DIAGNOSING THE ITALIAN DISEASE

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Abstract

We investigate why Italy's labor productivity stopped growing in the mid-1990s. We find no evidence that this slowdown is due to competition from China, Italy's protective labor regulations or increasingly inefficient institutions. 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. Italian firms lag in the adoption of meritocratic management, leading to lower ICT usage. We conclude that familism and cronyism are the ultimate causes of the Italian disease.

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1 Introduction

In the period 1996-2016, labor productivity (measured as GDP per hour worked) grew only 6 % in Italy, versus 30% in Germany and 41% in the United States (Figure 1). While the 2008 global financial crisis and the 2011 euro crisis are partially to blame for this poor performance, Italy's economic problems predate these crises. During the period 1996–2006, Italian labor productivity grew only 0.5% per year, accumulating a 17.4% gap vis-a-vis other advanced nations. Following the global financial crisis of the late 2000s, Italy did even worse. What could possibly have caused a slowdown of such magnitude? In this paper, we try to answer this question.

We start investigating this question by decomposing labor productivity growth (measured as GDP per hour worked) in a panel of 18 countries and 23 sectors, into the effect of four factors: physical capital accumulation, human capital accumulation, and total factor productivity (TFP) growth. We do so by weighting all sectors equally, in order to purge the effect of different sectorial composition (Figure 2). We find that, while Italy did invest less during this period, these lower investments can only explain 5 percentage points of this slowdown. After subtracting the effect of human capital and sectorial specialization, Italy's "missing" TFP growth, over the 1996-2006 period, becomes 21.1% (rather than shrinking). During this period, Italy's TFP actually *decreased* by 6.8%. In other words, Italy's lack of growth cannot easily be attributed to either failure to its sectorial specialization, a slowdown in capital accumulation, or a failure to improve the skill mix of the labor force.

Having ruled out the most basic explanations, we turn to institutional factors. Italy lags behind other developed countries across many dimensions. While these deficiencies might be able to explain why Italy is less productive overall, they cannot easily account for the drop in TFP that occurred in the mid-90s; 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. In order to explain Italy's drop in TFP it is necessary to identify a significant deterioration of the institutional environment, or some institutional factor which did not matter before 1995, and then became a major driver of competitiveness in latter years.

Interestingly, Italy's TFP started decreasing at the same time that US labor productivity started accelerating. In a seminal contribution, Bloom, Sadun and Reenen (2012a) have attributed the US's acceleration to the impact of the ICT revolution, which occurred in the same period. American firms were able to take advantage of ICTs thanks to meritocratic management practices, which have been shown to be strongly complementary with ICT capital Bresnahan et al. (2002); Brynjolfsson et al. (2002); Garicano and Heaton (2010). We also know that Italy stands out, among developed countries, for the scarce diffusion of these practice: Bandiera et al. (2008, 2015) documented this fact extensively using a combination of survey and administrative data, and linked it with certain cultural traits that are particularly prevalent in Italy. Can the interaction of the ICT revolution and lack of meritocracy explain Italy's productivity decline?[1]

We first investigate this hypothesis by analyzing EU KLEMS sector-level growth accounting data. This dataset includes estimates of both the impact of TFP growth and of ICT capital investments (computers, communication equipment, etc.) at the sector level. Under the assumptions of the standard growth accounting framework (Jorgenson et al., 1987, 2005), the combined effect of Management and ICT should be factored in the contribution of ICT capital to output growth. However, if spillovers in ICT investment are present, as the literature suggests (Stiroh, 2002), the effect of management-ICT complementarities will show up in TFP growth, without invalidating the growth accounting framework. We present a simple model of externalities to illustrate this effect.

Consistently with this hypothesis, we find that TFP grew faster in more ICT-intensive sectors in countries where firms are more likely to select, promote, and reward people based on merit, as captured by a measure we derived from answers to the World Economic Forum (WEF) expert survey. This effect explains between 24 and 80% of Italy's TFP growth gap.

We contrast this hypothesis with a set of alternative explanations, from the impact of China's accession to the WTO to the introduction of the Euro. We find the impact of China's accession to the WTO (Autor et al., 2013; Pierce and Schott, 2016) explains none of this gap, nor do Italy's rigid labor laws. The evidence in favor of any effect of the introduction of the Euro is weak.

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), aggregate data alone cannot rule out other possible interpretations. For this reason, we probe deeper with a firm-level dataset (the Bruegel-Unicredit EFIGE dataset).

Using response data from a large survey of European manufacturing firms, we construct a firm-level measure of meritocratic management which reflects the firm's actual organizational practices. In constructing this index, we follow previous work by Bloom, Sadun and Van Reenen (2012b) and Bandiera et al. (2008). Using our data, we confirm the stylized fact that Italian firms are particularly likely to select and reward their managers based on loyalty and connections, rather than performance (Figure 5).

The firm-level data exhibits 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

[1] This hypothesis has been advanced by Hassan and Ottaviano (2013) as well.

country and sector fixed effects.

Using EFIGE survey data, we can investigate directly whether the effect of Meritocratic management on TFP growth is mediated by a more intensive use of ICTs. Consistent with Garicano and Heaton (2010), we find that more meritocratic firms indeed utilize ICTs more. As for TFP growth, this correlation is stronger in sectors where ICTs have the largest impact on output growth.

These findings raise a further question: Why does Italy lag behind in the adoption of meritocratic management practices?[2] A plausible 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 with poorly-functioning credit markets (Caselli and Gennaioli, 2005, 2013) or where legal enforcement is inefficient or unavailable. Among developed countries, Italy stands out for its lack of competition in the banking sector, its inefficient legal system and the diffusion of tax evasion and bribes. Thus, a reasonable explanation is that, at the onset of the ICT revolution, Italy found itself with a managerial class that was unable 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.

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 2 describes our data. In Section 3, we explore the

[2] See Bloom and Van Reenen (2010) for a discussion of potential cross-country drivers of managerial practices

possible structural causes for the lack of productivity growth using sector-level data. In Section 4, we explore the robustness of our econometric estimates. In Section 5, we discuss alternative explanations. In Section 6, we analyze firm-level data. Section 7 provides suggestive evidence of why, in Italy, loyalty prevails over merit in the selection and rewarding of managers. In Section 8, we conclude.

2 Data and measurement

2.1 Growth accounting by country and sector

Our main source of sector-level data is the EU-KLEMS structural database (O'Mahony and Timmer, 2009). It contains harmonized measures of value added, capital, labor, total factor productivity and input compensation at the two-digit ISIC level for 25 European countries, as well as Australia, South Korea, Japan, and the United States, accounting for approximately half of the world's GDP. This level of disaggregation allows us to control for country and sector level confounders using fixed effects. It also allows us to study the interaction between country-specific factors and industry-specific factors. Data is available, depending on the country, from as far back as 1970.

Multiple releases of this dataset are available. Based on the degree of harmonization, and the need to merge this dataset with external data, we have chosen to use the 2011 release, which is based on the ISIC rev3.1 sector definition. Based on data availability, we use data from 1984 to 2006.

The dataset provides industry-level growth accounting. One of its key advantages is the ability to quantify separately the impact of ICT assets and non-ICT assets. In other terms, EU KLEMS breaks down value added growth at constant prices into: 1) TFP growth, 2) the contribution of ICT capital (computers, communication equipment, software...); 3) the contribution of non-ICT capital (land, buildings, machinery...); 4) the contribution of hours worked; 5) the contribution of human capital.

EU KLEMS measures the growth in "labor services" as the weighted average of the growth of hours worked by different worker categories, where the weights are given by the compensation share of each worker's category (age, sex, and skill level). Concordantly, human capital growth is defined as the difference in growth rates between labor services and unweighted hours worked.

We now proceed to summarize the EU KLEMS growth accounting methodology. Assume that, for every country *c*, sector *s*, time *t*, there exists a representative firm that produces output Y (measured as value added at constant prices) by combining capital K and labor L using a generic production function F :

$$Y_{cst} = A_{cst} \cdot F_{cst} \left(K_{cst}, L_{cst} \right) \tag{1}$$

where A is the firm-level total factor productivity. Capital itself is broken down into two different types: ICT capital, and non-ICT capital:

$$K_{cst} = K_{cst}\left(K^{I}_{cst}, K^{N}_{cst}\right) \quad . \tag{2}$$

Similarly, there are J different categories of workers, which differ by demographic factors, skill level, and so on. The total labor input is a combination of the hours worked by the different categories of workers

$$L_{cst} = L_{cst}\left(N^{1}_{cst}, N^{2}_{cst}, ..., N^{J}_{cst}\right) \tag{3}$$

where the total hours worked is defined as:

$$N_{cst} = \sum_{j=1}^{J} N^{j}_{cst} \quad . \tag{4}$$

Let P, R^I, R^N, W^j be, respectively, the prices of output, ICT capital, non-ICT capital and type-j labor and define the following notation for the natural logarithm of a generic variable X:

$$x_{cst} := \log X_{cst} \tag{5}$$

under the assumption of constant returns to scale and competitive markets, we have

$$P_{cst}Y_{cst} = R_{cst}K_{cst} + W_{cst}L_{cst} \tag{6}$$

where the sector-level price indices W and R are defined implicitly by:

$$R_{cst}K_{cst} = R^{I}_{cst}K^{I}_{cst} + R^{N}_{cst}K^{N}_{cst} \tag{7}$$

$$W_{cst}L_{cst} = \sum_{j=1}^{J} W^{j}_{cst}N^{j}_{cst} \quad . \tag{8}$$

As shown by Jorgenson et al. (1987, 2005), we can then obtain the sector-level growth of Total Factor Productivity (TFP) from the following equation:

$$\frac{dy_{cst}}{dt} = \underbrace{\frac{da_{cst}}{dt}}_{\text{TFP growth}} + \underbrace{\left(1 - \frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\frac{dk_{cst}}{dt}}_{\text{Capital Contribution}} + \underbrace{\left(\frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\frac{d\ell_{cst}}{dt}}_{\text{Labor Contribution}} \tag{9}$$

where we have used the first-order condition:

$$MRPL_{cst} = P_{cst} \cdot \frac{\partial Y_{cst}}{\partial L_{cst}} = W_{cst} \tag{10}$$

which, after multiplying both sides by L/PY yields:

$$\frac{\partial Y_{cst}}{\partial L_{cst}} \cdot \frac{L_{cst}}{Y_{cst}} = \frac{W_{cst} L_{cst}}{P_{cst} Y_{cst}} \quad . \tag{11}$$

The same result holds for capital. Also, the growth of capital and labor inputs can be further decomposed as:

$$\frac{dk_{cst}}{dt} = \left(\frac{R^I_{cst} K^I_{cst}}{R_{cst} K_{cst}}\right) \frac{dk^I_{cst}}{dt} + \left(\frac{R^N_{cst} K^N_{cst}}{R_{cst} K_{cst}}\right) \frac{dk^N_{cst}}{dt} \tag{12}$$

$$\frac{d\ell_{cst}}{dt} = \sum_{j=1}^{J} \left(\frac{W^j_{cst} N^j_{cst}}{W_{cst} N_{cst}}\right) \frac{dn^j_{cst}}{dt} \quad . \tag{13}$$

Based on these equilibrium relationships, the yearly growth of log value added at the sector level is decomposed, in the EU KLEMS database, into the sum of the following five flow variables:

$$\text{ICT Contribution}_{cst} \quad := \quad \left[\!\left[1 - \frac{W_{cst} L_{cst}}{P_{cst} Y_{cst}} \right]\!\right] \left[\!\left[\frac{R^I_{cst} K^I_{cst}}{R_{cst} K_{cst}} \right]\!\right] \Delta k^I_{cst} \tag{14}$$

$$\text{Non} - \text{ICT Contribution}_{cst} \quad := \quad \left[\!\left[1 - \frac{W_{cst} L_{cst}}{P_{cst} Y_{cst}} \right]\!\right] \left[\!\left[\frac{R^N_{cst} K^N_{cst}}{R_{cst} K_{cst}} \right]\!\right] \Delta k^N_{cst} \tag{15}$$

$$\text{Human Capital Contribution}_{cst} \quad := \quad \left[\!\left[\frac{W_{cst} L_{cst}}{P_{cst} Y_{cst}} \right]\!\right] \Delta \left(\ell_{cst} - n_{cst}\right) \tag{16}$$

$$\text{Hours Worked Contribution}_{cst} \quad := \quad \left[\!\left[\frac{W_{cst} L_{cst}}{P_{cst} Y_{cst}} \right]\!\right] \Delta n_{cst} \tag{17}$$

$$\Delta \log \text{TFP}_{cst} \quad := \quad \Delta y_{cst} - (14) - (15) - (16) - (17) \ = \ \Delta a_{cst} \tag{18}$$

where the delta (Δ) symbol represents taking the one-period time difference operator and the thick bracket $[\![\cdot]\!]$ represents taking the average between the beginning and end-of-period values of a variable.

As shown in Table 2, Panel A, over the 1996-2006 period, $\Delta\log TFP$ has an annual average of 0.012, and ranges from -0.292 to 0.20 (with a standard deviation of 0.0364). *ICT Contribution* has an annual average of 0.005, a standard deviation of 0.006 and ranges from -0.005 to 0.055. *Non-ICT Contribution* has an annual average of 0.008, a standard deviation of 0.013 and ranges from -0.028 to 0.095.

For further information on the EU KLEMS dataset, please refer to O'Mahony and Timmer (2009).

2.2 Trade data

In order to measure the impact of competition from China across countries and sectors, we need trade data by origin country, origin sector, destination country, destination sector and year. The output concept and industry classification must be compatible with EU KLEMS (value added and ISIC rev 3.1, respectively). The only database that satisfies all of these requirements is the World Input-Output database (WIOD), by Timmer et al. (2015). For each year, the dataset contains data for 41^2 country pairs × 28^2 sector pairs combinations, for a total of 1,317,904 observation in any given year.

We start by computing the "China Shock" in sector *s* to destination market *m* as

$$\text{China Shock}_{smt} := \left[\!\left[\frac{Y_{\text{China},smt}}{\sum_{c \neq \text{China}} Y_{csmt}} \right]\!\right] \cdot \Delta \log Y_{\text{China},smt} \tag{19}$$

where *m* identifies the country/sector of destination of the export. Y_{cmst} is the export in value added (at constant prices) of country *c*, sector *s,* into destination market *m* at time *t*. Note that the growth of Chinese export is multiplied by the market share of Chinese export vis-a-vis all its competitors in destination market *m*. The derivation and the rationale for this variable are explained more in detail in Appendix B.

Then, for every country *c* sector *s* we compute *China Exposure* as the weighted average of *China Shock* in sector *s* across all destination markets

$$\text{China Exposure}_{cst} = \sum_m \left[\!\left[\frac{Y_{csmt}}{\sum\limits_m Y_{csmt}} \right]\!\right] \cdot \text{China Shock}_{smt} \quad . \tag{20}$$

Notice that what makes *China Shock* specific to country *c* is the weighting, given by the share that destination market *m* represents *c.*

We aggregate across 41 destination countries (including a "Rest of the world" aggregate) and 23 destination sectors, implying that every observation of *China Exposure* is the result of taking a weighted average of 943 WIOD data points.

Summary statistics for *China Exposure* are also presented in Table 2, Panel A: it has a mean of 0.012, a standard deviation of 0.021 and it ranges from -0.001 to 0.193. For further information on the WIOD dataset, please refer to Timmer et al. (2015).

We also use a similar dataset, the OECD-WTO Trade in Value Added (TiVA) dataset, to compute the following metric of openness to international trade.

$$\text{Trade Openness}_{cst} = \frac{E_{cst} + I_{cst}}{Y_{cst}} \tag{21}$$

where *E* and *I* are, respectively, exports and imports in value added. The reason why we use a different database for this variable is that the TiVA dataset, unlike WIOD, provides country/sector-level estimates of *total* exports, imports and value added (the WIOD does not). At the same time, it does *not* provide a detailed breakdown of trade by destination country and sector, which we do require in order to compute *China Exposure*. The variable *Trade Exposure* has mean 0.897, standard deviation 0.849 and it ranges from 0.017 to 8.116.

2.3 Country-level variables

We present here variables that vary at the country level. Summary statistics are presented in Table 2, Panel B.

To measure the extent to which firms select, promote, and reward people based on merit, we construct a variable called *Country Meritocracy*. It is built using response data from the WEF Global Competitiveness Report Expert Opinion Survey (2012). We compute the variable 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]. The reason we opted to construct our own measure of meritocratic management, is that the pool of countries for which similar measures are already available (Bandiera et al., 2008; Bloom et al., 2012b) does not overlap with the EU KLEMS sample. Using an alternative variable would shrink the size of our sector-level dataset by 38% or more, resulting in insufficient country-level variation to identify the desired effect.

