance Indicators.	World Bank (through the Quality of Government OECD dataset)

Table 2: Descriptive statistics

In this set of tables, we present summary statistics for the variables presented in the following tables, sorted by their level of variation (firm, country, sector). Additional variables used for robustness tests are present in the appendix.

Panel A: Variables that vary across countries and sectors (1995–2006)

Variable	Obs	Mean	SD	Min	Max
ICT Contribution	414	0.005	0.006	-0.005	0.055
ICT Contribution × Country Meritocracy	414	0.023	0.030	-0.020	0.234
ΔChina Exposure	414	0.001	0.003	-0.001	0.027
ΔlogTFP	414	0.012	0.036	-0.292	0.204

Panel B: Variables that vary across countries

Variable	Obs	Mean	SD	Min	Max
Country Meritocracy	18	4.683	0.635	3.387	5.504
Employment Laws	18	0.535	0.201	0.164	0.745
ICT Infrastructure	18	5.894	0.708	4.317	6.904
Management Schools	18	5.109	0.645	3.963	6.121
Shadow Economy	18	0.172	0.055	0.086	0.270
ΔRule of Law	18	0.008	0.034	-0.088	0.062

Panel C: Variables that vary across sectors

Variable	Obs	Mean	SD	Min	Max
Govt Dependence	22	0.047	0.023	0.016	0.092
US Layoff Rate	20	0.052	0.017	0.022	0.090

Panel D: Variables that vary across firms

Variable	Obs	Mean	SD	Min	Max
Bureaucratic Frictions	12,444	0.208	0.406	0.000	1.000
CEO Age	14,701	4.254	1.038	1.000	7.000
Employees with Degree	14,749	0.094	0.134	0.000	1.000
Financial Frictions	12,444	0.341	0.474	0.000	1.000
Firm Meritocracy	14,205	1.554	1.272	0.000	5.000
ICT Usage	14,756	1.262	0.935	0.000	3.000
Labor Frictions	12,444	0.190	0.392	0.000	1.000
Temporary Employees	14,640	0.256	0.385	0.000	1.000
logEmployees	14,759	3.579	1.029	2.303	10.309
ΔlogTFP	9,878	0.002	0.073	-2.116	1.916

Table 3: Sector-level productivity regressions

This table displays estimation results of ordinary least squares (OLS) regressions of sector-level total factor productivity growth from the EU KLEMS dataset on several explanatory variables and interactions. In all regressions, the left-side variable is log TFP growth, averaged over a 11-year period. In panel A and B we use data for the 1995–2006 period. In panel C, we use data for the 1985–1995 period. Therefore, in each panel every data point is a country/sector. Government Dependence and US Layoff Rate vary at the sector level. Employment Laws, Government Inefficiency and Country Meritocracy vary at the country level. ICT Capital Contribution and ΔTrade Exposure vary at the country/sector level. Data are missing for one sector in Government Dependence and for three sectors in US Layoff Rate. Because source data for ΔTrade Exposure and ΔRule of Law begin in 1995, we use, for the regression in panel C, their values in 1996–2006 as a proxy for those in 1985–1995. Panel C regressions have fewer observations because growth accounting series are unavailable before 1995 for some countries/sectors.

Panel A: Years 1996–2006

	(1) ΔlogTFP OLS	(2) ΔlogTFP OLS	(3) ΔlogTFP OLS	(4) ΔlogTFP OLS	(5) ΔlogTFP OLS
ΔChina Exposure	0.009				-0.137
	(1.087)				(1.062)
US Layoff Rate × Employment Laws		-0.082			-0.112
		(0.375)			(0.343)
Govt Dependence × ΔRule of Law			-0.030		0.102
			(1.036)		(1.134)
ICT Contribution				-5.247**	-4.328***
				(2.151)	(1.237)
ICT Contribution × Country Meritocracy				1.094**	0.719**
				(0.510)	(0.304)
R^2	0.337	0.409	0.339	0.350	0.453
Observations	414	360	396	414	342
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓

Robust Standard Errors in Parentheses   * p<.10, ** p<.05, *** p<.01

Panel B: Years 1996–2006

	(1) ΔlogTFP OLS	(2) ΔlogTFP OLS	(3) ΔlogTFP OLS	(4) ΔlogTFP OLS	(5) ΔlogTFP OLS
ICT Contribution	-5.247**	-5.461	0.552	-3.278*	-10.540
	(2.151)	(3.359)	(1.016)	(1.676)	(6.545)
ICT Contribution × Country Meritocracy	1.094**				2.272**
	(0.510)				(0.910)
ICT Contribution × ICT Infrastructure		0.876			-0.424
		(0.599)			(0.818)
ICT Contribution × Shadow Economy			-4.480		12.270
			(4.699)		(8.774)
ICT Contribution × Management Schools				0.612*	0.004
				(0.364)	(0.405)
R^2	0.350	0.345	0.340	0.344	0.355
Observations	414	414	414	414	414
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓
Robust Standard Errors in Parentheses	* p<.10, ** p<.05, *** p<.01				

Panel C: Years 1985–1995

	(1) ΔlogTFP OLS	(2) ΔlogTFP OLS	(3) ΔlogTFP OLS	(4) ΔlogTFP OLS	(5) ΔlogTFP OLS
ΔChina Exposure	-1.118				-0.624
	(0.941)				(0.765)
US Layoff Rate × Employment Laws		0.663			0.538
		(0.427)			(0.420)
Govt Dependence × ΔRule of Law			1.090		2.344
			(1.846)		(1.708)
ICT Contribution				-7.277	0.550
				(4.943)	(3.648)
ICT Contribution × Country Meritocracy				1.167	-0.530
				(1.044)	(0.797)
R^2	0.152	0.340	0.152	0.162	0.386
Observations	345	300	330	345	285
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓
Robust Standard Errors in Parentheses	* p<.10, ** p<.05, *** p<.01				

Table 4: Firm-level productivity regressions

This table displays estimation results of ordinary least squares (OLS) regressions of firm-level total factor productivity growth computed using Amadeus data in the EFIGE dataset. In all regressions, the left-side variable is log TFP growth averaged over 2001–2007. Every data point is a firm. The variable ICT Contribution, which comes from the EU KLEMS dataset, varies at the country/sector level. The explanatory variable Firm Meritocracy ranges from 0 to 5, and is constructed using firm-level information from the EFIGE survey (see table 2 for details). The variable CEO Age is categorical: A unit increment represents a 10-year increase in the age of the firm's CEO. The variables Employees with Degree and Temporary Employees are expressed as a percentage of the firm's labor force and are part of the EFIGE survey response data. Labor Constraints is a dummy that varies at the firm level. We weight observations to ensure that the regression sample is representative.

	(1) ΔlogTFP OLS	(2) ΔlogTFP OLS	(3) ΔlogTFP OLS	(4) ΔlogTFP OLS
ICT Contribution	-1.610**	-1.606*	-1.107	-0.072
	(0.757)	(0.931)	(0.812)	(1.910)
Firm Meritocracy	0.001	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Firm Meritocracy × ICT Contribution	0.699**	0.664**	0.764**	0.784**
	(0.310)	(0.334)	(0.323)	(0.324)
Employees with degree			0.041***	0.042***
			(0.015)	(0.015)
Employees with degree × ICT Contribution			-4.118	-4.250
			(3.158)	(3.173)
CEO Age				0.001
				(0.001)
CEO Age × ICT Contribution				-0.255
				(0.425)
Temporary employees				-0.002
				(0.005)
Temporary employees × ICT Contribution				-0.005
				(1.538)
Labor Frictions		0.002		
		(0.002)		
R^2	0.017	0.018	0.020	0.020
Observations	9,485	7,309	9,481	9,436
Country Fixed Effects	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓

Robust Standard Errors in Parentheses * p<.10, ** p<.05, *** p<.01

Table 5: Firm-level ICT usage regressions

This table displays estimation results of ordered probit regressions of firm-level ICT Usage, from the EFIGE survey (2009). In all regressions, the left-side variable is a firm-level measure of ICT usage, which ranges from 0 to 3 and which we compute using information from the EFIGE survey (see table 2 for details). The variable ICT Contribution, which comes from the EU KLEMS dataset, varies at the country/sector level. The explanatory variable Firm Meritocracy ranges from 0 to 5, and is constructed using firm-level information from the EFIGE survey (see table 2 for details). The variable CEO Age is categorical: a unit increment represents a 10-year increase in the age of the firm's CEO. The variables Employees with Degree and Temporary Employees are expressed as percentage of the firm's labor force and are part of the EFIGE survey response data. Labor Constraints is a dummy that varies at the firm level. We weight observations to ensure that the regression sample is representative.

