Do Poor Countries Really Need More IT?

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Abstract: Productivity differences across countries are often attributed to differences in technological capabilities. This paper asks whether there are systematic cross-country differences in the adoption of information technologies (IT). We document a positive correlation between IT use and income, which weakens over time. However, given that IT use is an endogenous outcome of both technological capabilities and the abundance of complementary factors of production, it tends to over-state the degree of cross-country differences in technology. We propose two novel calibration approaches to address this problem. After accounting for endogenous differences in industrial composition, we find that there is no systematic relationship between income and IT capabilities.

JEL: O14, O33, O57, E22
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1. Introduction

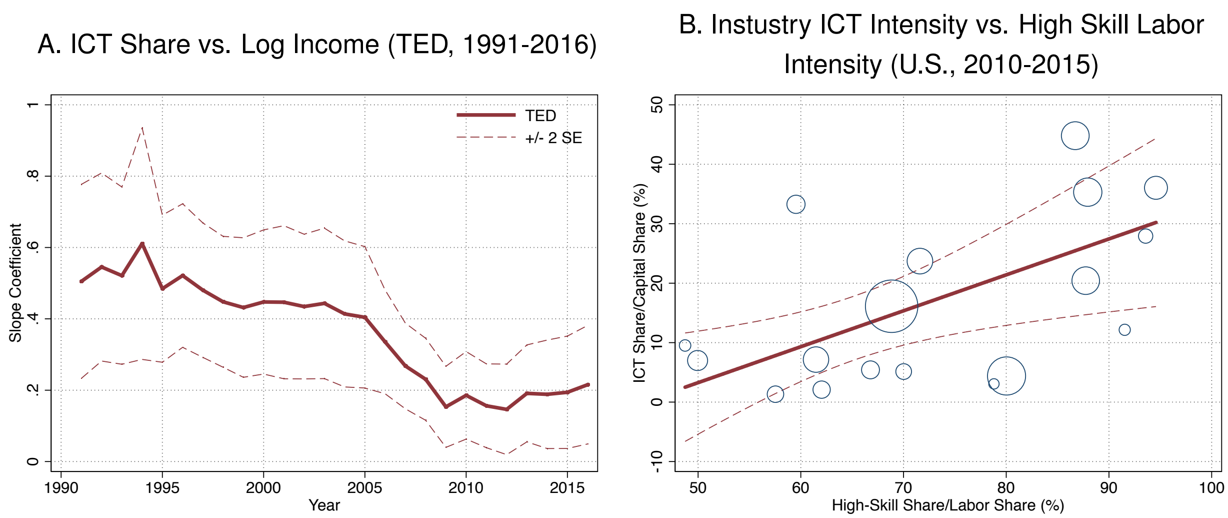
Cross-country differences in income have been shown to be driven primarily by cross-country differences in total factor productivity (TFP), which is typically measured as the Solow residual (Caselli, 2008): after accounting for cross-country differences in inputs, the remaining differences in output are attributed to productivity. While the Solow residual was traditionally interpreted as reflecting the level of a country's technology, today it is widely understood that other country characteristics are included in this residual as well, such as the degree of misallocation (Hsieh and Klenow, 2009).

Consequently, new approaches are being developed for assessing the direct contribution of cross-country differences in technology to differences in productivity. The dominant approach has been based on measuring cross-country differences in capital types that embody technology. For example, Comin and Hobijn (2010) and Comin and Mestieri (2017) track the abundance of 25 types of technology-intensive capital across countries, such as the ratio of phone lines to GDP. Comin and Mestieri (2017) find that the intensity with which countries use recently-invented types of technology-intensive capital, such as computers, is positively correlated with income per capita. Their findings suggest that differences in technological capabilities remain an important source of cross-country variation in output.

In this paper, we focus on information technologies (IT) and try to assess the degree of cross-country differences in IT diffusion. We start by documenting that the correlation between the share of income paid to the owners of IT-intensive capital (henceforth, Information and Communications Technology capital or ICT capital) and per capita income around the world has declined by at least a factor of two over the period 1991-2016, suggesting potential convergence in the adoption of IT (panel A of Figure 1).