Country Meritocracy has a mean of 4.683 and a standard deviation of 0.635. Italy has the lowest value: 3.387. Sweden has the highest: 5.504. This variable has the obvious downside of being perception-based and we do not want our empirical results to hinge on its specific construction. Unfortunately, we do not have access to data sources that allow us to compute an alternate measure of meritocratic management at the country level. We do, however, have access to a firm-level dataset, which allows us to gauge meritocratic management practices more objectively and granularly. This data is discussed in detail in 2.5.

As the main measure of regulatory protection of employment we use the composite index *Employment Laws* developed by Botero et al. (2004), which captures difficulty of hiring, rigidity of hours, difficulty of redundancy, and redundancy costs: it has a mean value of 0.535, a standard deviation of 0.201, and it ranges from 0.164 (Japan) to 0.745 (Spain). Italy has a value of 0.650.

Because we do not want our results to rely on the specific variable chosen to quantify this effect, we use an alternative measure for robustness: the OECD Employment Protection Legislation (EPL) composite index (version 1). This variable has a panel structure and is available for different countries with different start dates. We average it across the years included in the post-1995 sample period (1996-2006) for which it is available; if the earliest available year is after 2006, we use the earliest available datapoint. *Employment Protection* has mean 2.153, standard deviation 0.747 and it ranges from 0.260 (USA) to 3.310 (Czech Republic). Italy has a value of 2.76.

The variable *ICT Infrastructure* is a sub-index of the Networked Readiness Index, published by the World Economic Forum (2012); it measures the quality of ICT infrastructure that different countries have in place and is constructed by combining country-level data on mobile network coverage, the number of secure internet servers, internet bandwidth, and electricity production. *ICT Infrastructure* has mean 5.894, standard deviation 0.708 and it ranges from 4.317 (Hungary) to 6.904 (Sweden). Italy has a value of 4.779.

To control for cross-country differences in the quality of management training, we use the variable *Management Schools,* which is also derived from response data from a question of 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]. It has a mean of 5.109, a standard deviation of 0.645, and it ranges from 3.963 (Czech Republic) to 6.121 (Belgium). Italy has a value of 4.792.

Finally we also use the variable *Shadow Economy,* an estimate of size of the shadow economy, as a share of GDP, computed country-by-country by Schneider (2012): it has mean 0.172, standard deviation 0.055 and it ranges from 0.086 (USA) to 0.270 (Italy).

In Section 5, we take into account the effect of variation in institutional quality across countries and time. To do so, we use two indicators from the World Bank's Worldwide Governance Indicators (WGI): Rule of law and Control of Corruption. We use the changes in these variables (Δ*Rule of Law* and Δ*Control of Corruption*, respectively) over the period 1996-2006. Δ*Rule of Law* has mean 0.002, standard deviation

0.021 and it ranges from -0.063 (Italy) to 0.023 (Ireland). Δ*Control of Corruption* has mean -0.003, standard deviation 0.020 and it ranges from -0.034 (Czech Republic) to 0.027 (Japan). Italy has a value of 0.010.

One important caveat about these measures is that they are standardized within years: they do not therefore carry, in theory, cardinal meaning, but only ordinal meaning. We believe nonetheless that they are suitable for our analysis, for two reasons. Firstly, analysis by Kaufmann et al. (2006) finds "no systematic time-trends" in these indicators. Secondly, Acemoglu et al. (2006) argue that a country's distance from the technological frontier depends on the relative, rather than absolute quality of its institutions.

Nevertheless, for robustness, we also use a distinct, non-composite measure of the quality of government, computed by Chong et al. (2014), that is expressed in levels. This last variable, which is based on the length of time needed to get back a letter sent to a fictions address in a foreign country, we call *Govt Inefficiency*: it has mean 94.3, standard deviation 42.0 and ranges from 16.2 (USA) to 173.4 (Italy): a higher value corresponds to lower quality of public sector output.

2.4 Sector-level variables

We could not find an existing measure of how much each sector is dependent on government regulation and intervention. Thus, we constructed one by counting news in major economics and financial news outlets from Dow Jones' Factiva News Search database. We exploit the fact that, in this database, news are tagged by sector and topic. To construct our variable, we build a correspondence table between ISIC rev 3.1 (EU KLEMS's sector definition) with Factiva's industry tags.

The variable *Govt Dependence* is defined, for each sector s, as the number of news articles having "Government Contracts" or "Regulation/Government Policy" as topic, as a percentage of the total news articles for sector s. We consider the universe of articles from Dow Jones, the Financial Times, Reuters, and the Wall Street Journal published from 1984 to 2017. The value of this variable, for each sector, is displayed in Figure 4. It has mean 0.045, standard deviation 0.024 and it ranges from 0.020 (Basic Metals) to 0.126 (Agriculture, Forestry and Fishing).

In order to capture variation in the need for labor force mobility across sectors, we use mass layoff rates in US industries, computed by Bassanini and Garnero (2013) using data from Current Population Survey (CPS) displaced workers supplements covering the period 2000–2006 . The variable *US Layoff* has mean 0.052, standard deviation 0.017 and it ranges from 0.022 (Utilities) to 0.090 (Textiles and Apparel).

2.5 Firm-level data

For the firm-level analysis of Section 6, we use the EFIGE (European Firms in a Global Environment) dataset, developed by (Altomonte and Aquilante, 2012; Altomonte et al., 2012). The dataset covers 14,759 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, which allows 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%?" . We construct the variable *Firm Meritocracy* by summing the number of affirmative answers to the above questions: it has mean 1.554, standard deviation 1.272, and it ranges from 0 to 5. The average value for Italian firms is 1.07.

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 the variable *ICT Usage* as the sum of the affirmative answers to these questions: it has mean 1.262, standard deviation 0.935, and it ranges from 0 to 3.

The survey also collected 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 (34.1% of the firms in EFIGE), and/or second (39.2%), and/or third option (20.8%).

In order to corroborate our findings from aggregate EU KLEMS series, we need to build a firm-level measure of TFP. Unfortunately, there is no internally-consistent way to do this. The reason is that, in response to different data availability constraints and methodological challenges, the macroeconomics and the industrial organization (IO) literatures have developed widely different approaches to compute TFP, which are not consistent with each other (Foster et al., 2016).

The "macro" approach, exemplified by KLEMS, is to use aggregate value added at constant prices as the measure of output, assume perfect competition, and obtain production function parameters from the share of labor compensation in aggregate value added. IO economists, on the other hand, use (deflated) firm revenues or gross output as the output concept, assume imperfect competition and use complex econometric techniques to recover production function parameters from firm-level data.

Our data does not allow to resolve this debate. The best we can do, given our data, is to compute TFP at the firm-level, using a methodology that mimics as closely as possible the one used by EU KLEMS, and studying its robustness. In Sub-section 6.4, we discuss why this methodology is problematic if we wish to relax the assumption of perfect competition, and show how we can use EFIGE data to compute an alternative firm-level TFP growth series under the assumption of monopolistic competition. We will use this alternative TFP measure to investigate the robustness of our econometric results at the firm level to violations of the perfect competition assumption.

Our baseline, EU-KLEMS consistent measure of TFP at the firm level is given by the following formula:

$$\Delta \log \mathrm{TFP}_{it} = \Delta y_{it} - \left(1 - \frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta k_{it} - \left(\frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta \ell_{it} \quad . \tag{22}$$

Firm-level value added is computed as EBITDA+labor costs (which implies the same intermediate input definition as EU KLEMS), deflated using the EU KLEMS sector-level value added price index. Firm-level labor input is given by labor costs, deflated using the EU KLEMS sector-level price index. The firm-level capital stock is measured as Fixed Assets (lagged), deflated using sector-level GFCF price indices from the OECD Structural Analysis (STAN) dataset.[3]

BvD accounting data in the EFIGE dataset is available beginning in 2001: therefore (in order to avoid using data from the crisis) our firm-level TFP growth will be computed for the period 2001-2007. The resulting variable $\Delta \log TFP_{2001-2007}$ has mean 0.002, standard deviation 0.073 and it ranges from -2.116 to 1.916.

The dataset also contains information on the firms' workforce composition. We use the percentage of employees with a university degree and the percentage of employees with temporary employment contracts. The variable *Employees with Degree* has mean mean 0.094, standard deviation 0.134; the variable *Temporary employees* has mean 0.256 and standard deviation 0.385.

The EFIGE dataset is built out of the stratified sample of firms that received the EFIGE survey. It

[3]We use OECD StAn capital deflators because capital deflators for France and Hungary are not provided directly in the EU KLEMS dataset (due to confidentiality constraints). OECD StAn is the most similar database to EU KLEMS and uses the same sector definition.

is equipped by its authors with sampling weights which ensure that when we use survey data EFIGE is representative of the population of manufacturing firms.

By contrast, when EFIGE is matched with firm financials obtained from the Amadeus dataset, it inherits the sample selection issues of Amadeus. To address this problem, every time financial information is employed, we use the methodology developed by Pellegrino and Zheng (2017) to generate new sampling weights that make the sample representative.

For further information on the EFIGE dataset, please refer to Altomonte and Aquilante (2012).

3 Evidence from sector-level data

3.1 Decomposing labor productivity growth by country

In order to understand Italy's low labor productivity growth, for each country *c* and sector *s,* we decompose the log growth of GDP per hour worked during 1996-2006, following the EU KLEMS methodology. Subtracting the growth of hours worked from both sides of (18) and using the constant returns to scale assumption, we obtain the following decomposition of labor productivity (GDP/hour worked):

$$\underbrace{\Delta\left(y_{cst}-n_{cst}\right)}_{\text{LP growth}} = \underbrace{\Delta a_{cst}}_{\text{TFP growth}} + \underbrace{\left[\!\left[1-\frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right]\!\right]\cdot\frac{R^I_{cst}K^I_{cst}}{R_{cst}K_{cst}}\cdot\Delta\left(k^I_{cst}-n_{cst}\right)+}_{\text{ICT Contribution}} \tag{23}$$

$$+\underbrace{\left[\!\left[1-\frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right]\!\right]\cdot\frac{R^N_{cst}K^N_{cst}}{R_{cst}K_{cst}}\cdot\Delta\left(k^N_{cst}-n_{cst}\right)}_{\text{Non}-\text{ICT Contribution}}+\underbrace{\left[\!\left[\frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right]\!\right]\cdot\Delta\left(\ell_{cst}-n_{cst}\right)}_{\text{Human Capital Contribution}} \quad .$$

This decomposition is shown for each of the countries in EU KLEMS in Table 3 and, graphically, in Figure 2. The sector weight is the same (1/23) for all sectors in each country, in order to sterilize the effect of differences in specialization across countries.

Italy has by far the lowest labor productivity growth over the 11 year period: 5% vs an average of 33% for all other EU-KLEMS countries. The only other country with a single-digit labor productivity growth is Spain (9%). During the same period Sweden saw its labor productivity soar by 49%. When we decompose labor productivity growth in its four components we find that most of the action is in the residual (the TFP). For Italy, changes in labor composition added 1.3 percentage points to labor productivity growth (versus an average of 3.4%). Investment in non-ICT capital contributed 7.9 percentage points (versus an average of 9.9%). ICT capital investments contributed 2.5 percentage points versus an average of 5.5%. Based on OECD aggregate data, Hassan and Ottaviano (2013) attribute the low labor productivity growth in Italy to low ICT investments. These figures seem to suggest that ICT investments only played a secondary role. The overwhelming share of Italy's labor productivity growth gap remains unexplained, absorbed into TFP: Italian TFP *shrank* by 6.8% during this period, while for the average country it grew by 14.2%, amounting to a gap of 21 percentage points.

Overall, this analysis suggests that very little of Italy's gap in labor productivity growth 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 TFP growth. This result is not specific to Italy. The countries that do better in terms of labor productivity growth (Hungary, Austria, Sweden) are also the same that do better in terms of TFP growth. The same is true for the two laggards (Italy and Spain). Thus, we need to explain why Italian TFP growth fell behind. This is what we will try to do next.

3.2 Decomposing output growth by sector

In Table 4 we perform the same decomposition by sector. Not surprisingly, the sectors experiencing the greatest labor productivity growth tend to be the most high-tech sector, while the laggards tend to be services or brick-and-mortar sectors.

The variance across sectors is much larger than across countries: the fastest growing sector, electrical equipment (30 to 33) experienced a labor productivity growth during the period of 88%. In the second one, Post and Telecommunication, labor productivity grew by 73%. By contrast, Real estate and business services (70 to 74) and fuel production (23) showed a decline in labor productivity.

By and large, the observed differences in labor productivity growth are mostly driven by differences in TFP growth.

3.3 Productivity growth during the ICT revolution

We observed that high-tech sectors grew more both in labor productivity and TFP than low-tech ones. Similarly, if we exclude Hungary that is still catching up, we observe that richer countries (like Sweden and Austria) grew more than poorer ones (like Spain and Italy), contrary to what traditional growth models would predict. Most of these differences seem to be driven by variation in TFP growth. What can explain these patterns?

The mid-1990s marked the beginning of the ICT revolution. One of the unique characteristics of ICT capital investment is the strong complementarity with organisational capital (Brynjolfsson and Hitt, 2003; Brynjolfsson et al., 2002). Consistent with this hypothesis, Bloom et al. (2012a) show that differences in management style between Europe and the United States can explain why labor productivity growth in the Old Continent fell behind the U.S. one after 1995. Is it possible that similar differences within Europe can explain our observed patterns? If so, could this help explain Italy's TFP drop?

Before we move on to investigate this hypothesis further, however, we need to ask one question. Why would the effect of ICT/management complementarities show up in TFP, rather than in the contribution of ICT capital? If the marginal productivity of ICT capital varies systematically across firms or countries according to managerial practices (and these are constant over time) then this should be reflected by the compensation share of ICT capital. To see why this is the case, consider a simplified version of the model presented in Bloom et al. (2012), in which the production function varies at the sector level and the output concept is value added. Managerial capital is captured by the unobserved input M, which we assume for simplicity to vary across countries, and which has the effect of increasing the output-ICT capital elasticity:

$$Y_{cst} = A_{cst} \cdot M_c \cdot \left(K_{cst}^I\right)^{\alpha_{cst}^{KI} + \sigma M_c} \left(K_{cst}^N\right)^{\alpha_{cst}^{KN}} \left(L_{cst}\right)^{1-\sigma M_c - \alpha_{cst}^{KI} - \alpha_{cst}^{KN}} \tag{24}$$

the first order condition for ICT capital is

$$MRPK_{cst}^I = \left(\alpha_{cst}^I + \sigma M_c\right) \frac{P_{cst} Y_{cst}}{K_{cst}^I} = R_{cst}^I \tag{25}$$

implying:

$$\frac{R_{cst}^I K_{cst}^I}{P_{cst} Y_{cst}} = \left(\alpha_{cst}^I + \sigma M_c\right) \tag{26}$$

the contribution of ICT capital to output growth equals

$$\text{ICT Contribution}_{cst} = \left(\alpha_{cst}^I + \sigma M_c\right) dk_{cst}^I = \frac{\partial y_{cst}}{\partial k_{cst}^I} dk_{cst}^I \tag{27}$$

and TFP growth is given as before, by:

$$\Delta \log \text{TFP}_{cst} = da_{cst} \tag{28}$$

hence, the complementarity between ICTs and management style is captured by *ICT Contribution* and does not affect TFP growth.

For ICT-management complementarities to have an impact on TFP growth, we need to expand the growth accounting framework. We do so by assuming externalities in ICT capital accumulation. While there are other modeling choices (see 3.5) that could account for the observed correlations this is, in our view, the simplest and most parsimonious way to allow ICT capital to affect TFP growth.

3.4 Modeling externalities

Let us start with the simplest version of the firm-level production function with externalities à la Romer (1986) which we assume for simplicity to be a Cobb-Douglas function:

$$Y_{it} = A_{it} \cdot \left(K_{it}^{I}\right)^{\alpha_{cst}^{KI}} \left(K_{it}^{N}\right)^{\alpha_{cst}^{KN}} \left(L_{it}\right)^{\alpha_{cst}^{L}} \tag{29}$$

where A depends on the country/sector-level accumulation of ICT capital $\left(K_{cst}^{I}\right)$:

$$A_{it} = \overline{A}_{it} \left(K_{cst}^{I}\right)^{M_i \cdot \alpha_{cst}^{KI}} \quad . \tag{30}$$

M is a country-level parameter that reflects country differences in the adoption of meritocratic management practices and $\overline{A}_{it}$ is the exogenous component of TFP. Bloom et al. (2012a) and Garicano and Heaton (2010) assume that there are complementarities between meritocratic management and ICT capital at the *firm* level. We assume a similar complementarity between meritocratic management and ICT capital at the *aggregate* level. For example, a firm that compensates management according to performance can benefit more from electronic data that suppliers and customers generate when they digitize their production process. Note that the magnitude of this externality depends on how ICT-intensive a firm's production process is, as proxied by the elasticity α^{KI}. In the context of the previous example, this assumption implies that the impact of having digitized customers and suppliers is greater if you are more digitized yourself.