	(1) ICT Usage O.Probit	(2) ICT Usage O.Probit	(3) ICT Usage O.Probit
ICT Contribution	-4.496 (12.172)	-0.206 (12.548)	18.735 (30.014)
Firm Meritocracy	0.130*** (0.012)	0.116*** (0.013)	0.113*** (0.013)
Firm Meritocracy × ICT Contribution	12.803** (4.977)	11.999** (5.067)	12.385** (5.097)
Employees with Degree		0.761*** (0.119)	0.807*** (0.120)
Employees with Degree × ICT Contribution		-24.577 (32.864)	-28.696 (33.038)
CEO Age			0.012 (0.014)
CEO Age × ICT Contribution			-5.481 (6.651)
Temporary Employees			0.014 (0.059)
Temporary Employees × ICT Contribution			14.098 (19.069)
Observations	14,204	14,196	14,058
Country Fixed Effects	✓	✓	✓
Sector Fixed Effects	✓	✓	✓
Robust Standard Errors in Parentheses	* p<.10, ** p<.05, *** p<.01		

Table 6: Meritocracy and Competitive Frictions regressions

This table displays estimation results of probit regressions of firm-level dummy variables representing the firms' answers to the multiple-choice question "Indicate the main factors preventing the growth of your firm" from the EFIGE survey (2010). The explanatory variable Firm Meritocracy ranges from 0 to 5, and is constructed using firm-level information from the EFIGE survey (see table 2 for details). "Italy" is a dummy variable identifying Italian firms.

	(1) Financial Constraints Probit	(2) Labor Frictions Probit	(3) Bureaucratic Frictions Probit
Italy	-0.126	0.395	0.274
	(0.206)	(0.445)	(0.390)
Firm Meritocracy	-0.059**	-0.089**	-0.074***
	(0.027)	(0.043)	(0.026)
Firm Meritocracy × Italy	0.062**	0.056	0.072***
	(0.027)	(0.043)	(0.027)
Observations	11,950	11,950	11,950
Sector Fixed Effects	✓	✓	✓
Standard Errors Clustering Variable	Country	Country	Country

Robust Standard Errors in Parentheses * p<.10, ** p<.05, *** p<.01

Diagnosing the Italian Disease

APPENDIX

This appendix contains robustness tests to sector-level regressions of table 3 that utilize additional variables. In table 1-bis, we provide variable descriptions for the additional variables utilized.

Tables 3A-bis and 3B-bis replicate the analyses of tables 3A and 3B using alternative measures of Employment protection laws, change in the quality of government and exposure to foreign competition. In particular, *ΔChina Exposure* is replaced by *ΔTrade Openness*, which is time-variation, sector-level of the main explanatory variable of interest in Frankel and Romer (1999) and Alcalá and Ciccone (2004) (the latter use GDP at PPP as denominator, although in our case it does not make a difference since we use time differences, combined with country and sector fixed effects).

Table 3C-bis replicates the analysis of tables 3C using *ICT Contribution* computed over the period 1996–2006 instead of the 1985–1995. The rationale for this specification is to perform a test of the "parallel trend assumption". In other words, we want to ensure that sectors in which ICT capital had the highest impact on growth in the "post" period, in high-meritocracy countries, were not growing faster in 1985–1995. To use a diff-in-diff analogy, while in table C we let the "treated sectors" vary between the pre-treatment period and the post-treatment period, here we impose they be the same, as it would happen in a traditional diff-in-diff specification. Consistently with the parallel trend assumption being respected, we do not find the interaction variable *ICT Contribution*$_{96\text{-}06}$ × *Country Meritocracy* to have a statistically significant effect on TFP growth over the 1985–1995 period.

Table 3A-ter replicates the analysis of table 3A, by excluding three emerging European countries for which data is not available in the pre-treatment period 1985–1995 (Czech Republic, Hungary, Slovenia).

Table 3A-quater replicates the analysis of table 3A, using data from the previous release (March 2008) of the EU KLEMS dataset. For this release, TFP growth is only available up to 2005. The dataset includes 3 more countries (Korea, Luxembourg, Portugal) but 2 fewer sectors (most of the services sectors are absent). In this version of EU KLEMS, growth accounting is performed on gross output, not value added.