While the correlation between the income share of ICT and income per capita remains positive, we argue that this is not necessarily reflective of systematic cross-country differences in technological capabilities. Our main argument is that, given the strong complementarity between ICT capital and skilled labor (e.g., Akerman, Gaarder and Mogstad, 2015; Gaggl and Wright, 2017), a simple measurement of the abundance of ICT capital is likely to understate the underlying technological capabilities in low income countries. To illustrate this, Panel B of Figure 1 documents a strong correlation between the industry-level intensity of ICT use and its intensity of skilled labor in the US. If sectors that utilize ICT capital more intensely also happen to be more intensive in skilled labor, then countries that have larger endowments of skilled

Figure 1: The ICT Share Around the World (TED)



Notes: Panel A illustrates the relationship between the ICT share and income per capita over the period 1991 through 2016 for at least 79 countries (depending on the year) based on the Conference Board's Total Ecoomy Database (TED). The solid line reports the slope coefficients for regressions of the log ICT income share on year effects and year-log-income interactions (no constant) with standard errors clustered on country. Panel B plots the ICT share of capital income against the high skill share of labor income for 18 broad sectors in the United States. The underlying estimates for sector specific income shares are taken from Eden and Gaggl (2018) and tabulated in Table 1. The fitted regression line is weighted by value added, which is graphically illustrated by the size of the circles, and the dashed lines represent 95% confidence intervals.

labor would choose to specialize in industries that tend to be more intensive in ICT capital as well, even if their technological capabilities are identical. Cross-country differences in ICT capital abundance could therefore be driven by different endowments of skilled and unskilled labor, rather than just by differences in technological capabilities.

The distinction between the abundance of skilled labor and technological capabilities may seem pedantic to some: if technological capabilities reflect the know-how necessary in order to use ICT capital efficiently, shouldn't they be *embodied* in skilled labor? Not necessarily. For example, health services in the US are intensive in both ICT capital and in skilled labor (see Table 1). However, the skills necessary in order to become a medical doctor mostly have very little to do with computer literacy or the ability to utilize ICT capital effectively; rather, doctors' training primarily involves learning about human biology and optimal health practices. Pursuing computer literacy programs may have little to do with an economy's ability to produce high-quality doctors or specialize in health services.

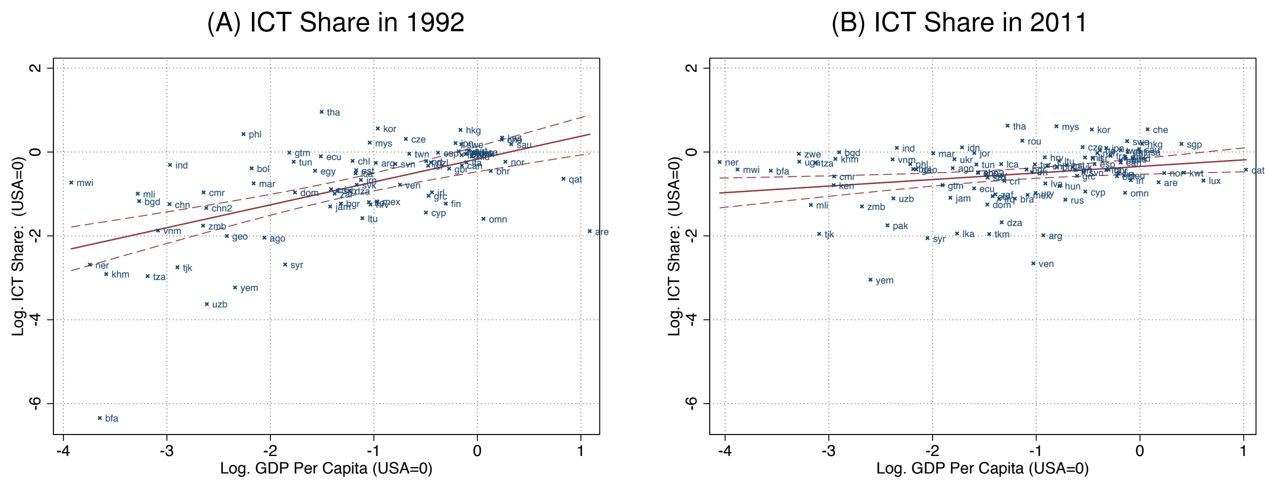
We consider a simple structural framework to capture the idea that ICT capital abundance is simultaneously determined by a country's technological capabilities and its endowment of skilled labor. For a given industry, ICT-capital intensity is increasing in the country's level of technology adoption. Industrial composition is determined endogenously based on the country's technological capabilities as well as its endowments of other factors of production.

We calibrate the model using two alternative strategies. The first approach combines cross-country data on industry-level value added with estimates of the aggregate ICT income share. Based on a country's industrial composition, we are able to back out the level of IT capabilities that is consistent with its aggregate ICT capital intensity. Intuitively, if two countries have the same industrial composition but different ICT capital intensities, then the country that uses ICT capital less intensely must have lower IT capabilities. Our estimates suggest a strong correlation between income per capita and IT capabilities in the early 1990s, and a much weaker (yet positive) correlation by 2010.