Given these assumptions, TFP growth at the firm level is given by:

$$\Delta \log \text{TFP}_{it} = \Delta\overline{a}_{it} + M_i \cdot \underbrace{\alpha_{cst}^{KI} \cdot \Delta k_{cst}^{I}}_{\text{ICT Contribution}_{cst}} \quad . \tag{31}$$

At the EU KLEMS level, we do not observe capital as a stock, but only in changes; as a result, we are going to estimate equation (31) in changes. Furthermore, we do not observe firm-level TFP, but sector level-TFP. Finally, We don't observe Meritocracy at the firm level, but only a country-level proxy: the variable *Country Meritocracy*, which is described in Section 2. We therefore estimate the following relationship:

$$\Delta \log \text{TFP}_{cst} = \Delta\overline{a}_{cst} + M_c \cdot \text{ICT Contribution}_{cst} \quad . \tag{32}$$

Since we don't know the nature of the relationship between the "true" country-level meritocracy M_c and the observed proxy *Country Meritocracy*, we assume the following linear relationship:

$$M_c = \beta_1 + \beta_2 \cdot \text{Country Meritocracy}_c \quad . \tag{33}$$

Substituting equation (33) into (32), we obtain the following regression specification, which we implement in long-term differences (as in Brynjolfsson and Hitt, 2003):

$$\begin{aligned} \Delta \log \text{TFP}_{cs} = \gamma_c + \varsigma_s + \beta_1 \cdot \text{ICT Contribution}_{cs} \\ + \beta_2 \cdot (\text{ICT Contribution}_{cs} \times \text{Country Meritocracy}_c) + \varepsilon_{cs} \end{aligned} \tag{34}$$

where the term γ_c is a country fixed effect and ς_s is a sector fixed effect. In other terms, if there are externalities in ICT adoption, 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 capital to value added growth.

3.5 Myopia as an alternative mechanism

Externalities are not the only way in which TFP growth might be dependent on the contribution of ICT capital. A simpler explanation could be based on the failure of firms to recognize the complementarities between ICT and organizational capital. Since there is a discussion even among economists about whether these complementarities exist, it might be reasonable to assume that firms ignore them in their maximization process.

If firms ignore these complementarities, they would equalize

$$P_{it} \cdot \frac{\partial Y_{it}}{\partial K^I_{it}} = \alpha^I_{cst} \frac{P_{it} Y_{it}}{K^I_{it}} = R^I_{it} \tag{35}$$

the result would be an under-investment in K^I and a residual TFP which incorporates the effect of complementarities.

Thus, for all practical purposes, the effects in an externalities model and a myopic model are the same. Therefore, we will not try to disentangle the two empirically.

3.6 Identification

One of the advantages of using the above specification, is that we can easily control for country and sector-level factors using fixed effects, which absorb all potential country-level confounders. Hence, our main identification concerns regard: 1) the possibility of an omitted variable that correlates with *ICT Contribution* and varies both across countries and sectors (and therefore is not absorbed by fixed effects); 2) the possibility that causality goes from productivity to *ICT Contribution* and not the other way round, as implied by equation (34).

To test for the possibility of an omitted variable, we look separately at the post-treatment period (1996-2006) and the pre-treatment one (1985-1995). If our findings were caused by an omitted variable correlated with the interaction between *ICT Contribution* and *Country Meritocracy*, then interaction should predict TFP even before the ICT revolution, i.e. in the pre-treatment sample.

Even if the parallel trend assumption is satisfied, we are concerned that ICT capital growth, the main component of *ICT Contribution*, may depend on sector-level productivity growth. This would be the case in a simple neoclassical growth model, where the rate of capital accumulation along a balanced growth path is directly proportional to the growth of aggregate productivity. If country and sector fixed effects fail to control for this effect, it is possible that the OLS estimates of β_2 might capture not just the causal effect of Meritocracy and ICT on TFP growth, but also the directionally opposite effect of TFP on ICT capital accumulation.

To rule out this possibility, we exploit differences and similarities between ICT capital and non-ICT capital. If indeed factors tend to accumulate at a higher rate in sectors where TFP grows faster, this should conceivably affect ICT capital as well as non-ICT capital. If, instead, there is an externality of ICT capital accumulation on TFP that is mediated by meritocratic management, we would expect TFP growth to correlate with the interaction of *Country Meritocracy* and *ICT Contribution*, but not with the interaction of *Country Meritocracy* and *Non-ICT Contribution*.

One way to incorporate this intuition into our econometric analysis is to use *Non-ICT Contribution* as a sort of placebo treatment. If indeed *ICT Contribution* is as good as exogenous, then we expect the same regression analysis to not yield a statistically significant result when *Non-ICT Contribution* is used in its place.

In a separate specification, we use the same intuition to construct an instrument for *ICT Contribution*:

$$Z_{cst}^{ICT} = \left[\!\left[1 - \frac{W_{cst} L_{cst}}{P_{cst} Y_{cst}} \right]\!\right] \left[\!\left[\frac{R_{cst}^{I} K_{cst}^{I}}{R_{cst} K_{cst}} \right]\!\right] \Delta \left(k_{cst}^{I} - k_{cst}^{N} \right) \tag{36}$$

which is identical to its endogenous counterpart, except for the fact that the growth of ICT capital is here replaced by the differential rate of accumulation of ICT capital vis-à-vis non-ICT capital. For the exclusion restriction to hold, it is necessary that, conditional on country and sector fixed effects, faster technical progress does not differentially affect ICT and non-ICT capital accumulation.

The advantage of using the IV approach is that we can add more instrumental variables. A simple way to obtain another instrument for *ICT Contribution* is to average the variable across countries:

$$\overline{\text{ICT Contribution}}_{st} = \frac{1}{C} \sum_{c} \text{ICT Contribution}_{cst} \quad . \tag{37}$$

This instrument is simple and intuitive, but it has the disadvantage of being collinear with sector fixed effects: therefore, it cannot be used on its own, but only when interacted with *Country Meritocracy* - and when the instrument defined in equation (36) is also used. We use this additional instrument to over-identify the model: this in turn allows us to perform a Sargan-Hansen test, which provides us with a useful diagnostic of whether the exclusion restrictions are satisfied in the data.

3.7 Sector-level TFP growth regressions

The estimation results for the specification in equation (34) are shown in Table 5. Column 1 shows the OLS estimates when *ICT Contribution* alone is used. It does not appear to predict the growth rate of TFP: the estimated coefficient is not statistically different from zero. In column 2, we interact *ICT Contribution* with *Country Meritocracy*. In this specification, we find that the interaction coefficient is positive and statistically significant at the 5% level.

In column 3, we perform a "placebo" regression, using *Non-ICT Contribution* in place of *ICT Contribution*. Contrary to the previous specification, the interaction of this variable with *Country Meritocracy* does not appear to predict TFP growth across countries and sectors: the interaction coefficient is negative and not statistically significant. In column 4, we perform an Instrumental Variable regression, using the variables presented in equations (36) and (37) as instruments for *ICT Contribution*. The IV coefficient for the interaction of *ICT Contribution* and *Country Meritocracy* is positive, statistically significant and quantitatively close to the OLS estimate. We also present an under-identification test statistic (Kleibergen-Paap): it rejects the null hypothesis that the first-stage coefficients are jointly zero. The Sargan-Hansen test and the Wu-Hausman test yield p-values way above rejection thresholds, which we take as a reassurance that there are no "red flags" of endogeneity in our analysis.

Finally, in column 5, we test the parallel trend assumption by using, as dependent variable, the growth of TFP in the period 1985-1995 instead of 1996-2006. The coefficient estimates for *ICT Contribution* and its interaction with *Country Meritocracy* are statistically and economically insignificant: this suggests that, in our empirical design, the parallel trend assumption is satisfied.

In Figure 3, we summarize these results graphically: we sort countries according to their value of *Country Meritocracy* [4], and sectors according to their (cross-country, post-1995) average value of *ICT Contribution.* i.e. how much growth in value added is attributable to higher ICT investments. We divide both countries and sectors into terciles: we label the top country tercile of meritocracy as "High Merit" and the bottom tercile as "Low Merit"; concordantly, we label the top tercile of sectors as "High ICT" and the bottom tercile as "Low ICT". Then, we sort countries/sectors into four groups: "High/High", "High/Low", "Low/High", "Low/Low". For each of these groups we compute the cross-country, median TFP growth during the period 1985–2006. We then plot the four TFP indices so obtained, using 1995 as the base year.

As we can see from Figure 3, before 1995 TFP growth was fairly similar across all four groups. By contrast, 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 come the low-ICT sectors in high-meritocracy countries (9.8%) and last the high ICT sectors in low-meritocracy, with barely positive growth (5.3%).

3.8 Magnitude of the Effect

How much of the Italian TFP growth gap can be explained by smaller ICT externalities due to lack of meritocracy? To answer this question we subtract from aggregate TFP growth, the effect of ICT externalities, for of all countries in our sample, and compute the "adjusted" TFP growth gap for Italy. If we assume that the variable *Country Meritocracy* is perfectly observed, Italy's TFP gap drops from 21.1% to 15.9% (a drop of a quarter) once we control for the externality.

Country-level meritocracy however, is likely to be 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 interaction variable *Country Meritocracy* $\times$ *ICT Contribution* . Assuming a reliability of Meritocracy of 65%, and correcting for the errors-in-variable problem, the TFP gap of Italy drops to just 4.1% percentage points. Thus, the "Meritocracy" effect can easily explain 80% of the Italian TFP growth gap.

[4] We exclude countries for which there is no TFP data before 1995 (Czech Republic, Hungary and Slovenia), so that graph shows the same countries before and after 1995

4 Robustness

4.1 Potential confounders of meritocracy

Because meritocracy correlates, at the country level, with many other institutional variables, we want to make sure that the observed effect is truly due to meritocracy and not to other factors. To this purpose, in Table 6, we regress TFP growth across countries and sectors on a batch of potential confounders of *Country Meritocracy*, interacted with *ICT Contribution*. In particular, we use measures of *ICT infrastructure* and the quality of *Management Schools* computed by the World Economic Forum, as well as estimates of the size of the *Shadow Economy* computed by Schneider (2012), all interacted with the ICT capital contribution. These variables are described in detail in Section 2.

ICT infrastructure and *Shadow Economy* (columns 2-3) don't seem to have a significant impact on TFP growth, when interacted with *ICT Contribution*. *Management Schools*, on the other hand, is borderline significant (10%, column 4). In column 5, we re-introduce *Country Meritocracy* and control for all these other interactions, only the interaction *ICT Contribution* $\times$ *Country Meritocracy* remains statistically significant.

In the appendix, we reproduce this table using an alternative batch of potential confounders, which include an alternative measure of management training based on the number of GMAT score reports received by business schools in each country, an estimate of average firm size by the OECD, and Barro-Lee human estimates of human capital.

4.2 Small sample size and mismeasurement of meritocracy

Two obvious weaknesses of our sector-level analysis are the small size of the dataset and the fact that we have to resort to a perception-based measure of meritocratic management. We address both of these shortcomings by augmenting our analysis with a firm-level dataset in Section 6.

Additionally, our firm-level data can be used to validate the World Economic Forum measure of *Meritocracy.* Based on Bloom et al. (2012a)'s insight that it is the location of the firm's ownership that determines the ability to leverage ICT, we average the firm-level measure of meritocracy from EFIGE at the headquarter country-level. We can then correlate *Country Meritocracy* and *Firm Meritocracy* across 44 countries. This relationship can be seen in Figure 6. The R^2 of this regression is 64.5%, which suggests that *Country Meritocracy* is an acceptable proxy for our sector-level regressions. Nevertheless, we have accounted for measurement error in computing the explanatory effect on Italy's productivity growth gap, as mentioned in 3.8[5].

[5]Unfortunately, we cannot use this alternative HQ country-level averages in Table 6 regressions because the set of countries does

4.3 Emerging Europe and Italy

We want to exclude the possibility that our results are entirely driven by Italy, which has by far the lowest Meritocracy score among the countries in our sample. In Appendix A (Table 13), we repeat our estimation without Italy. Not only does the coefficient remain statistically significant, but its magnitude is very similar to the one estimated in Table 5. We do the same (Table 14) for our China regressions.

Moreover, our sample includes three developing European countries - Czech Republic, Hungary and Slovenia - for which no growth accounting data is available before 1995. Hence, in the Appendix A (Tables 15-16), we show that our results are robust to the exclusion of these countries.

4.4 Mismeasurement of the production function

In the EU-KLEMS framework, sector-level input expenditures are used to estimate production function elasticities. This approach has drawbacks that are well documented.

In the last twenty years, significant advances have been made in production function estimation that leverage firm-level data: econometric techniques have been introduced that account for sample selection and simultaneity in the production function (see for example Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009). Unfortunately, these approaches are not implementable in our setting: this is the case both for our sector-level data and our firm-level data. The reason is that we do not observe the input of ICT capital at the firm level. Hence, we are forced to rely on EU KLEMS output/capital elasticities.

In Appendix B, we investigate the robustness of our estimates from Table 5 to mismeasurement of parameters of the production function. In particular, we worry about how non-constant returns to scale and mismeasurement of the output/capital elasticities might bias our measures of Total Factor Productivity growth. We argue, and subsequently provide evidence by using the GMM framework, that if such mismeasurement exists, it is small and does not undermine our estimates.

5 Alternative explanations

5.1 The China shock

In this section, we want to consider alternative explanations for Italy's dismal productivity growth. The main competing explanation is trade integration.

China's 2001 entry in the WTO threatened Italy's market share in global manufactures (Tiffin, 2014),

not overlap well with EU KLEMS. The same applies for the measures developed by Bloom and Van Reenen (2007).

precisely at the time when Italy had given up exchange rate flexibility by joining the euro. Contemporary trade theory (see Melitz, 2003) suggests that trade liberalization should have a positive impact on productivity, since it favors the downsizing of less productive firms and the reallocation of factors towards more productive ones. However, this might not necessarily have been the case for countries, such as Italy, in which labor regulation might have hindered such reallocation. It is indeed possible for a sector's productivity to decrease in the wake of a demand shock if the firms operating in that sector are unable to adjust their scale in response to the shock. In other words, while in the US, where there are fewer labor markets frictions, competition from Chinese products resulted in significant displacement of manufacturing workers and productivity gains (Pierce and Schott, 2016), in Italy the effect might have been reversed, causing sizable productivity losses with moderate effects on employment.

In order to test this hypothesis, we regress TFP growth across countries and sectors on a proxy of the magnitude of the China shock (*China Exposure*). The result of estimating this specification are presented in Table 7, Column 1. As expected, we find a positive, albeit not statistically significant effect of *China Exposure* on productivity growth. The economic significance of this coefficient can be described as follows: if competition from China causes value added in a country/sector to drop by 10%, we expect TFP to rise by about 0.4% as a consequence.

If the impact of the China shock on TFP growth is mediated by labor regulation, we should find that the positive effect of *China Exposure* on TFP growth is reverted for countries that make it difficult to reallocate labor by granting a lot of regulatory protection to employees. To capture this in our regression specification, in Column 2 we interact *China Exposure* with a measure of labor market employment protection. As our primary measure, we use a composite index of employment law strictness from Botero et al. (2004). As an alternative measure of employment regulations we use, in column 3, OECD's Employment Protection Legislation index. The resulting regression equation is:

$$\begin{aligned}\Delta \log \mathrm{TFP}_{cs} &= \gamma_c + \varsigma_s + \beta_1 \cdot \text{China Exposure}_{cs} \\ &\quad + \beta_2 \cdot (\text{China Exposure}_{cs} \times \text{Employment Laws}_c) + \varepsilon_{cs} \quad . \end{aligned} \tag{38}$$

The regression intercept is allowed to vary across countries and sectors through the inclusion of fixed effects; there is no time variation in the variables because we use long-term differences/averages. The results of these regressions are presented in columns 2 and 3. Both interaction effects are statistically insignificant: moreover, the effect is positive, contrary to what would be needed to explain Italy's slowdown.