In table 3D, we show that the effect of *ICT Contribution* × *Country Meritocracy* on TFP growth is still statistically significant after controlling for an interaction of *ΔChina Exposure* and a measure of employment protection. This interaction control variable captures the possibility that labor reallocation, over the period 1996–2006, was most needed in sectors which were most exposed to increased competition from Chinese imports.

In table 3E, we show that the effect of *ICT Contribution* × *Country Meritocracy* on TFP growth is still statistically significant after controlling for an interaction of *ΔTrade Openness* and the dummy variable *Scale Intensiveness*, which identifies scale-intensive sectors according to the industry taxonomy of Pavitt (1984). The rationale behind the inclusion of this interaction variable is that the main channel through which opening of trade might have caused a slowdown in productivity among developed countries, outside labor reallocation, is economies of scale. As a consequence, if *ΔTrade Openness* has a causal negative effect on TFP growth over this period, we might be able to identify such effect by studying the differential impact of this variable across scale-intensive v/s non scale-intensive sectors. In the same table, we also show that our results are robust to controlling for the effect of two alternative measures of the quality of government. Differently from the measures used in table 3A and 3A-bis, these two measures are derived from a single source and capture the level, as opposed to the change, in the quality of public services. While we find that *ΔTrade Openness* × *Scale Intensiveness* has a negative, statistically significant effect on growth, this does not appear to change the coefficient for *ICT Contribution* × *Country Meritocracy*. Moreover, by performing a calculation similar to the one described in section 3.3, we find that the combined effect of *ΔTrade Openness* and *Scale Intensiveness* does not explain any of Italy's TFP growth gap. This reflects the fact that, while it is possible that opening up trade could have negatively impacted TFP growth in Scale-intensive sectors, the intensity of this "treatment" was not in fact particularly strong for Italy.

Tables 4-bis and 5-bis replicate the analyses of tables 4 and 5 adding the size of the firm (measured as the log number of employees) as an additional control variable. This control variable is omitted from the main specification due to reverse causation concerns: in many general equilibrium models with heterogeneous firms, the equilibrium size of the firm is determined by the firm's productivity (which is here partially captured by the left-hand size variable, *ΔlogTFP*).

Table 1-bis: Appendix Variables Descriptions

Variable	Description	Source
Employment Protection	OECD Employment Protection Legislation Index, averaged over all years in 1996–2006 for which data is available (or, if unavailable in all years, earliest available figure).	OECD
Firm Size	Average size of firms in the country, computed as the ratio of employees to enterprises, as reported in the Structural Business Statistics (SBS) dataset in 2012.	OECD
GMAT Received	Number of GMAT Score Reports received by management schools in the country, divided by the country's population (in thousands of people), estimated by the UN Statistics Division.	GMAC / United Nations
Government Inefficiency	Average number of days needed for the authors of Chong et al. (2014) to get back a letter sent to an inexistent address in a certain country.	Chong et al. (2014)
Human Capital	Barro-Lee index of country-level human capital.	Penn World Table 9.0
Judicial Inefficiency	Average of two measures: the first is the estimated number of days needed to collect a bounced check. The other is the estimated number of days to evict a tenant for non-payment of rent.	Djankov et al. (2004)
logEmployees	log number of employees reported by the firm in the answer to question B3 of the EFIGE questionnaire.	Bruegel-Unicredit EU-EFIGE Dataset
Scale Intensiveness	Dummy identifying scale-intensive sectors according to Pavitt's (1984) industrial sectors taxonomy. We consider broad ISICv3 sectors 24 and 35 as scale-intensive, although the subsectors 2423 and 353 are not.	Pavitt (1984) / Kubielas (2007)
ΔControl of Corruption	Average yearly change in Control of Corruption Index, from the World Governance Indicators.	World Bank (through the Quality of Government OECD dataset)
ΔTrade Openness	The variable is the change in "Trade Openness" from 1995 to 2005. We define "Trade Exposure" as Imports + Exports as a percentage of domestic output. Sector-level Imports, Exports and Output are measured in current US$ and are sourced from the TiVA dataset, which contains trade data that can be merged to EU KLEMS for the years 1995, 2000 and 2005.	OECD/WTO Trade in Value Added (TiVA) Database

Table 3-bis: Sector-level productivity regressions

This table displays estimation results of ordinary least squares (OLS) regressions of sector-level total factor productivity growth from the EU KLEMS dataset on several explanatory variables and interactions. The table is similar to Table 3. The difference is that each of the control variables that vary at the country level is here replaced by an alternate control variable. In Panel A and B, Δ*China Exposure* is replaced by Δ*Trade Openness*; *Employment Laws* is replaced by *Employment Protection*; Δ*Rule of Law* is replaced by Δ*Control of Corruption*; *ICT Infrastructure* is replaced by *Human Capital*; *Shadow Economy* is replaced by *Firm Size*; *Management Schools* is replaced by *GMAT Received*. In Panel C, the ICT contribution to value added in 1985–1995 is replaced by that of 1996–2006, in the spirit of a difference-in-difference analysis.