The main drawback of this first approach is the limited availability of detailed value-added data by industry for a wide variety of countries, forcing us to focus on rather broad industry classifications, which are potentially too broad to fully account for the complementarity between ICT capital and skilled labor. For example, the services industry includes both sectors like finance, which are very intensive in both ICT capital and in skilled labor, and sectors like retail which are not. An economy that specializes in services may therefore be concentrated in highly ICT-intensive sectors or in unskilled sectors. As our calibration requires us to associate a single ICT intensity to all service sectors, we will incorrectly attribute a low level of IT adoption to low-income countries who specialize in services that are less intensive in ICT capital.

Our second calibration approach tackles this problem by showing directly how a country's ICT capital intensity is determined in equilibrium by its technological capabilities and its abundance of other factors of production. This second strategy requires the construction of new estimates of ICT capital stocks and prices, as well as data on employment and wages for skilled and unskilled labor, delivering even starker results: in 2011, there is no correlation between income per capita and IT capabilities. Rather, cross-country differences in the abundance of ICT capital are driven entirely by cross-country differences in the abundance of complementary factors of production.

Figure 2: The ICT Share Around the World (TED)



Notes: Panels A and B illustrate the relationship between the ICT share and income per capita for the years 1992 and 2011 based on the Conference Board's Total Economy Database (TED). The solid lines are fitted linear regressions and the dashed lines are 95% confidence intervals.

2. Two Stylized Facts

We establish two stylized facts: first, while richer countries tend to use ICT capital more intensely, the relationship between ICT intensity—as measured by the share of income paid to the owners of ICT capital—and income per capita has declined by at least a factor of two since the early 1990s; second, at least in the United States and other high income countries, sectors that use ICT capital intensely also tend to be intensive in skilled labor.

To establish the first fact, we use estimates for the ICT income share from the Conference Board's Total Economy Database (TED). To the best of our knowledge, the TED contains the most comprehensive set of estimates for the ICT share around the world, covering 79 countries in 1991 and 102 countries in 2016 at various levels of development (see Tables A.6 and A.7 in Appendix A for details on country coverage). Figure 2 plots the relationship between the ICT share and income per capita, both for 1992 and 2011.[1] To the extent that the ICT income share is reflective of the intensity with which ICT capital is used in

[1]Note that we choose to plot 1992 and 2011 as these are the first and last year in our own estimates of the ICT share, described in Appendix A.4.

Table 1: Industry Income Shares: U.S. Avg. 2010-2015

Industry	Value Added (% of total)	Capital Share (% of VA)		Labor Share (% of VA)	
		ICT	NICT	High Skill	Low Skill
	(1)	(2)	(3)	(4)	(5)
Information	4.80	28.46	50.50	19.90	1.14
Admin.	3.01	19.94	40.01	23.84	16.20
Management	1.86	16.74	43.21	37.48	2.57
Prof./ Services	7.02	13.58	16.72	60.45	9.25
Health	7.29	13.35	24.47	54.68	7.50
Wholesale trade	5.97	11.35	36.53	37.31	14.80
Finance and insurance	6.91	9.59	37.39	46.52	6.50
Manufacturing	24.99	9.37	48.77	28.82	13.04
Agriculture	1.20	6.47	61.53	15.59	16.40
Real Estate	13.19	3.58	78.09	14.66	3.66
Education	1.15	2.78	20.07	70.62	6.53
Other Serv.	2.24	2.63	48.71	34.07	14.59
Retail trade	5.87	2.60	33.80	39.10	24.50
Transp./Wareh.	2.91	2.38	41.58	37.42	18.61
Accom./Food	2.72	1.70	79.60	11.60	7.10
Construction	3.65	1.36	18.17	40.20	40.27
Mining	2.47	1.18	87.77	6.36	4.69
Arts/Entertain.	0.98	0.84	26.77	57.04	15.34

Notes: The table summarizes averages for the 2010-2015 in the United States. Industries are sorted in decreasing order by ICT share. Value added (VA) and capital stock values are taken from the BEA. Earnings data are taken from the CPS March supplements. The classification of ICT and non-ICT (NICT) assets is taken from Eden and Gaggl (2018). Low skill workers are those with at most a high school degree, while high skill workers are those with some college or more education.

production, these figures suggest that richer countries were faster to adopt ICT. However, by 2011 the correlation between income and the ICT share has nearly vanished. In fact, panel A of Figure 1 suggests that the slope coefficient has declined by at least a factor of two since the early 1990s.