The penetration of Chinese exports could be itself the result of low TFP growth in the country of destination. By averaging the China shock across countries-of-destination in the construction of *China Exposure*, we mitigate this concern. To further alleviate endogeneity concerns about *China Exposure*, we use an instrumental variable. Our instrument, like *China Exposure*, is also a weighed average of the effect of the variable *China Shock* across destination markets; however, it differs from *China Exposure* in that it excludes the domestic market from the domain of summation:

$$Z_{cst}^{China} = \sum_{m \neq (c,s)} \left[\!\left[\frac{Y_{csmt}}{\sum_{m \neq (c,s)} Y_{csmt}} \right]\!\right] \cdot \text{China Shock}_{smt} \quad . \tag{39}$$

In column 4, we carry out the instrumental variable regression, obtaining similar results. The estimated coefficients become larger in absolute terms (0.243 for the baseline coefficient and 1.086 for the interaction with *Employment Laws*). The p-value for the Kleibergen-Paap test is below 0.01, suggesting that the first stage is strong. The Wu-Hausman test yields a p-value of over 0.044, somewhat confirming our suspicion that *China Exposure* might be endogenous.

One potential concern is that the China shock might have impacted all sectors equally, resulting in insufficient within-country variation to identify the effect of interest. Empirically, this does not appear to be an issue. By computing the ratio of the 75th percentile to the 25th percentile of *China Exposure*, we find that there is significant heterogeneity: the country/sector at the 75th percentile of the distribution is 8 times as exposed to demand shocks from China as the country/sector lying at the 25th percentile. Furthermore, if there was not enough country/sector variation, it would be impossible for the China shock to explain the Italian disease, because the shock would have hit all countries equally.

In sum, these findings suggest that, between 1995 and 2006, productivity tended to grow faster, not slower, in countries/sectors that were more exposed to competition from China. This effect does not appear to reverse for countries with strong regulatory protection of workers, regardless of the measure used. Hence, the hypothesis that competition from China (combined with domestic labor market rigidity) caused Italy's slowdown does not find support in the data.

5.2 Labor market regulation

Some commentators Calligaris et al. (2016) attribute Italy's TFP drop to a lack of labor market flexibility. The evidence in Table 7 suggests that this is not the case. However, the lack of findings in the previous regression might be due to the fact that China's entry into the WTO is not the only possible reason why factors might need to be reallocated. In order to test the labor reallocation hypothesis more broadly, we adopt an alternate variable to gauge the sectorial need for labor reallocation: *US Layoff Rate*. It is defined as the rate of mass layoffs in US industries, computed by Bassanini and Garnero (2013) using data from the CPS biennial displaced workers supplement. The rationale for using this variable, similar to that of the financial dependence metric used in Rajan and Zingales (1998), is that we know United States to have minimal labor market distortions, and thus we hope to capture the technological demand for labor reallocation.

In Table 7, column 5, we interact this variable with country-level *Employment Laws*. As expected, the coefficient is negative, suggesting slower TFP growth in countries with rigid laws in sectors where the need for reallocation is high; this effect is, however, quantitatively small and not statistically significant from zero.

5.3 The Eurozone accession

As the ICT revolution gained footing, Italy and other European countries adopted a common currency, the Euro, preventing competitive devaluation. This restriction might have affected Italian exports due to the fact that Italian exports had greatly benefited from competitive devaluation in the past.

In the short term, a decrease in external demand for Italian products can adversely affect productivity through several channels. First, there is a scale effect. A reduction in export volumes can slow down or reverse firm growth, harnessing TFP gains from scale and learning-by-doing. Second, a decrease in external demand for Italian products has a negative impact on the profitability of Italian firms. To the extent firms are liquidity constrained, this reduction in profitability can also lead to a reduction in investments in R&D and new technologies, slowing down not only labor productivity but also TFP growth. The third potential channel is labor adjustment costs. In the absence of growth in internal demand, a decrease in external demand forces Italian firms to cut back production, at least temporarily. If firms cannot easily lay off workers in response to this shock, productivity will drop, the more so the harder it is to lay off workers (i.e., the stronger employment protection is). All these negative effects should be short term. In the long term, if there is a permanent drop in demand for Italian products, firms will eventually adjust or close. If they adjust, they will probably be forced to increase productivity. If they close, the least productive firms will close first, increasing the average productivity simply through a compositional effect. Thus, the predictions for the long term are the opposite. While it is hard to imagine that 10 years are still the short term, we should let the data speak. If this were the case, the sectors that would more affected would be those more open to trade at the beginning of the period and the countries that would be more affected are those with stricter labor protection laws.

In Table 8, column 1 we regress TFP growth on *Trade Openness* (defined in Section 2) as well country and sector fixed effects. We find the effect of *Trade Openness* to be economically and statistically indistinguishable from zero. In columns 2, we add an interaction term with *Employment Laws*. We find that the interaction term is negative and borderline significant (at 10% confidence level) giving some credence to Euro hypothesis. In column 3, we add to this specification our key explanatory variables *ICT Contribution* as well as it interaction with *Country Meritocracy*. The interaction term *ICT Contribution* × *Country Meritocracy* has a positive, statistically significant coefficient that is very similar in magnitude to the one obtained in Table 5. Interestingly, also the interaction between *Trade Openness* and *Employment Laws* remains negative and statistically significant, suggesting that the two explanations are orthogonal. In column 4, we test the robustness of this latter result by replacing *Employment Laws* with its OECD-supplied counterpart *Employment Protection.* We find that the interaction term *ICT Contribution* × *Country Meritocracy* remains positive and statistically significant, while the interaction *Trade Openness* × *Employment Protection* is found to be statistically and economically insignificant.

In sum, while we cannot reject the Euro hypothesis, the evidence in favor of it is weak and it doesn't seem to undermine the ICT-based one.

5.4 Labor market reforms and shadow employment

Starting from 1997, the Italian government passed a series of legislative measures that regulated certain categories of temporary and part-time work; this includes the well known "Biagi Law", the "Pacchetto Treu" as well as Law "2002 n.189", which allowed for the regularization of illegal work of non-EU immigrants. The aim of these regulations was, at least in part, to reduce shadow employment and increase official employment.

Some observers, notably Krugman (2012) in a New York Times column, suggested that this might have biased employment growth statistics upwards for Italy, bringing down Italy's productivity: according to this theory, Italy's productivity slowdown might be nothing more than a statistical artifact.

Unfortunately, we are unable to determine whether or to what extent this effect is present in the EU KLEMS labor input time series. However, we can present two pieces of evidence which suggest that, if this effect exists, it cannot account but for a small fraction of Italy's productivity growth gap.

First, recent empirical analysis of matched Italian employer-employees data (see Daruich et al. 2018) determined that the increase in aggregate employment as a result of the reforms was minimal. Second, the Italian Statistics Institute (iStat) has been computing estimates of the incidence of undeclared work since the early 90s. We recovered these estimates for the years 1992, 1997 and 2003, from a statistical document that iStat (2005) produced for a parliamentary commission. These estimates allow us to perform a back-of-the envelope calculation of the potential effect that these regulations might have had, based on conservative assumptions.

According to the Istat estimates, the incidence of undeclared workers as a percentage of total employment was 13.4% in 1992, 14.8% in 1997, and then again 13.4% in 2003. We make the conservative assumptions that 1) this effect is totally missed by EU KLEMS employment data; 2) irregular work would have grown between 1997 and 2003 by the same percentage amount it did between 1992 and 1997, had the labor market reforms not been passed. Then, employment growth has been overestimated by, at most, 2.8%. By multiplying this by an assumed labor elasticity of 2/3, we obtain an upper bound to TFP underestimation of 1.9%, which is trivial vis-a-vis Italy's 21.1% TFP growth gap.

5.5 An institutional decline?

An alternative explanation to Italy's productivity decline is that Italy experienced, over the 1996-2006 period, a decline in the quality of its institutions. Over this period, in fact, Italy recorded the sharpest decline in "Rule of Law" (one of the Worldwide Governance Indicators) within our sample (Gros, 2011). If Italy's government is the real culprit of the TFP drop, we should observe that the sectors more dependent on regulations and government inputs should experience a sharper TFP drop.

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 is defined, for each sector, as the ratio of total news counts having "government" as the topic to total news for that sector. Figure 4 shows how this variable varies across EU KLEMS sectors. This measure has been validated by both Akcigit et al. (2017) and Giordano et al. (2015), who find a positive correlation between the variation in public sector efficiency across Italian provinces and the level of value added per employee.

In Table 9, column 1, we regress TFP growth on the interaction between *Government Dependence* and Δ*Rule of Law.* We find that this variables have no significant effect on TFP growth. Similarly, we verify that our results from Table 9 are not sensitive to how we measure variation in institutional quality: in columns 2 and 3, we show that there is no substantial difference in the results when we use, *Control of Corruption* or *Govt Inefficiency* (Chong et al., 2014; Djankov et al., 2003) as alternative measures of institutional quality.

In column 4, we include all three interaction effects, as well as additional explanatory variables from the regressions of Tables 5, 7 and 8 into a single specification. We find a statistically significant effect of the interaction term *Govt Dependence* $\times$ *Govt Inefficiency*: however, the effect has the opposite sign as expected (positive). The effect of the interaction term *ICT Contribution* $\times$ *Country Meritocracy*, is positive, statistically significant (at the 1% confidence level) and broadly unchanged in magnitude.

6 Evidence from firm-level data

6.1 TFP growth regressions

An even better way to ensure that our findings from Section 3 are not spurious is to try and corroborate them using a firm-level dataset. To this purpose, we use Bruegel's EFIGE database, which allows us to compute a firm-level measure of meritocratic management, which we call *Firm Meritocracy* (see Section 2). This measure, besides varying at the firm level, it has the advantage of reflecting factual information about firm characteristics, as opposed to perceptions. Figure 5 shows the distribution of this variable by country. Notice that Italy exhibits a distribution of this firm-level meritocracy that is way left-skewed with respect to other countries in our sample. Almost half of the Italian firms in our sample score zero. Figure 6 shows that *Firm Meritocracy* is highly correlated with *Country Meritocracy*.

As explained in Section 2, we compute annual growth rates in firm-level TFP growth in a way consistent with the EU KLEMS methodology, by using firm financials from the Amadeus-BvD dataset, for the period 2001-2007. If indeed meritocratic management mediates the productivity-enhancing effects of ICT adoption, we should observe, at the firm level, the same qualitative effect that we estimated in Section 3.

In Table 10, column 1, we reproduce a similar specification as in Table 5, column 1 using firm-level data. One difference with respect to the sector-level analysis is that sector-level TFP growth is replaced by firm-level TFP growth, and that *Country Meritocracy* is now replaced by *Firm Meritocracy*. In addition, the greater degrees of freedom allow us to control not just for country and sector fixed effects but for country-by-sector fixed effects. This allows us to control for potential reverse-causation of TFP on ICT capital accumulation even better than we did in our sector-level analysis with EU KLEMS data[6]. Because *Firm Meritocracy* is not absorbed by country × sector fixed effects, it is now also included as a standalone variable.

The estimates obtained from the EFIGE firm-level regressions are presented in Table 10. The interaction effect of *ICT Contribution* and *Firm Meritocracy* is positive and statistically significant, mimicking our findings with sector-level KLEMS data.

One of the advantages of the EFIGE firm-level dataset is that we can estimate the effect of labor market frictions on growth. We do so by using firm responses on the major impediments to growth. This variable, *Labor Frictions*, is described in Section 2. Surprisingly, the coefficient of this variable is positive (not negative as expected) albeit not statistically significant.

[6] In the reported table, we do not control for firm size since our only consistently-available measure of size at the firm level is observed at the end of the panel, and therefore could be influenced by cross-firm differences in productivity growth. Nevertheless, to make sure that our results are robust, we repeat this set of regression in appendix Table 10, by controlling for the number of employees.

At the firm level, one important determinant of 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. We add this variable, as well as its interaction with *ICT contribution*, as a control, in columns 3. Unsurprisingly, the variable *Employees with Degree* has a positive and statistically significant effect on TFP growth. However, when interacted with *ICT contribution*, it has a negative, statistically non-significant coefficient. Most importantly, inserting this variable does not change the effect of the interaction term between *Firm Meritocracy* and *ICT Contribution*.

6.2 Temporary workers and gerontocracy in the firm

The Italian labor market reforms of the late 90's and early 2000's, which we previously mentioned in 5.4, might have contributed to Italy's productivity slowdown through a different channel. Daveri and Parisi (2015) (henceforth DP), suggest that these reforms had the effect of increasing the incidence of temporary employment contracts , which in turn reduced the firms' incentives to invest in training. According to DP, this effect, combined with the elevated age of Italian CEOs, limited the ability of Italian firms to innovate, ultimately causing the productivity slowdown.

This hypothesis can potentially threaten identification in our econometric analysis if meritocratic management correlates with either CEO age or the proclivity to use temporary employment contracts. We account for this alternative hypothesis by adding the percentage of temporary workers and the age of the firm's CEO (which EFIGE measures in decades) as control variables, to the regression of Table 10, column 3. To make sure that Firm Meritocracy is not actually capturing the effect of neither of these variables, we also interact them with *ICT Contribution*. The results are shown in the adjacent column 4.

In contrast with the findings of DP, we find that the percentage of temporary workers does not have a statistically significant effect on productivity growth. CEO age has actually a positive and statistically significant effect on productivity growth. The estimated impact of meritocracy and its interaction with *ICT Contribution* remains broadly unchanged. Provided that our controls are not impacted by significant measurement error, we can therefore reasonably exclude that our findings of 6.1 are confounded by the effects described by DP.

6.3 ICT usage regressions

Because Italy does not appear to under-invest significantly in ICT capital, our argument is that its productivity slowdown is due to a lower ability to exploit these technologies. Using firm-level data, we can test whether this interpretation is consistent with the data. 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. The construction of this variable is outlined in Section 2.

In Table 11, column 1, we estimate an Ordered Probit regression of *ICT Usage* on the same set of explanatory variables as in Table 10. If the joint effect of *Firm Meritocracy* and *ICT Contribution* is mediated by the effective integration of ICTs in the firm's management, we would expect their interaction to predict higher values of *ICT Usage*.

We find that more meritocratic firms tend to use ICT more. This effect is more pronounced in sectors where the contribution of ICT capital was larger. Both effects are statistically significant. Based on these estimates, when a firm in a typical sector 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%. The effect is even stronger in the more ICT-intensive sectors.

In Table 11, columns 2-3, 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 coefficients of *Firm Meritocracy* and *ICT Contribution*, as well as their interaction, remain substantially unchanged.

In column 3, we add *CEO Age* and *Temporary Employees* as additional control variables, together with their interaction with *ICT Contribution*. The coefficients for these variables are not statistically different from zero, with the exception of the interaction term *Temporary Employees* × *ICT Contribution*, which has a p-value just below 10. The sign of the coefficient, however is the opposite of what we would expect given DP (positive rather than negative).

6.4 Imperfect competition, revenue and output productivity

In Sub-section 2.5, we warned that, while our firm-level measure of TFP is consistent with EU KLEMS methodology, it is susceptible to violations of the assumption of perfect competition. This is because we deflate value added using a sector-level index. If markets are not perfectly competitive and firms charge a markup, our measure of TFP will capture idiosyncratic variation in firm-level prices. As a consequence, it will be akin to revenue-based productivity (TFPR). This is problematic, because TFPR is known to capture a variety of factors than are unrelated to actual productivity (TFPQ), such as firm-level distortions (Hsieh and Klenow, 2009)[7].

In order to make sure that our firm-level econometric results are not reliant on the assumption of per-

[7]Specifically, we worry about the possibility that our firm-level results might be biased if our TFP measure incorporates variations in markups, which would then become an omitted variable in the regression . The bias on the main coefficients would be positive if more meritocratic firms increased their markups (rather than their physical productivity), in more ICT-intensive sectors.

fect competition, we want to build an alternative (robust) firm-level measure of TFP growth that may not necessarily be consistent with the EU KLEMS approach. The simplest way to do that is to use firm-level output deflators. Unfortunately, while the EFIGE dataset contains plenty of information about management, workforce and IT usage, it falls short of providing firm-level price data. To correct for firm-level variation in prices, we therefore resort to an insight of De Loecker (2011) which allows us to do so by using sector-level prices alone: this requires imposing some structure on demand.