Panel A-bis: years 1996-2006

	(1) ΔlogTFP OLS	(2) ΔlogTFP OLS	(3) ΔlogTFP OLS	(4) ΔlogTFP OLS	(5) ΔlogTFP OLS
ΔTrade Openness	-0.013***				-0.054
	(0.001)				(0.054)
US Layoff Rate × Employment Protection		0.029			0.001
		(0.109)			(0.113)
Govt Dependence × ΔControl of Corruption			-0.995*		-1.085*
			(0.577)		(0.653)
ICT Contribution				-5.247**	-4.231***
				(2.151)	(1.247)
ICT Contribution × Country Meritocracy				1.094**	0.692**
				(0.510)	(0.306)
R^2	0.414	0.410	0.341	0.350	0.457
Observations	414	360	396	414	342
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓

Robust Standard Errors in Parentheses * p<.10, ** p<.05, *** p<.01

Panel B-bis: years 1996-2006

	(1) ΔlogTFP OLS	(2) ΔlogTFP OLS	(3) ΔlogTFP OLS	(4) ΔlogTFP OLS	(5) ΔlogTFP OLS
ICT Contribution	-5.247**	3.196	-1.026	-0.405	0.355
	(2.151)	(3.880)	(0.774)	(0.595)	(3.933)
ICT Contribution × Country Meritocracy	1.094**				1.268
	(0.510)				(0.826)
ICT Contribution × Human Capital		-1.062			-1.912
		(1.096)			(1.468)
ICT Contribution × Firm Size			0.050*		-0.000
			(0.028)		(0.059)
ICT Contribution × GMAT Received				0.449	0.049
				(0.505)	(0.747)
R^2	0.350	0.340	0.347	0.339	0.359
Observations	414	414	391	414	391
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓

Robust Standard Errors in Parentheses * p<.10, ** p<.05, *** p<.01

Panel C-bis: years 1985-1995

	(1) ΔlogTFP OLS	(2) ΔlogTFP OLS	(3) ΔlogTFP OLS	(4) ΔlogTFP OLS	(5) ΔlogTFP OLS
ΔChina Exposure	-1.118				-0.446
	(0.941)				(0.764)
US Layoff Rate × Employment Laws		0.663			0.577
		(0.427)			(0.452)
Govt Dependence × ΔRule of Law			1.090		2.323
			(1.846)		(1.717)
ICT Contribution$_{96-06}$				0.414	0.587
				(6.171)	(4.052)
ICT Contribution$_{96-06}$ × Country Meritocracy				0.030	-0.195
				(1.201)	(0.837)
R^2	0.152	0.340	0.152	0.153	0.345
Observations	345	300	330	345	285
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓

Robust Standard Errors in Parentheses * p<.10, ** p<.05, *** p<.01

Table 3-ter: Sector-level productivity regressions

This table displays estimation results of ordinary least squares (OLS) regressions of sector-level total factor productivity growth from the EU KLEMS dataset on several explanatory variables and interactions. The table is similar to Table 3. The difference is that Czech Republic, Hungary and Slovenia, for which no data is available in the 1985–1995 subsample, are excluded.