The second stylized fact is a strong industry-level correlation between the ICT capital intensity and the intensity of skilled labor. Table 1 shows both ICT and non-ICT (NICT) shares as well as high-skill and low-skill labor income shares for 18 broad US sectors, averaged over the period 2010-2015. The disaggregated capital income shares are taken directly from Eden and Gaggl (2018) while high-skill and low-skill labor shares are constructed from the U.S. Current Population Survey March supplements (CPS-MARCH), again in analogy to the methodology by Eden and Gaggl (2018).[2] In particular, while the aggregate ICT share is approximately around 3-4% during this period (see Eden and Gaggl, 2018), the ICT share at the sector level

[2]The main difference with Eden and Gaggl (2018) is that we here disaggregate labor by sector and we distinguish between high- and low-skill workers rather than routine and non-routine workers. Our definition of high-skill follows the standard definition in labor economics, based on years of schooling. In particular, we consider a worker with some college or more as "high-skill".

Table 2: Industry Specialization: 14 EU Countries (EU KLEMS, Avg. 2010-2015)

		Capital Stock	Labor Share (% of VA)		
Industry	Value Added (% of total)	\$ICT/\$Capital	High Skill	Middle Skill	Low Skill
	(1)	(2)	(3)	(4)	(5)
Information and Communication	4.87	25.01	35.67	19.97	2.66
Finance and Insurance	6.53	17.13	28.46	23.18	2.63
Prof., Scient., Tech., Admin. & Support	9.73	9.19	35.93	29.44	10.08
Other Services	1.74	6.66	30.86	45.12	13.18
Wholsale/Retail Trade; Repair	11.56	6.39	17.08	39.44	13.06
Manufacturing	16.23	3.93	18.29	32.42	11.57
Arts, Entertainment & Rec.	1.34	3.68	31.69	30.01	8.11
Construction	6.07	3.07	13.96	46.11	18.37
Health and Social Work	7.26	3.03	39.96	37.08	7.12
Accomodation & Food	2.57	2.72	10.67	47.49	19.85
Education	5.18	2.49	62.80	20.16	3.55
Transtportation & Storage	5.18	2.16	12.55	38.95	14.44
Public Sector	6.30	2.05	33.29	32.40	6.64
Utilities	3.08	1.85	11.54	16.69	5.21
Mining & Quarrying	0.91	1.43	10.19	21.58	6.64
Agriculture, Forestry, Fishing	1.80	0.42	16.85	51.50	27.95
Real Estate	9.86	0.12	2.99	3.52	0.78

Notes: The table summarizes averages for 2010-2015 based on EU KLEMS data for the following EU Countries: AT, CZ, DE, DK, ES, FI, FR, IT, LU, NL, SE, SI, SK, and UK. Industries are sorted in decreasing order by the fraction ICT in total capital values. High/low/middle skilled workers in the EU KLEMS database are defined as follows: high=university graduate or more; middle=intermediate; low=no high school diploma.

ranges from 0.84% in the arts and entertainment sector to 28.46% in the information services sector. At the same time, the high-skill labor share ranges from 6.36% in mining to 70.62% in the education sector. Of course, much of this variation is driven by variation across industries in the overall labor share: for example, the mining sector has a very low aggregate labor share, while the professional and service sector has a very high aggregate labor share. Thus, to see the patterns of specialization, it is more useful to relate the ICT share as a fraction of the capital share to the high-skill share as a fraction of the labor share, an exercise we illustrate in panel B of Figure 1. This figure clearly illustrates that the sectors that use high-skill labor more intensely are also the ones that use ICT more intensely.

Unfortunately, we cannot directly replicate this exercise for other countries, particularly not for low income countries, due to data constraints. However, we can check a closely related correlation based on EU KLEMS data for 14 relatively high income EU countries over the period 2010-2015.[3] Table 2 shows

[3] The countries for which the 2017 version of the EU KLEMS database has the relevant data are AT, CZ, DE, DK, ES, FI, FR, IT, LU, NL, SE, SI, SK, and UK.