We follow the predominant practice in the literature and assume CES demand, yielding the following firm-level demand function:

$$Y_{it} = Y_{cst}\left(\frac{P_{it}}{P_{cst}}\right)^{-\sigma} \tag{40}$$

where the parameter σ is the elasticity of substitution, and Y_{cst} and P_{cst} are the country/sector-level output and price indices. Rearranging this demand function yields the following expression for the (estimated) real log output growth at the firm level:

$$\Delta\hat{y}_{it} = \Delta y_{cst} + \frac{\sigma}{\sigma-1}\left[\Delta\log\left(P_{it}Y_{it}\right) - \Delta\log\left(P_{cst}Y_{cst}\right)\right] \tag{41}$$

which we can compute using firm-level value added in conjunction with sector-level value added (volume and price indices) from the EU KLEMS dataset.

Our dataset does not allow us to estimate the elasticity of substitution σ, therefore we use the conservative approach of inputing low values of σ (similar to Hsieh and Klenow, 2009). Notice that, as σ becomes large (demand approaches perfect competition), output growth in equation (41) converges to our baseline TFP measure (value added deflated using sector-level price indices).

We use this estimate of firm-level output growth to compute an alternative measure of TFP:

$$\Delta\log\mathrm{TFP}_{it} = \Delta\hat{y}_{it} - \left(1 - \frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta k_{it} - \left(\frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta\ell_{it} \tag{42}$$

input volumes and shares for capital and labor are the same as in equation (22).

In Appendix D, we present alternative estimates of our regression of Table 10 where the dependent variable is TFP computed according to equation (42), using the values of the elasticity of substitution $\sigma = 5$ and $\sigma = 3$, which account for substantial deviations from perfect competition. Because we implement the regression in long-term differences, we can reasonably assume that short-term demand shocks are being averaged out. We also present additional estimations, in which we use a similar TFP measure, computed using the gross output concept (rather than value added).

7 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 of translating ICT investments into productivity seems to have cost Italy between 5 and 17 percentage points of TFP growth (see Sub-section 3.8).

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 of fully exploiting the ICT revolution. If this were the case, then convergence in the long run might not occur without a policy intervention.

But what are the advantages of loyalty-based management? Caselli and Gennaioli (2005, 2013), for example, argue that allocating power to cronies rather than talented managers can be individually efficient (while socially inefficient) in the presence of credit frictions and/or lack of product market competition. An alternative explanation is that loyalty-based management might better function in environments where legal enforcement is either inefficient or unavailable. Among developed countries, Italy stands out for its lack of competition in the banking sector, 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 are asked to identify the main factors constraining the growth of your firm. We focus on three most cited constraints, namely: financial constraints, labor regulation, and bureaucracy. In Table 12, 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.

8 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 competition from China. We also do not find any evidence supporting the claim that excessive protection of employees or deteriorating institutions are 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 appears to be an extreme form of the "European" disease identified by Bloom et al. (2012a). We find evidence for this hypothesis using both country/sector-level data and firm-level data.

Based on our analysis of firm-level survey data, Italian firms show a strong proclivity to select, promote, and reward people based on loyalty rather than merit. We link the prevalence of this loyalty-based managerial model with the lower productivity of Italian ICT investments. In addition, at the firm level, we can show that ICT usage is less pronounced in less meritocratic firms.

In Italy, loyalty-based management is not necessarily a leftover of the past. Correlational evidence from our firm-level data suggests that, even today, un-meritocratic managerial practices provide a comparative advantage in the Italian institutional environment. Our conclusion is that familism and cronyism are the ultimate cause of the Italian disease.

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Figure 1: Aggregate labor productivity in selected countries (1974-2016)

This chart shows GDP per hour worked for USA, Germany, France and Italy in 1974-2016 in 2010 US$.

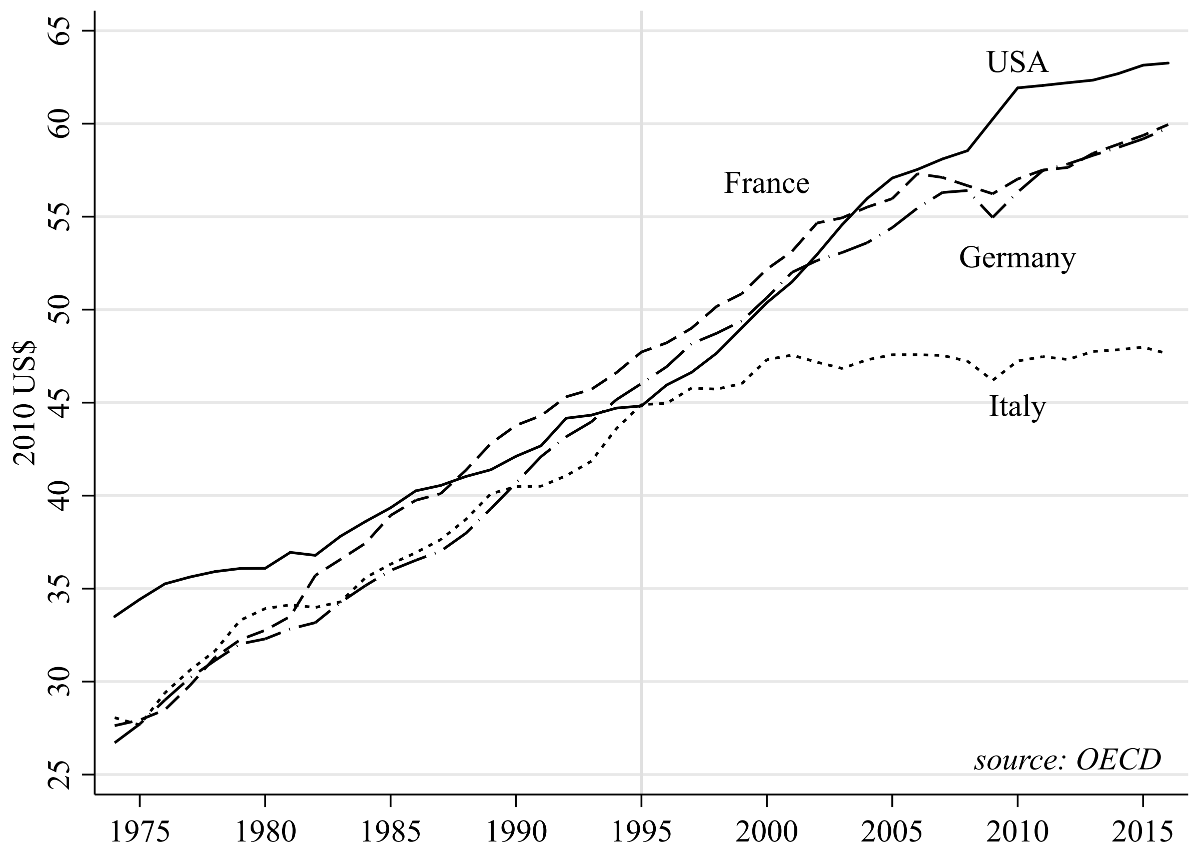

Figure 2: Decomposition of labor productivity growth (unweighted, 1996-2006)

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.

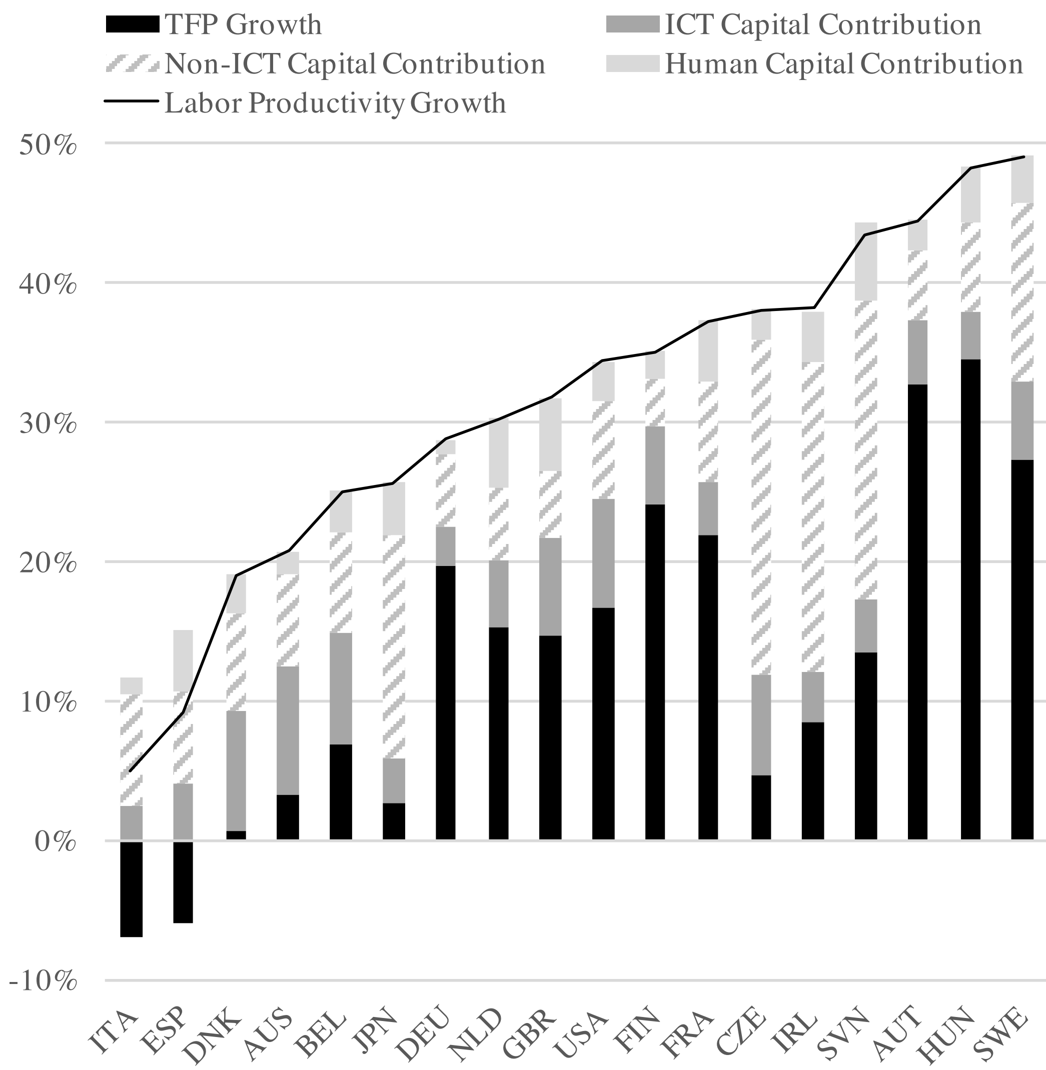

Figure 3: Productivity growth by country Meritocracy and sector ICT intensiveness

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 1996–2006). We take the median TFP growth rate for each group/year. giving equal weight to all country/sectors. Czech Republic, Hungary and Slovenia are excluded since there is no TFP data for these countries before 1995.

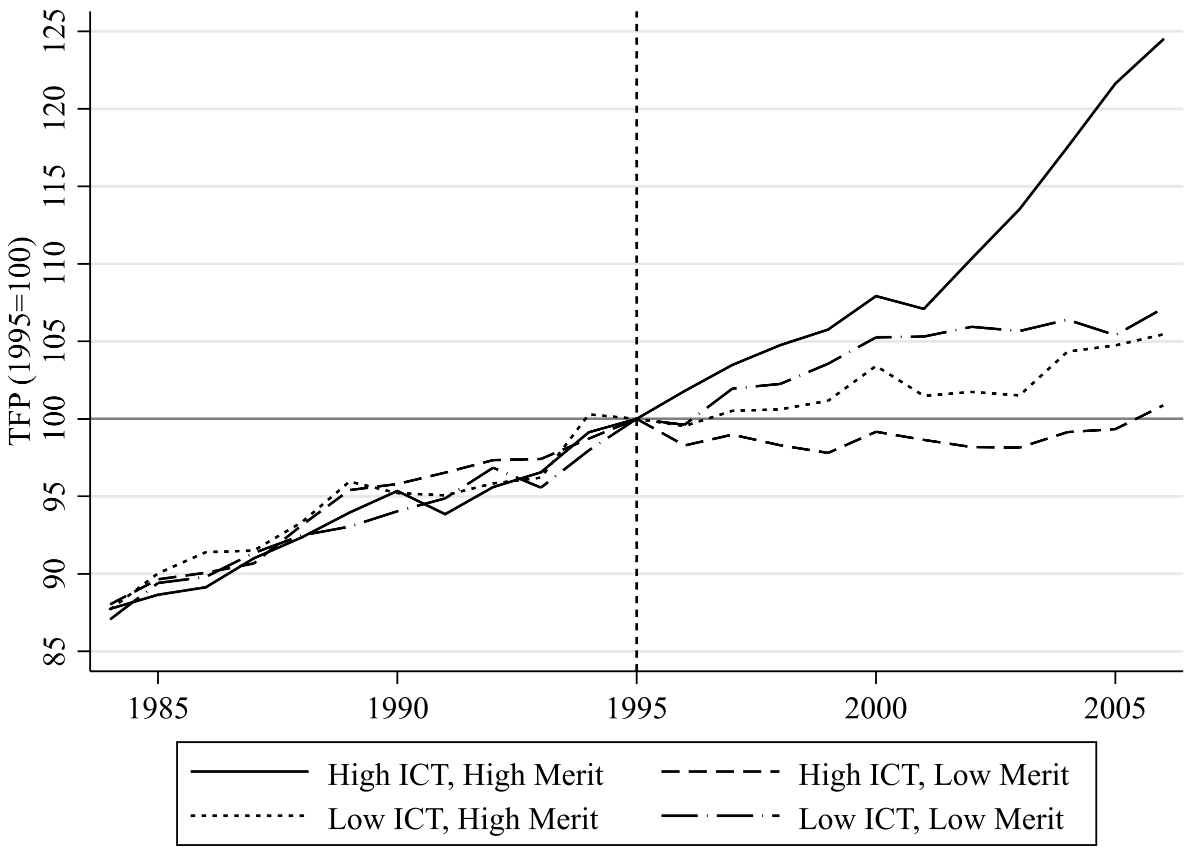

Figure 4: Government dependence scores

This chart depicts values of the variable *Govt Dependence*, built using news count data from Dow Jones' Factiva News Search service. We exploit the Factiva topic and industry "tags". *Govt Dependence* is defined, for each sector, as the share of news articles having the topic tag "Government Contracts" or "Regulation/Government Policy". We use all news articles from Dow Jones, the Financial Times, Reuters, and the Wall Street Journal published from January 1^{st} 1984 to December 31^{st} 2017.

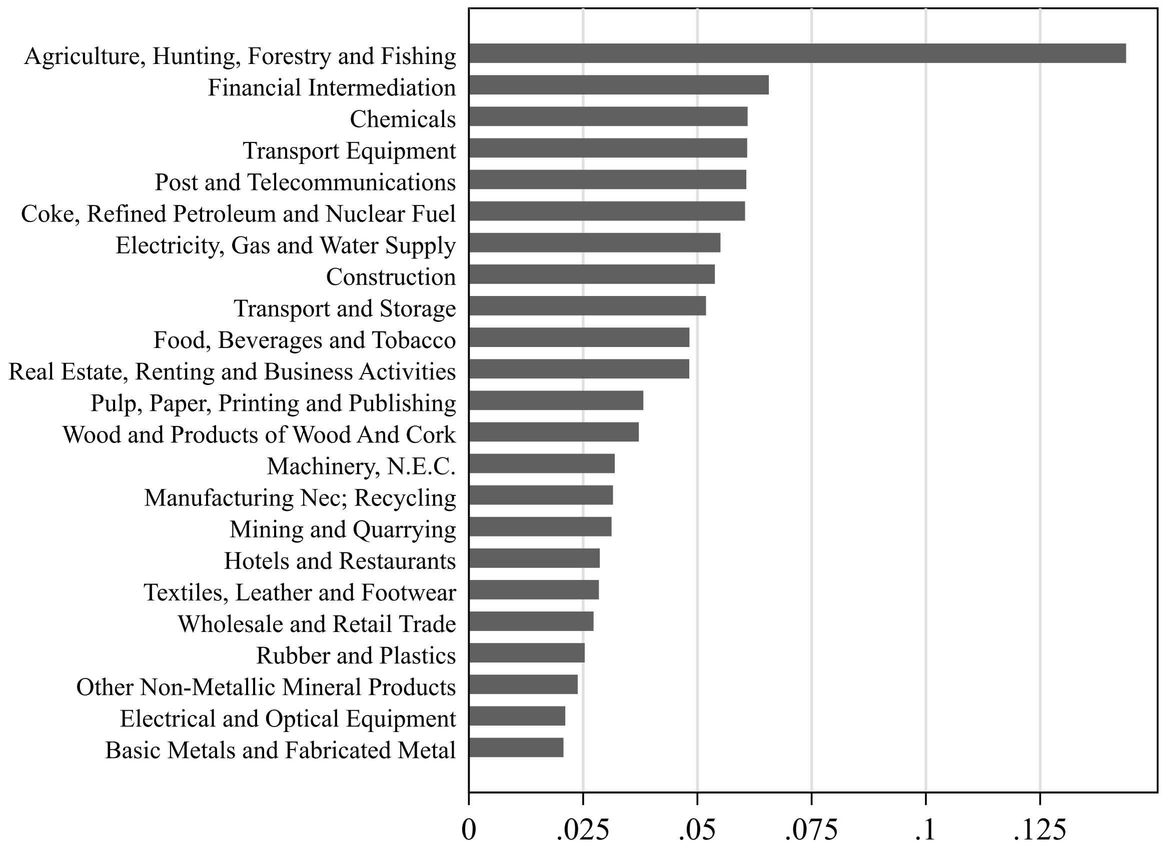

Figure 5: Distribution of firm-level Meritocracy

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.