Panel A-ter: years 1996-2006 (excludes Emerging Economies)

	(1) ΔlogTFP OLS	(2) ΔlogTFP OLS	(3) ΔlogTFP OLS	(4) ΔlogTFP OLS	(5) ΔlogTFP OLS
ΔChina Exposure	-0.298 (1.094)				-0.578 (1.045)
US Layoff Rate × Employment Laws		-0.094 (0.399)			-0.152 (0.356)
Govt Dependence × ΔRule of Law			-0.293 (0.998)		-0.311 (1.115)
ICT Contribution				-6.346* (3.525)	-5.501* (2.959)
ICT Contribution × Country Meritocracy				1.304* (0.738)	0.966 (0.602)
R^2	0.392	0.434	0.397	0.402	0.457
Observations	345	300	330	345	285
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓

Robust Standard Errors in Parentheses * p<.10, ** p<.05, *** p<.01

Table 3-quater: Sector-level productivity regressions

This table displays estimation results of ordinary least squares (OLS) regressions of sector-level total factor productivity growth from the EU KLEMS dataset on several explanatory variables and interactions. The table is similar to Table 3. The difference is that instead of using the 2009 release of the EU KLEMS dataset, data from the 2008 release is used: TFP growth and *ICT Contribution* are computed in terms of Gross Output as opposed to Value added (with Intermediate Inputs as an additional input). There are 3 more countries and 2 fewer sectors in this version of the dataset (a large part of the service sector is missing in this case).

Panel A-quater: years 1996-2005 - March '08 release of EU KLEMS
(includes 3 additional countries; excludes 2 macro-sectors, TFP based on Output, not Value Added)

	(1) ΔlogTFP OLS	(2) ΔlogTFP OLS	(3) ΔlogTFP OLS	(4) ΔlogTFP OLS	(5) ΔlogTFP OLS
ΔChina Exposure	0.028 (0.361)				-0.182 (0.363)
US Layoff Rate × Employment Laws		-0.141 (0.149)			-0.223 (0.140)
Govt Dependence × ΔRule of Law			0.188 (0.547)		0.034 (0.569)
ICT Contribution				-3.546*** (1.258)	-3.353*** (1.222)
ICT Contribution × Country Meritocracy				0.570** (0.285)	0.492* (0.294)
R^2	0.333	0.356	0.337	0.389	0.468
Observations	439	342	418	439	323
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓

Robust Standard Errors in Parentheses   * p<.10, ** p<.05, *** p<.01

Table 3D: Sector-level productivity regressions

This table displays estimation results of ordinary least squares (OLS) regressions of sector-level total factor productivity growth from the EU KLEMS dataset on several explanatory variables and interactions. In all regressions, the left-hand side variable is log TFP growth averaged over a 12-year period. Every data point is a country/sector. *Employment Laws*, *Employment Protection* and *Country Meritocracy* vary at the country level. *ICT Contribution* and *ΔChina Exposure* vary at the country/sector level.

Panel D: years 1996-2006

	(1) ΔlogTFP OLS	(2) ΔlogTFP OLS	(3) ΔlogTFP OLS	(4) ΔlogTFP OLS
ΔChina Exposure	-0.057 (1.380)	-0.190 (2.249)		0.085 (1.394)
ΔChina Exposure × Employment Laws	0.251 (3.716)			0.267 (3.613)
ICT Contribution			-5.247** (2.151)	-5.263** (2.177)
ICT Contribution × Country Meritocracy			1.094** (0.510)	1.097** (0.516)
ΔChina Exposure × Employment Protection		0.149 (1.368)		
R^2	0.337	0.337	0.350	0.350
Observations	414	414	414	414
Country Fixed Effects	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓

Robust Standard Errors in Parentheses * p<.10, ** p<.05, *** p<.01

Table 3E: Sector-level productivity regressions

This table displays estimation results of ordinary least squares (OLS) regressions of sector-level total factor productivity growth from the EU KLEMS dataset on several explanatory variables and interactions. In all regressions, the left-hand side variable is log TFP growth averaged over a 12-year period. Every data point is a country/sector. *Government Inefficiency*, *Judicial Inefficiency* and *Country Meritocracy* vary at the country level. *ICT Capital Contribution* and *ΔTrade Openness* vary at the country/sector level. *Scale Intensiveness* is a dummy variable that varies at the sector level.

Panel E: years 1996-2006

	(1) ΔlogTFP OLS	(2) ΔlogTFP OLS	(3) ΔlogTFP OLS	(4) ΔlogTFP OLS	(5) ΔlogTFP OLS
ΔTrade Openness	0.052** (0.022)				0.050** (0.022)
ΔTrade Openness × Scale Intensiveness	-0.065*** (0.022)				-0.064*** (0.022)
Govt Dependence × Govt Inefficiency		-0.001 (0.001)			-0.000 (0.001)
Govt Dependence × Judicial Inefficiency			-0.000 (0.000)		-0.000 (0.000)
ICT Contribution				-5.247** (2.151)	-5.989*** (1.827)
ICT Contribution × Country Meritocracy				1.094** (0.510)	1.188** (0.471)
R^2	0.424	0.340	0.340	0.350	0.448
Observations	414	396	396	414	396
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓