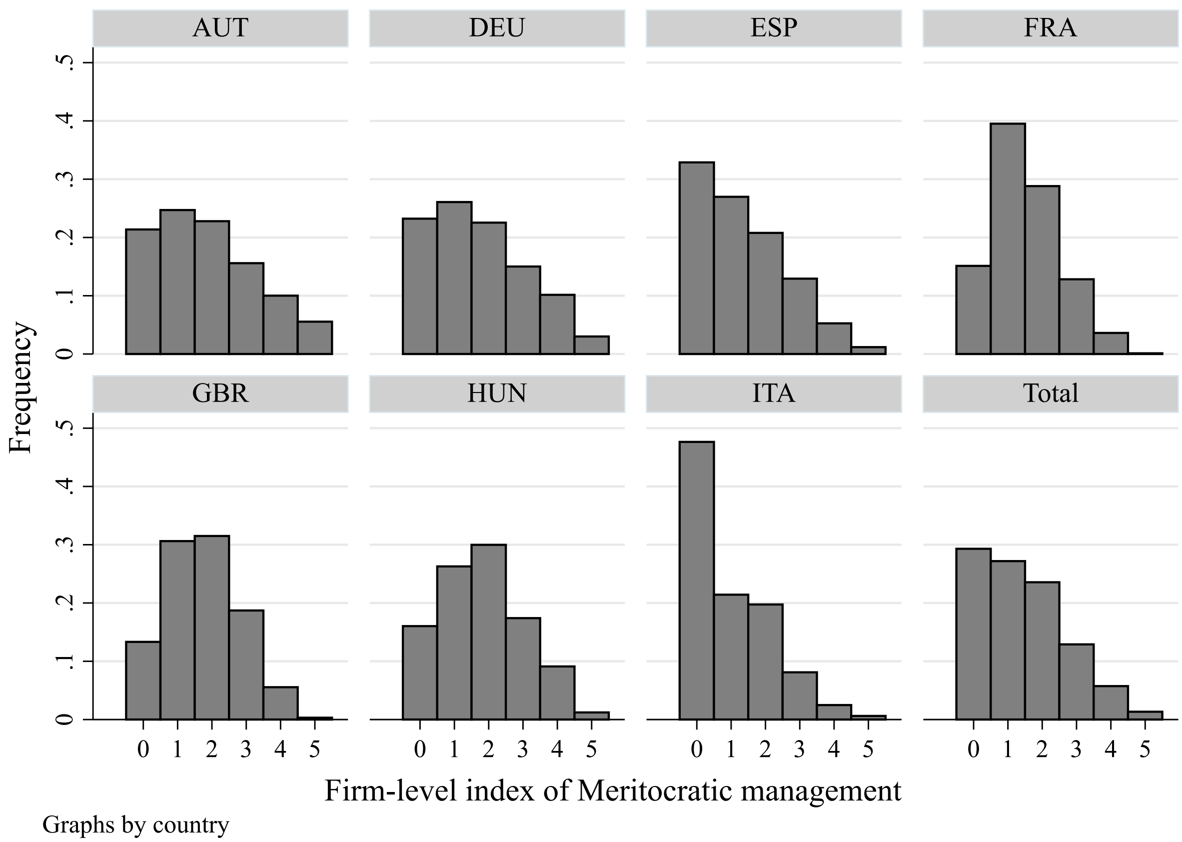

Figure 6: Firm-level and country-level Meritocracy

The following figure plots of our country-level measure of meritocratic management, derived from WEF surveys, against our firm-level meritocratic management metric, constructed from firm-level EFIGE survey data. The latter is averaged at the level of the country of headquarters. To account for the fact that all the firms in our sample are operating in Austria, France, Germany, Hungary, Italy, Spain or the UK, the Firm-level score is adjusted by including a dummy variable for these 7 countries on the right hand side of the regression equation here depicted. The effect of the dummy is summed to these firms' meritocracy score. Countries that are represented by fewer than 10 firms in the EFIGE dataset are excluded.

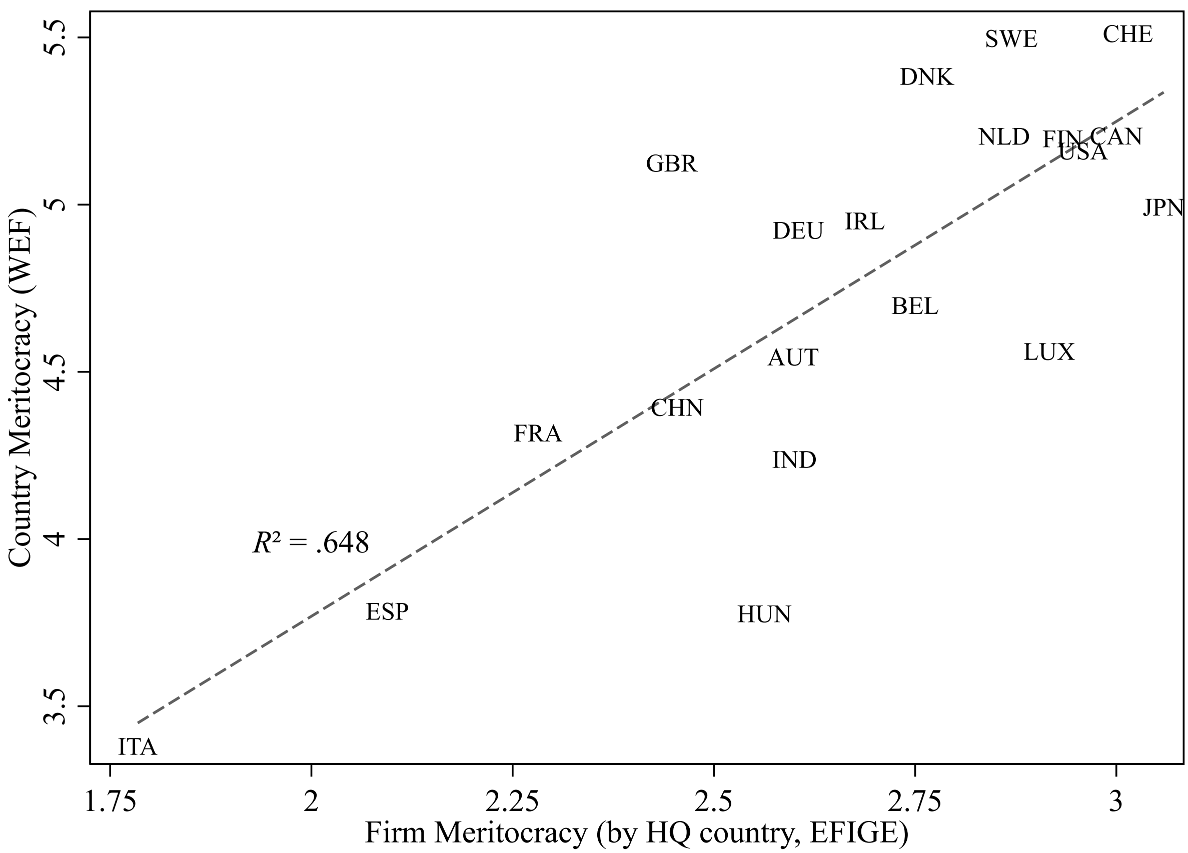

Table 1: Variables Descriptions

Variable	Description	Source
Bureaucratic Frictions	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."	Bruegel-Unicredit EU-EFIGE Dataset
CEO Age	Age of current CEO/company head in years, grouped into seven categories: <25, 26-35, 36-45, 46-55, 56-65, 66-75, >75.	Bruegel-Unicredit EU-EFIGE Dataset
China Exposure	Predicted effect of China exports growth on domestic output, by country and sector. Computed assuming that the effect of China export growth is symmetric across all competitor countries. See Section 2 for derivation.	World Input/Output Database
Country Meritocracy	Average of three Global Competitiveness Report Expert Surveys (2012): 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].	World Economic Forum, 2012
Employees with degree	(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.	Bruegel-Unicredit EU-EFIGE Dataset
Employment Laws	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).	Botero et al. (2004)
Financial Constraints	Dummy equal to one if the firm selects "Financial Constraints" when prompted to "indicate the main factors that hamper the growth of your firm."	Bruegel-Unicredit EU-EFIGE Dataset
Firm Meritocracy	Takes on integers 0–5. It is the sum of the affirmative answers to the following questions: 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%?". 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.	Bruegel-Unicredit EU-EFIGE Dataset
Government Dependence	Ratio of government-related news to total sector news in a pool of articles from Dow Jones, Financial Times, Reuters, and the Wall Street Journal from 1984 to 2017. 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.	Factiva News Search
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)

ICT Contribution	Average yearly contribution of ICT (Information and Communication Technologies) 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
Non-ICT Contribution	Average yearly contribution of non-ICT (Information and Communication Technologies) 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 non-ICT assets share of capital compensation (estimated using current rental prices), times the rate of growth in non-ICT capital (estimated through a perpetual inventory model).	EU KLEMS
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 and 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). Estimated by the authors using a latent variable, Multiple Indicators Multiple Causes (MIMIC) model.	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
Trade Openness	Sector-level exports (Domestic value added embodied in foreign final demand) plus imports (Foreign value added embodied in domestic final demand), divided by value added. All variables measured in 1995 in millions US$.	OECD-WTO TiVA Dataset
ΔControl of Corruption	Average yearly change in Control of Corruption Index, from the Worldwide Governance Indicators (time series sourced through the Quality of Government OECD dataset)	World Bank
ΔlogTFP	Average log growth of total factor productivity growth over a certain period: 1996-2006 for sector-level data and 2001-2007 for firm-level data, unless otherwise noted. It is estimated as the residual growth in value added at constant prices after subtracting the contributions of capital and of the labor services (see Section 2 for more information). For firm-level data, we use output/input elasticities and deflators for added value and labor input from the EU KLEMS dataset, as well as capital deflators from the OECD Structural Analysis (StAn) dataset.	sector-level: EU KLEMS firm-level: Bruegel-Unicredit EU-EFIGE, EU KLEMS and OECD.
ΔRule of Law	Average yearly change in Rule of Law Index, from the Worldwide Governance Indicators (time series sourced through the Quality of Government OECD dataset)	World Bank

Table 2: Descriptive statistics

We present here summary statistics for our main variables, sorted by their level of variation (firm, country, sector). Additional variables (used for robustness tests) are presented in the appendix.

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

Variable	Obs	Mean	SD	Min	Max
China Exposure	414	0.012	0.021	-0.001	0.193
ICT Contribution	414	0.005	0.006	-0.005	0.055
Non-ICT Contribution	414	0.008	0.013	-0.028	0.095
Trade Openness	414	0.897	0.849	0.017	8.116
ΔlogTFP$_{96\text{-}06}$	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
Employment Protection	18	2.153	0.747	0.260	3.310
Firm Size	17	18.129	10.284	6.183	39.289
Govt Inefficiency	18	94.256	41.955	16.200	173.400
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
ΔControl of Corruption	18	-0.003	0.020	-0.034	0.027
ΔRule of Law	18	0.002	0.021	-0.063	0.023

Panel C: Variables that vary across EU KLEMS sectors

Variable	Obs	Mean	SD	Min	Max
Govt Dependence	23	0.045	0.024	0.020	0.126
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
ΔlogTFP$_{01\text{-}07}$	9,880	0.004	0.150	-2.301	2.355

Table 3: Decomposition of labor productivity growth, by country

This table presents the breakdown, at the country level, of the 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 human capital. For this table, 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.

Country	TFP Growth	ICT Capital Contribution	Non-ICT Capital Contribution	Human Capital Contribution	Labor Productivity Growth
AUS	3.4%	9.2%	6.6%	1.6%	20.8%
AUT	32.7%	4.7%	4.9%	2.3%	44.5%
BEL	7.0%	7.9%	7.3%	2.9%	25.1%
CZE	4.7%	7.2%	24.1%	2.1%	38.1%
DEU	19.7%	2.9%	5.1%	1.1%	28.8%
DNK	0.6%	8.6%	7.1%	2.8%	19.1%
ESP	-6.0%	4.1%	6.7%	4.4%	9.2%
FIN	24.2%	5.5%	3.5%	2.0%	35.1%
FRA	22.0%	3.7%	7.3%	4.5%	37.3%
GBR	14.6%	7.1%	4.8%	5.2%	31.8%
HUN	34.6%	3.3%	6.4%	4.1%	48.3%
IRL	8.5%	3.6%	22.2%	3.7%	38.2%
ITA	-6.8%	2.5%	7.9%	1.3%	5.0%
JPN	2.6%	3.3%	16.0%	3.8%	25.7%
NLD	15.3%	4.8%	5.2%	5.1%	30.3%
SVN	13.5%	3.8%	21.4%	5.6%	43.4%
SWE	27.4%	5.5%	12.8%	3.4%	49.0%
USA	16.7%	7.8%	7.0%	2.8%	34.4%
Average ex.Italy	14.2%	5.5%	9.9%	3.4%	32.9%
Difference vs. Italy	21.1%	3.0%	2.0%	2.1%	28.0%

Table 4: Decomposition of labor productivity growth, by sector

This table presents the breakdown, at the sector level, of the 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 human capital. For this table, 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.

Sector	Code	TFP Growth	ICT Capital Contribution	Non-ICT Capital Contribution	Human Capital Contribution	Labor Productivity Growth
Agriculture, Hunting, Forestry and Fishing	01t05	26.6%	0.8%	8.6%	3.4%	39.4%
Mining and Quarrying	10t14	-1.0%	2.6%	19.8%	1.7%	23.1%
Food, Beverages and Tobacco	15t16	-0.9%	3.5%	10.6%	3.6%	16.7%
Textiles, Leather and Footwear	17t19	17.5%	2.8%	8.6%	5.5%	34.5%
Wood and Products of Wood And Cork	20	18.8%	2.5%	6.2%	3.7%	31.3%
Pulp, Paper, Printing and Publishing	21t22	13.8%	8.3%	11.5%	3.7%	37.3%
Coke, Refined Petroleum and Nuclear Fuel	23	-41.6%	6.1%	28.5%	3.9%	-4.8%
Chemicals and Chemical Products	24	16.3%	4.7%	21.6%	2.7%	45.4%
Rubber and Plastics	25	26.4%	2.5%	8.8%	3.6%	41.4%
Other Non-Metallic Mineral Products	26	20.2%	3.9%	9.5%	3.4%	37.0%
Basic Metals and Fabricated Metal	27t28	14.2%	2.5%	4.4%	3.6%	24.9%
Machinery, Nec	29	25.4%	4.4%	10.5%	4.0%	44.3%
Electrical and Optical Equipment	30t33	63.8%	7.3%	12.4%	4.1%	87.9%
Transport Equipment	34t35	30.8%	3.7%	9.9%	3.6%	48.0%
Manufacturing Nec; Recycling	36t37	12.5%	2.8%	5.4%	4.8%	25.6%
Electricity, Gas and Water Supply	40t41	10.6%	4.7%	18.9%	1.4%	35.4%
Construction	45	-4.8%	1.7%	2.8%	2.5%	2.3%
Wholesale and Retail Trade	50t52	16.0%	6.0%	7.4%	2.5%	31.8%
Hotels and Restaurants	55	-10.5%	2.3%	3.4%	2.2%	-2.4%
Transport and Storage	60t63	3.2%	4.9%	6.8%	2.3%	17.2%
Post and Telecommunications	64	36.0%	22.8%	11.9%	2.9%	73.5%
Financial Intermediation	65t67	17.4%	16.5%	0.2%	3.9%	38.0%
Real Estate, Renting and Business Activities	70t74	-10.9%	4.9%	-2.6%	2.2%	-6.7%

Table 5: Sector-level TFP-ICT Regressions

This table displays estimation results of Ordinary Least Squares (OLS) and Instrumental Variable (IV) regressions of sector-level total factor productivity growth from the EU KLEMS dataset on *ICT Contribution*, *Non-ICT Contribution* and interaction terms. In all regressions, the left-side variable is log TFP growth, averaged over a 11-year period. In columns 1-4, we use data for the 1996–2006 period. In column 6, we use data for the 1985–1995 period. Each observation represents a country-sector. *Country Meritocracy* varies at the country level. $\Delta\log TFP$, *ICT Contribution* and *Non-ICT Contribution* vary at the country/sector level.

	(1) $\Delta\log TFP_{96-06}$ OLS	(2) $\Delta\log TFP_{96-06}$ OLS	(3) $\Delta\log TFP_{96-06}$ OLS	(4) $\Delta\log TFP_{96-06}$ IV	(5) $\Delta\log TFP_{85-95}$ OLS
ICT Contribution	-0.350	-5.247**		-4.714***	0.414
	(0.598)	(2.151)		(1.620)	(6.171)
ICT Contribution × Country Meritocracy		1.094**		0.833**	0.030
		(0.510)		(0.342)	(1.201)
Non-ICT Contribution			0.525		
			(2.171)		
Non-ICT Contribution × Country Meritocracy			-0.077		
			(0.444)		
R^2	0.338	0.350	0.339	0.344	0.153
Kleibergen-Paap underid. test P-value				0.000	
Sargan-Hansen overid. test P-value				0.349	
Wu-Hausman exogeneity test P-value				0.469	
Observations	414	414	414	414	345
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓

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

Table 6: Sector-level TFP-ICT Regressions with additional country-level covariates

This table displays estimation results of Ordinary Least Squares (OLS) regressions of sector-level total factor productivity growth from the EU KLEMS dataset on *ICT Contribution* and interaction terms. In all regressions, the left-side variable is log TFP growth, averaged over the 1996–2006 period. Each observation represents a country-sector. *Country Meritocracy*, *ICT Infrastructure*, *Shadow Economy* and *Management Schools* vary at the country level. $\Delta\log TFP$ and *ICT Contribution* vary at the country/sector level.

	(1)	(2)	(3)	(4)	(5)
	$\Delta\log\mathrm{TFP}_{96-06}$	$\Delta\log\mathrm{TFP}_{96-06}$	$\Delta\log\mathrm{TFP}_{96-06}$	$\Delta\log\mathrm{TFP}_{96-06}$	$\Delta\log\mathrm{TFP}_{96-06}$
	OLS	OLS	OLS	OLS	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

Table 7: Sector-level TFP-China regressions

This table displays estimation results of Ordinary Least Squares (OLS) and Instrumental Variable (IV) regressions of sector-level total factor productivity growth from the EU KLEMS dataset on *China Exposure*, *US Layoff Rate* and interaction terms. In all regressions, the left-side variable is log TFP growth, averaged over a the 1996–2006 period. Each observation represents a country-sector. *Employment Laws*, and *Employment Protection* vary at the country level. *US Layoff Rate* varies at the sector level. $\Delta\log TFP$ and *China Exposure* vary at the country/sector level.

	(1) $\Delta\log TFP_{96-06}$ OLS	(2) $\Delta\log TFP_{96-06}$ OLS	(3) $\Delta\log TFP_{96-06}$ OLS	(4) $\Delta\log TFP_{96-06}$ IV	(5) $\Delta\log TFP_{96-06}$ OLS
US Layoff Rate × Employment Laws					-0.082
					(0.375)
China Exposure	0.040	0.034	-0.059	0.243	
	(0.060)	(0.183)	(0.271)	(0.480)	
China Exposure × Employment Laws		0.012		1.086	
		(0.325)		(1.193)	
China Exposure × Employment Protection			0.047		
			(0.120)		
R^2	0.337	0.337	0.337	0.204	0.409
Kleibergen-Paap underid. test P-value				0.002	
Wu-Hausman exogeneity test P-value				0.044	
Observations	414	414	414	414	360
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓

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

Table 8: Sector-level TFP-Trade Openness 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 *Trade Openness* and interaction terms. In all regressions, the left-side variable is log TFP growth, averaged over the 1996–2006 period. Each observation represents a country-sector. *Employment Laws* and *Employment Protection* vary at the country level. $\Delta\log TFP$, *Trade Openness* and *ICT Contribution* vary at the country/sector level.

	(1)	(2)	(3)	(4)
	$\Delta\log TFP_{96-06}$	$\Delta\log TFP_{96-06}$	$\Delta\log TFP_{96-06}$	$\Delta\log TFP_{96-06}$
	OLS	OLS	OLS	OLS
ICT Contribution			-5.841***	-5.785***
			(1.993)	(1.920)
ICT Contribution × Country Meritocracy			1.219**	1.206**
			(0.500)	(0.486)
Trade Openness	-0.002	0.018**	0.020**	0.017
	(0.006)	(0.008)	(0.008)	(0.020)
Trade Openness × Employment Protection				-0.009
				(0.011)
Trade Openness × Employment Laws		-0.039*	-0.041**	
		(0.020)	(0.021)	
R^2	0.338	0.359	0.376	0.361
Observations	414	414	414	414
Country Fixed Effects	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓

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

Table 9: TFP-government effectiveness 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 *ICT Contribution* and interaction terms. In all regressions, the left-side variable is log TFP growth, averaged over 1995–2006 period. Each observation represents a country-sector. *Country Meritocracy*, Δ*Rule of Law*, Δ*Control of Corruption*, and *Employment Laws* vary at the country level. Δlog*TFP* and *Trade Openness* vary at the country/sector level.

	(1) ΔlogTFP$_{96-06}$ OLS	(2) ΔlogTFP$_{96-06}$ OLS	(3) ΔlogTFP$_{96-06}$ OLS	(4) ΔlogTFP$_{96-06}$ OLS
ICT Contribution				-5.085*** (1.245)
ICT Contribution × Country Meritocracy				0.945*** (0.302)
Trade Openness				0.012 (0.018)
Trade Openness × Employment Laws				0.005 (0.027)
US Layoff Rate × Employment Laws				-0.074 (0.317)
Govt Dependence × ΔRule of Law	1.512 (1.939)			-0.354 (4.148)
Govt Dependence × ΔControl of Corruption		2.145 (2.597)		3.479 (4.215)
Govt Dependence × Govt Inefficiency			0.001 (0.001)	0.005** (0.002)
R^2	0.337	0.337	0.338	0.473
Observations	414	414	414	360
Eurozone Entry Controls				✓
Country Fixed Effects	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓

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

Table 10: 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. 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. Observations are weighted to ensure that the regression sample is representative.

	(1) $\Delta \log TFP_{01-07}$ OLS	(2) $\Delta \log TFP_{01-07}$ OLS	(3) $\Delta \log TFP_{01-07}$ OLS	(4) $\Delta \log TFP_{01-07}$ OLS
Firm Meritocracy	-0.001 (0.002)	-0.001 (0.002)	-0.002 (0.002)	-0.002 (0.002)
Firm Meritocracy × ICT Contribution	2.181*** (0.695)	2.123*** (0.687)	2.355*** (0.724)	2.413*** (0.730)
Employees with degree			0.055** (0.023)	0.057** (0.023)
Employees with degree × ICT Contribution			-8.445 (8.163)	-8.522 (8.175)
CEO Age				0.004** (0.002)
CEO Age × ICT Contribution				-1.204 (0.837)
Temporary employees				-0.001 (0.008)
Temporary employees × ICT Contribution				-0.298 (2.854)
Labor Frictions		0.002 (0.004)		
R^2	0.034	0.038	0.035	0.036
Observations	9,486	7,309	9,482	9,437
Country × Sector Fixed Effects	✓	✓	✓	✓

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

Table 11: 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. 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. 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. Observations are weighted to ensure that the regression sample is representative.

	(1) ICT Usage O.Probit	(2) ICT Usage O.Probit	(3) ICT Usage O.Probit
Firm Meritocracy	0.127*** (0.013)	0.113*** (0.013)	0.112*** (0.013)
Firm Meritocracy × ICT Contribution	13.078** (5.177)	12.358** (5.244)	12.170** (5.276)
Employees with degree		0.770*** (0.119)	0.811*** (0.121)
Employees with degree × ICT Contribution		-29.676 (33.180)	-31.024 (33.318)
CEO Age			0.011 (0.014)
CEO Age × ICT Contribution			-5.174 (6.694)
Temporary employees			-0.047 (0.068)
Temporary employees × ICT Contribution			47.695* (24.359)
Observations	14,204	14,196	14,058
Country × Sector Fixed Effects	✓	✓	✓

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

Table 12: Meritocracy and Competitive Frictions

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. "Italy" is a dummy variable identifying Italian firms. Observations are weighted to ensure that the regression sample is representative.

	(1)	(2)	(3)
	Financial constraints	Labor Frictions	Bureaucratic Frictions
	Probit	Probit	Probit
Italy	-0.135	0.364	0.242
	(0.213)	(0.450)	(0.399)
Firm Meritocracy	-0.059**	-0.090**	-0.075***
	(0.027)	(0.042)	(0.026)
Firm Meritocracy × Italy	0.063**	0.059	0.075***
	(0.028)	(0.043)	(0.028)
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

Appendices (for online publication)

Appendix A: Robustness to change in sample/specification

This appendix contains robustness tests to sector-level regressions of Tables 6-7. We show that our results from Section 3 are robust to exclusion of emerging countries and Italy, and to using alternative sets of country-level variables. Tables 13 and 14 replicate the analysis of Tables 5 and 7, by excluding Italy. Tables 15 and 16 replicate the analysis of Tables 5 and 7, by excluding three emerging European countries for which data is not available in the pre-treatment period 1985-1995 (Czech Republic, Hungary, Slovenia). Table 17 replicates the analysis of Table 6, using an alternative set of country-level variables.

Table 13: Sector-level TFP-ICT Regressions

This table replicates the analysis of Table 5, excluding Italy.

	(1) $\Delta \log TFP_{96-06}$ OLS	(2) $\Delta \log TFP_{96-06}$ OLS	(3) $\Delta \log TFP_{96-06}$ OLS	(4) $\Delta \log TFP_{96-06}$ IV	(5) $\Delta \log TFP_{85-95}$ OLS
ICT Contribution	-0.273	-5.447**		-5.197***	0.285
	(0.607)	(2.179)		(1.596)	(6.527)
ICT Contribution × Country Meritocracy		1.161**		0.959***	0.050
		(0.516)		(0.345)	(1.284)
Non-ICT Contribution			0.940		
			(2.351)		
Non-ICT Contribution × Country Meritocracy			-0.161		
			(0.480)		
R^2	0.324	0.338	0.326	0.332	0.152
Kleibergen-Paap underid. test P-value				0.000	
Sargan-Hansen overid. test P-value				0.709	
Wu-Hausman exogeneity test P-value				0.346	
Observations	391	391	391	391	322
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓

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

Table 14: Sector-level TFP-China regressions

This table replicates the analysis of Table 7, excluding Italy.

	(1)	(2)	(3)	(4)	(5)
	$\Delta \log TFP_{96-06}$	$\Delta \log TFP_{96-06}$	$\Delta \log TFP_{96-06}$	$\Delta \log TFP_{96-06}$	$\Delta \log TFP_{96-06}$
	OLS	OLS	OLS	IV	OLS
US Layoff Rate × Employment Laws					-0.006
					(0.379)
China Exposure	0.042	0.017	-0.086	0.203	
	(0.061)	(0.185)	(0.279)	(0.478)	
China Exposure × Employment Laws		0.049		1.359	
		(0.328)		(1.230)	
China Exposure × Employment Protection			0.061		
			(0.123)		
R^2	0.323	0.323	0.324	0.143	0.414
Kleibergen-Paap underid. test P-value				0.003	
Wu-Hausman exogeneity test P-value				0.026	
Observations	391	391	391	391	340
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓

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

Table 15: Sector-level TFP-ICT Regressions

This table replicates the analysis of Table 5, excluding Czech Republic, Hungary and Slovenia.

	(1) $\Delta \log TFP_{96-06}$ OLS	(2) $\Delta \log TFP_{96-06}$ OLS	(3) $\Delta \log TFP_{96-06}$ OLS	(4) $\Delta \log TFP_{96-06}$ IV	(5) $\Delta \log TFP_{85-95}$ OLS
ICT Contribution	0.295	-6.346*		-2.073	0.414
	(0.618)	(3.525)		(3.930)	(6.171)
ICT Contribution × Country Meritocracy		1.304*		0.407	0.030
		(0.738)		(0.772)	(1.201)
Non-ICT Contribution			-5.420**		
			(2.647)		
Non-ICT Contribution × Country Meritocracy			1.041*		
			(0.544)		
R^2	0.393	0.402	0.417	0.397	0.153
Kleibergen-Paap underid. test P-value				0.000	
Sargan-Hansen overid. test P-value				0.805	
Wu-Hausman exogeneity test P-value				0.214	
Observations	345	345	345	345	345
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓

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

Table 16: Sector-level TFP-China regressions

This table replicates the analysis of Table 7, excluding Czech Republic, Hungary and Slovenia.

	(1) $\Delta \log TFP_{96-06}$ OLS	(2) $\Delta \log TFP_{96-06}$ OLS	(3) $\Delta \log TFP_{96-06}$ OLS	(4) $\Delta \log TFP_{96-06}$ IV	(5) $\Delta \log TFP_{96-06}$ OLS
US Layoff Rate × Employment Laws					-0.094 (0.399)
China Exposure	0.064 (0.052)	0.055 (0.171)	0.187 (0.230)	0.304 (0.488)	
China Exposure × Employment Laws		0.017 (0.317)		0.442 (1.176)	
China Exposure × Employment Protection			-0.058 (0.106)		
R^2	0.393	0.393	0.394	0.304	0.434
Kleibergen-Paap underid. test P-value				0.002	
Wu-Hausman exogeneity test P-value				0.218	
Observations	345	345	345	345	300
Country Fixed Effects	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓

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

Table 17: Sector-level TFP-ICT Regressions with additional country-level covariates

This table replicates the analysis of Table 6 using an alternative set of country-level variables. *Human Capital* is compiled by Barro and Lee and sourced via the Penn World Tables (v9.0). *Firm Size* is the average size of firms obtained from the OECD SBS database, obtained by dividing the total number of employees by the total number of establishments. *GMAT Received* is the number of GMAT score reports received by business schools in the relevant country, per thousands of heads of population.

	(1)	(2)	(3)	(4)	(5)
	$\Delta \log TFP_{96-06}$	$\Delta \log TFP_{96-06}$	$\Delta \log TFP_{96-06}$	$\Delta \log TFP_{96-06}$	$\Delta \log TFP_{96-06}$
	OLS	OLS	OLS	OLS	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

Appendix B: Derivation of the variable *China Exposure*

In this appendix we derive analytically our variable *China Exposure* . We start from the following identity, which breaks down the demand of market *m* for product *s* into two components: the demand share which is filled by China and the demand share which is filled by every other country:

$$D_{smt} = Y_{\text{China},smt} + Y_{(\text{China}),smt} \tag{43}$$

where

$$Y_{(\text{China}),smt} := \sum_{c \neq \text{China}} Y_{csmt} \tag{44}$$

then, by rearranging equation (43) with $Y_{(\text{China}),smt}$ on the left hand side, taking logs and differentiating both sides with respect to time, we can break down the log growth of China's competitors' share in market *m,* into two effects. The first captures the growth of the destination market, while the second captures the (negative) effect of competition from China on the market share of its competitors:

$$\frac{d \log Y_{(\text{China}),smt}}{dt} = \underbrace{\left[\frac{D_{smt}}{Y_{(\text{China}),smt}}\right] \frac{d \log D_{smt}}{dt}}_{\text{Growth of destination market}} - \underbrace{\left[\frac{Y_{\text{China},smt}}{Y_{(\text{China}),smt}}\right] \frac{d \log Y_{\text{China},smt}}{dt}}_{\text{Competition from China}} \tag{45}$$

Our measure the effect of the China shock, measured at the level of the destination country *m,* is the discrete-time approximation of the latter component. Using again equation (43), it can be re-written as:

$$\text{China Shock}_{mst} := \left[\!\left[\frac{Y_{\text{China},mst}}{\sum_{c \neq \text{China}} Y_{csmt}} \right]\!\right] \cdot \Delta \log Y_{\text{China},smt} \tag{46}$$

Aggregating across countries, we obtain our measure of the exposure of country *c* sector *s* to the China shock:

$$\text{China Exposure}_{cst} = \sum_{m} \left[\!\left[\frac{Y_{csmt}}{\sum_{m} Y_{csmt}} \right]\!\right] \cdot \text{China Shock}_{smt} \tag{47}$$

Appendix C: Robustness to production function mismeasurement

A key step in the EU KLEMS growth accounting is that output-input elasticities are estimated using sector-level input compensation shares. This approach cannot accommodate adjustment costs or deviation from perfect competition.