Robust Standard Errors in Parentheses   * p<.10, ** p<.05, *** p<.01

Table 4-bis: Firm-level productivity regressions

This table displays estimation results of ordinary least squares (OLS) regressions of firm-level total factor productivity growth computed using Amadeus data in the EFIGE dataset. In all regressions, the left-side variable is log TFP growth averaged over 2001–2007. Every data point is a firm. The variable ICT Contribution, which comes from the EU KLEMS dataset, varies at the country/sector level. The explanatory variable Firm Meritocracy ranges from 0 to 5, and is constructed using firm-level information from the EFIGE survey (see table 2 for details). The variable CEO Age is categorical: a unit increment represents a 10-year increase in the age of the firm's CEO. The variables Employees with Degree and Temporary Employees are expressed as a percentage of the firm's labor force and are part of the EFIGE survey response data. Labor Constraints is a dummy that varies at the firm level. We weight observations to ensure that the regression sample is representative.

	(1) ΔlogTFP OLS	(2) ΔlogTFP OLS	(3) ΔlogTFP OLS	(4) ΔlogTFP OLS
logEmployees	-0.002**	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
ICT Contribution	-1.641**	-1.648*	-1.130	-0.114
	(0.757)	(0.933)	(0.812)	(1.907)
Firm Meritocracy	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Firm Meritocracy × ICT Contribution	0.729**	0.702**	0.797**	0.816**
	(0.310)	(0.335)	(0.324)	(0.325)
Employees with degree			0.041***	0.042***
			(0.015)	(0.015)
Employees with degree × ICT Contribution			-4.204	-4.334
			(3.164)	(3.179)
CEO Age				0.001
				(0.001)
CEO Age × ICT Contribution				-0.251
				(0.425)
Temporary employees				-0.002
				(0.005)
Temporary employees × ICT Contribution				0.001
				(1.538)
Labor Frictions		0.002		
		(0.002)		
R^2	0.017	0.019	0.020	0.021
Observations	9,485	7,309	9,481	9,436
Country Fixed Effects	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓

Robust Standard Errors in Parentheses * p<.10, ** p<.05, *** p<.01

Table 5-bis: Firm-level ICT usage regressions

This table displays estimation results of ordered probit regressions of firm-level ICT Usage, from the EFIGE survey (2009). In all regressions, the left-side variable is a firm-level measure of ICT usage, which ranges from 0 to 3 and which we compute using information from the EFIGE survey (see table 2 for details). The variable ICT Contribution, which comes from the EU KLEMS dataset, varies at the country/sector level. The explanatory variable Firm Meritocracy ranges from 0 to 5, and is constructed using firm-level information from the EFIGE survey (see table 2 for details). The variable CEO Age is categorical: a unit increment represents a 10-year increase in the age of the firm's CEO. The variables Employees with Degree and Temporary Employees are expressed as percentage of the firm's labor force and are part of the EFIGE survey response data. Labor Constraints is a dummy that varies at the firm level. We weight observations to ensure that the regression sample is representative.

	(1) ICT Usage O.Probit	(2) ICT Usage O.Probit	(3) ICT Usage O.Probit
logEmployees	0.216*** (0.012)	0.224*** (0.012)	0.226*** (0.012)
ICT Contribution	-1.396 (12.297)	2.911 (12.670)	22.136 (30.189)
Firm Meritocracy	0.081*** (0.013)	0.064*** (0.013)	0.062*** (0.013)
Firm Meritocracy × ICT Contribution	9.967** (5.007)	8.739* (5.092)	9.131* (5.125)
Employees with degree		0.851*** (0.119)	0.898*** (0.120)
Employees with degree × ICT Contribution		-20.983 (33.124)	-25.220 (33.347)
CEO Age			0.004 (0.014)
CEO Age × ICT Contribution			-5.739 (6.713)
Temporary employees			-0.005 (0.059)
Temporary employees × ICT Contribution			16.966 (19.312)
Observations	14,204	14,196	14,058
Country Fixed Effects	✓	✓	✓
Sector Fixed Effects	✓	✓	✓
Robust Standard Errors in Parentheses	* p<.10, ** p<.05, *** p<.01		