Control function approaches to production function estimation tools (see for example Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009), cannot be convincingly implemented in our setting: this is the case for both our sector-level data (these methods require firm-level data) as well as our firm-level data (we do not observe the input of ICT capital at the firm level, but only at the sector-level).

As a consequence, for our sector-level analysis, we are forced to rely on EU KLEMS productivity estimates. If the KLEMS capital-output elasticity is biased, the EU KLEMS estimates of TFP growth are going to be biased as well. In this Appendix, we argue that, if such mismeasurement exists, it does not undermine our econometric results: in our specific setting, if anything, mismeasurement of the output/capital elasticity seems to attenuate the estimated effect of ICT on productivity growth.

To see why this is the case, it is important to first clarify two points. First, the EU KLEMS TFP estimates are not based on a panel regression of output on inputs, but on growth accounting. In this framework, the key unobservable needed to estimate TFP, that is, the output/capital elasticity, is not estimated econometrically, but backed out from the aggregate labor compensation share. Second, we are trying to measure the effect of ICT and meritocracy on the *estimated*, not the *actual* total factor productivity. Our objective is not to use sector or firm-level data to produce new measures of TFP. Our data does not allow us to. Rather, our objective is to explain why the TFP growth of Italy, measured using the KLEMS methodology, diverged from that of other countries around the mid-90s, regardless of whether it is biased or not. In this Sub-section, we investigate how unobserved bias in the KLEMS TFP might affect our estimates.

Growth accounting is based on the assumption of perfectly competitive markets, which allows to obtain the output-capital elasticity as one minus the labor share of value added. If firms charge a markup, then the labor share and the capital share sum to less than the total revenues; as a consequence, the KLEMS estimate of the output/capital elasticity is likely to be upward biased. To see how this bias might affect the regression specified in equation (34), let us suppose, for the sake of tractability, that the capital share over-estimates the actual output/capital elasticity by a fixed δ percent - that is:

$$\left(1-\frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)=(1+\delta)\,\frac{\partial f_{cst}}{\partial k_{cst}} \tag{48}$$

this implies that the *true* contribution ICT capital is also over-estimated, in EU KLEMS, by the same factor:

$$\text{ICT}\ \widehat{\text{Contribution}}_{cst} = (1+\delta)\,\frac{\partial f_{cst}}{\partial k^{I}_{cst}}\Delta k^{I}_{cst} \tag{49}$$

We use the hat ^ notation to indicate that the EU KLEMS estimates are now potentially biased. Let us re-derive the regression specification from equation (34) accordingly:

$$\begin{aligned}
\Delta \log \widehat{\text{TFP}}_{cst} &\coloneqq \Delta y_{cst} - \left(1 - \frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta k_{cst} - \left(\frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta \ell_{cst} \\
&= \Delta y_{cst} - (1+\delta)\,\frac{\partial f_{cst}}{\partial k_{cst}}\Delta k_{cst} - \left[1 - (1+\delta)\,\frac{\partial f_{cst}}{\partial k_{cst}}\right]\Delta \ell_{cst} \\
&= \Delta a_{cst} + \frac{\beta_1}{1+\delta}\cdot \text{ICT}\ \widehat{\text{Contribution}}_{cst} \\
&\quad + \frac{\beta_2}{1+\delta}\cdot \text{ICT}\ \widehat{\text{Contribution}}_{cst}\cdot \text{Country Meritocracy}_c \\
&\quad - \frac{\delta}{1+\delta}\left(1 - \frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta\left(k_{cst} - \ell_{cst}\right)
\end{aligned} \tag{50}$$

In what follows, it is of crucial importance for the reader to understand that it is *not* the objective of our econometric exercise to consistently estimate the β parameters. Instead, we want to quantify how much of the variation in the *estimated* TFP can be accounted for by the interaction of meritocracy and the *estimated* contribution of ICT. In other words, when mismeasurement is present, our objective is to consistently estimate β / (1+δ), not β. When no mismeasurement is present, the two are the same.

Having made this key distinction, notice that measurement bias in the output/capital elasticity introduces, in the regression equation, an additional error term:

$$\text{KL Error}_{cst} = \left(1 - \frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta\left(k_{cst} - \ell_{cst}\right) \tag{51}$$

this error term includes the log growth of the capital / labor ratio, and depends positively on the growth of ICT capital. Because this term appears with a minus sign in the regression and is incorporated in the error term, it biases the econometric estimate of β / (1+δ) downwards. This implies that, provided that δ is non-negative, our empirical estimates of the reaction coefficient β / (1+δ) are, in the worst-case scenario, conservative when the capital/output ratio is mismeasured.

Equation (50) suggests a way to verify econometrically that our estimates from Table 3 are robust to mismeasurement of the output/labor elasticity. First, consider the standard identification assumption of OLS:

$$\mathbb{E}\left(\varepsilon_{cs}\begin{bmatrix}\text{Country Meritocracy}_c\cdot\text{ICT Contribution}_{cs}\\ \text{ICT Contribution}_{cs}\end{bmatrix}\middle|\gamma_c,\varsigma_s\right)=0 \tag{52}$$

where ε is the residual term of regression 34. Suppose now that there is no mismeasurement in the output/capital elasticity and that the exogenous component of TFP growth is orthogonal to the capital/labor ratio: then, ε is equal to Δa and orthogonal to *KL Error*. This implication can be tested by re-estimating regression equation (34) in GMM using the following expanded set of moment conditions

$$\mathbb{E}\left(\varepsilon_{cs}\begin{bmatrix}\text{Country Meritocracy}_c\cdot\text{ICT Contribution}_{cs}\\ \text{ICT Contribution}_{cs}\\ \text{KL Error}_{cs}\end{bmatrix}\middle|\gamma_c,\varsigma_s\right)=0 \tag{53}$$

and performing a Hansen J test: if there is mismeasurement, as described in equation (50), the J test will tend to reject, and the GMM coefficient estimates will be closer to the true coefficient than OLS. Hence, unless we find that 1) the GMM coefficient for the interaction term is lower than the OLS one and 2) the J test null hypothesis is rejected, our OLS estimates should be, at worst, conservative.

Using the the very same intuition, we can also investigate the robustness of our estimates to violations of the constant returns to scale (CRS) assumption, which underpins the KLEMS growth accounting framework. Suppose, for example, that

$$\frac{\partial f_{cst}}{\partial k_{cst}}+\frac{\partial f_{cst}}{\partial \ell_{cst}}=(1+\delta)\neq 1 \tag{54}$$

then we have the following amended regression specification:

$$\begin{aligned}\Delta\log\widehat{\text{TFP}}_{cst}&\coloneqq\Delta y_{cst}-\left(1-\frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta k_{cst}-\left(\frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta\ell_{cst}\\ &=\Delta y_{cst}-\frac{1}{1+\delta}\cdot\frac{\partial f_{cst}}{\partial k_{cst}}\Delta k_{cst}-\frac{1}{1+\delta}\cdot\left[1-\frac{\partial f_{cst}}{\partial k_{cst}}\right]\Delta\ell_{cst}\\ &=\Delta a_{cst}+\frac{\beta^1}{1+\delta}\cdot\text{ICT }\widehat{\text{Contribution}}_{cst}\\ &\quad+\frac{\beta^2}{1+\delta}\cdot\text{ICT }\widehat{\text{Contribution}}_{cst}\cdot\text{Country Meritocracy}_c\\ &\quad+\frac{\delta}{1+\delta}\cdot\text{KL Contribution}_{cst}\end{aligned} \tag{55}$$

where

$$\text{KL Contribution}_{cst} = \left(1 - \frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta k_{cst} + \left(\frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta \ell_{cst} \tag{56}$$

Again, by estimating the regression equation with an added instrument

$$\mathbb{E}\left(\varepsilon_{cs}\begin{bmatrix}\text{Country Meritocracy}_c \cdot \text{ICT Contribution}_{cs}\\ \text{ICT Contribution}_{cs}\\ \text{KL Contribution}_{cs}\end{bmatrix}\middle|\gamma_c, \varsigma_s\right) = 0 \tag{57}$$

and performing a J test, we can obtain a valuable diagnostic of the robustness of our coefficient estimates to violations of the CRS assumption. We conduct both estimations in Table 18. In both cases, the GMM estimate of the interaction coefficient of *Country Meritocracy* and *ICT Contribution* is slightly higher than the OLS (1.312 and 1.123, respectively) and the Sargan statistic has a p-value above 10. We take this result as a reassurance that our econometric results are not inflated by mis-measurement of the production function parameters.

Table 18: GMM Estimates

	(1) ΔlogTFP$_{96-06}$ GMM	(2) ΔlogTFP$_{96-06}$ GMM
ICT Contribution	-6.452*** (2.377)	-5.711*** (1.811)
ICT Contribution × Country Meritocracy	1.312** (0.520)	1.123** (0.461)
Hansen overid. J test P-value	0.232	0.516
Observations	414	414
Additional instrument	KL Error	KL Contribution
Country Fixed Effects	✓	✓
Sector Fixed Effects	✓	✓
Robust Standard Errors in Parentheses	* p<.10, ** p<.05, *** p<.01	

Appendix D: Robustness to imperfect competition

In this appendix, we explore the robustness of our firm level TFP regressions. In particular, we want to investigate the importance of the assumption of perfect competition in the computation of TFP growth. This assumption underpins the computation of our baseline estimates of firm TFP, which use, as the measure of output volume, firm-level value added (EBITDA+labor costs), deflated using sector level indices from EU KLEMS.

In Tables (19)-(20) we repeat the estimation of Table (10) by recomputing the dependent variable, the growth of firm-level total factor productivity, according to equation (42). To compute this alternative TFP measure, we need to assume a value for the elasticity of substitution parameter σ. We show regression results for conservative values $\sigma = 5$ and $\sigma = 3$. For $\sigma = \infty$, TFP growth converges to our baseline estimate (value added deflated using sector-level price indices).

In Tables (21)-(22) we repeat out firm-level TFP regressions by again recomputing the dependent variable in a way similar to that of (42), but using gross output, instead of value added, as the output concept.

Table 19: Firm-level productivity regressions

This table replicates the analysis of Table 10, using the alternative firm-level value added-based TFP growth computed according to equation (42), using demand elasticity of substitution $\sigma = 5$.

	(1) ΔlogTFP$_{01-07}$ OLS	(2) ΔlogTFP$_{01-07}$ OLS	(3) ΔlogTFP$_{01-07}$ OLS	(4) ΔlogTFP$_{01-07}$ OLS
Firm Meritocracy	0.001 (0.002)	0.001 (0.002)	-0.000 (0.002)	-0.001 (0.002)
Firm Meritocracy × ICT Contribution	2.058** (0.830)	2.025** (0.817)	2.280*** (0.873)	2.400*** (0.883)
Employees with degree			0.074*** (0.028)	0.076*** (0.028)
Employees with degree × ICT Contribution			-11.178 (10.279)	-11.386 (10.284)
CEO Age				0.002 (0.002)
CEO Age × ICT Contribution				-1.280 (0.996)
Temporary employees				-0.000 (0.010)
Temporary employees × ICT Contribution				-2.551 (3.463)
Labor Frictions		0.001 (0.004)		
R^2	0.033	0.037	0.034	0.035
Observations	9,833	7,656	9,829	9,779
Country × Sector Fixed Effects	✓	✓	✓	✓

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

Table 20: Firm-level productivity regressions

This table replicates the analysis of Table 10, using the alternative firm-level value added-based TFP growth computed according to equation (42), using demand elasticity of substitution $\sigma = 3$.

	(1) $\Delta \log TFP_{01-07}$ OLS	(2) $\Delta \log TFP_{01-07}$ OLS	(3) $\Delta \log TFP_{01-07}$ OLS	(4) $\Delta \log TFP_{01-07}$ OLS
Firm Meritocracy	0.003	0.002	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Firm Meritocracy × ICT Contribution	2.162**	2.196**	2.376**	2.514**
	(0.991)	(0.972)	(1.048)	(1.061)
Employees with degree			0.098***	0.102***
			(0.034)	(0.034)
Employees with degree × ICT Contribution			-12.771	-13.216
			(12.624)	(12.624)
CEO Age				-0.000
				(0.003)
CEO Age × ICT Contribution				-1.232
				(1.186)
Temporary employees				-0.001
				(0.012)
Temporary employees × ICT Contribution				-3.517
				(4.062)
Labor Frictions		-0.001		
		(0.005)		
R^2	0.030	0.034	0.032	0.033
Observations	9,833	7,656	9,829	9,779
Country × Sector Fixed Effects	✓	✓	✓	✓
Robust Standard Errors in Parentheses	* p<.10, ** p<.05, *** p<.01			

Table 21: Firm-level productivity regressions

This table replicates the analysis of Table 10, using an alternative gross output-based measure of TFP growth at the firm level. It is computed according to the following formula

$$\Delta \log \mathrm{TFP}_{it} \;=\; \Delta\hat{y}_{it} - \left(1 - \frac{P^X_{cst}X_{cst} + W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta k_{it} - \left(\frac{W_{cst}L_{cst}}{P_{cst}Y_{cst}}\right)\Delta \ell_{it} - \left(\frac{P^X_{cst}X_{cst}}{P_{cst}Y_{cst}}\right)\Delta x_{it}$$

where Y is not value added but gross output, estimated at the firm level using demand elasticity of substitution $\sigma = 5$. P^X and X are intermediate input prices and volume, respectively.

	(1) ΔlogTFP$_{01-07}$ OLS	(2) ΔlogTFP$_{01-07}$ OLS	(3) ΔlogTFP$_{01-07}$ OLS	(4) ΔlogTFP$_{01-07}$ OLS
Firm Meritocracy	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Firm Meritocracy × ICT Contribution	0.945** (0.451)	1.001** (0.495)	0.982** (0.439)	1.024** (0.446)
Employees with degree			0.044*** (0.015)	0.046*** (0.015)
Employees with degree × ICT Contribution			-3.970 (3.741)	-4.281 (3.746)
CEO Age				-0.002* (0.001)
CEO Age × ICT Contribution				-0.105 (0.494)
Temporary employees				-0.002 (0.005)
Temporary employees × ICT Contribution				-1.225 (1.771)
Labor Frictions		0.000 (0.002)		
R^2	0.027	0.033	0.029	0.031
Observations	9,498	7,319	9,494	9,448
Country × Sector Fixed Effects	✓	✓	✓	✓

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

Table 22: Firm-level productivity regressions

This table replicates the analysis of Table 10, using an alternative gross output-based measure of TFP growth at the firm level. It is computed according to the following formula

$$\Delta \log \mathrm{TFP}_{it} \quad = \quad \Delta \hat{y}_{it} - \left(1 - \frac{P^X_{cst} X_{cst} + W_{cst} L_{cst}}{P_{cst} Y_{cst}}\right) \Delta k_{it} - \left(\frac{W_{cst} L_{cst}}{P_{cst} Y_{cst}}\right) \Delta \ell_{it} - \left(\frac{P^X_{cst} X_{cst}}{P_{cst} Y_{cst}}\right) \Delta x_{it}$$

where Y is not value added but gross output, estimated at the firm level using demand elasticity of substitution $\sigma = 3$. P^X and X are intermediate input prices and volume, respectively.

	(1) ΔlogTFP$_{01-07}$ OLS	(2) ΔlogTFP$_{01-07}$ OLS	(3) ΔlogTFP$_{01-07}$ OLS	(4) ΔlogTFP$_{01-07}$ OLS
Firm Meritocracy	0.004** (0.002)	0.002 (0.002)	0.003 (0.002)	0.002 (0.002)
Firm Meritocracy × ICT Contribution	1.013 (0.620)	1.125* (0.670)	1.031* (0.606)	1.093* (0.615)
Employees with degree			0.059*** (0.021)	0.063*** (0.021)
Employees with degree × ICT Contribution			-4.552 (5.244)	-5.114 (5.247)
CEO Age				-0.005*** (0.002)
CEO Age × ICT Contribution				-0.110 (0.676)
Temporary employees				-0.004 (0.007)
Temporary employees × ICT Contribution				-2.383 (2.409)
Labor Frictions		-0.001 (0.003)		
R^2	0.028	0.034	0.030	0.034
Observations	9,498	7,319	9,494	9,448
Country × Sector Fixed Effects	✓	✓	✓	✓

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