Table 3: ICT Abundance and High Skilled Labor (EU KLEMS, Avg. 2010-2015)

	Dep. Var.: \$ICT/\$Capital		
Rel. Labor Share	(1)	(2)	(3)
High Skill Workers	0.139***		
	(0.0322)		
Middle Skill Workers		-0.163***	
		(0.0451)	
Low Skill Workers			-0.215***
			(0.0568)
Observations	236	236	236
Country FEs	yes	yes	yes

Notes: The table reports country-industry level regression of the share of ICT in total current cost capital values on the labor share of high/middle/low skilled workers out of the total industry level labor share. The data are country and industry specific averages for 2010-2015 based on EU KLEMS data for the following EU Countries: AT, CZ, DE, DK, ES, FI, FR, IT, LU, NL, SE, SI, SK, and UK. The 17 industries we use are listed in Table 2. High/low/middle skilled workers in the EU KLEMS database are defined as follows: high=university graduate or more; middle=intermediate; low=no high school diploma. The regressions are weighted by country-specific industry value added.

measures that are similar to those reported in Table 1 for 17 industry aggregates with sufficient relevant data. For instance, the 2017 industry level EU KLEMS database does not report disaggregated capital shares that are comparable to the ones reported in Table 2 for the US. However, we can tabulate the fraction of ICT in the total value of capital at current cost (column 2), which suggests a similar ranking of industries by "ICT abundance" within the 14 EU Countries over the same period. Similarly, while the EU KLEMS does report disaggregated labor shares, they group workers into three "skill groups" that don't line up perfectly with our split for the US. In particular, the middle skill group includes both high school graduates (which we classified as "low skill" in the US) and workers with "some college" (which we classified as "high skill" in the US).

Despite these differences, we find a strong cross-industry correlation between ICT capital intensity and high-skill labor intensity, similar to our finding for the U.S. To illustrate, Table 3 reports the results of regressing the fraction of ICT in total capital values (in percent) on the share of high/middle/low skill labor compensation in total labor compensation (in percent) as well as a complete set of country effects. The findings broadly confirm our observation that industries that are more ICT abundant tend to disproportionately employ more high skill labor. Consistent with the polarization literature (Acemoglu and Autor, 2011), the opposite is true for middle and low skill workers.

3. Disentangling ICT Adoption and Industrial Specialization

The stylized facts presented in Section 2 suggest that cross-country differences in ICT capital abundance may be driven, in part, by cross-country differences in the abundance of skilled labor. To formalize this idea, we consider the following model. In each economy, there are J sectors indexed $j = 1, ..., J$. There are four production inputs: skilled (L_s) and unskilled labor (L_u) as well as ICT (K_i) and NICT capital (K_n). The production function in sector j is given by the Cobb-Douglas production function:

$$Y_j = \left[K_{n,j}^{\alpha_{n,j}} \left(AL_{s,j}\right)^{\alpha_{s,j}} \left(AL_{u,j}\right)^{\alpha_{u,j}}\right]^{\frac{1-\theta\alpha_{i,j}}{\alpha_{n,j}+\alpha_{s,j}+\alpha_{u,j}}} K_{i,j}^{\theta\alpha_{i,j}}, \tag{1}$$

where $\alpha_{n,j}, \alpha_{s,j}, \alpha_{u,j}, \alpha_{i,j} \geq 0$ and $\alpha_{n,j} + \alpha_{s,j} + \alpha_{u,j} + \alpha_{i,j} = 1$. While some parameters and inputs may vary across countries and time, for the ease of exposition we suppress explicit time and country indexes.

This model features two productivity parameters: $A > 0$ is a labor-augmenting productivity parameter while $\theta \geq 0$ is a parameter capturing IT capabilities. Note that a higher θ implies that ICT capital is used more intensely in every industry. For example, $\theta = 0$ captures an environment in which producers do not have the necessary know-how to use ICT capital in a productive fashion. Thus, additional ICT capital will not contribute to output. In contrast, higher values of $\theta > 0$ indicate production processes that are able to benefit increasingly from additional ICT inputs. Aggregate GDP in each country is given by

$$Y = \sum_j P_j Y_j, \tag{2}$$

where P_j is the price of output in industry j. Given the Cobb-Douglas production structure at the industry level, and assuming that ICT capital is paid its marginal product, the income of ICT capital in industry j is $\theta\alpha_{i,j} P_j Y_j$ and the aggregate income share of ICT is then given by

$$s_i = \sum_j \frac{\theta\alpha_{i,j} P_j Y_j}{\sum_j P_j Y_j} = \theta \sum_j \alpha_{i,j} \left(\frac{P_j Y_j}{\sum_j P_j Y_j}\right) \tag{3}$$

The income share of ICT therefore depends not only on θ but also on the extent to which the economy chooses to produce in industries that use ICT capital more intensely (those with higher $\alpha_{i,j}$). This industrial specialization, in turn, may depend on both θ and on the abundance of other factors of production.

We emphasize that, although we assume a unitary elasticity of substitution at the industry level, this model allows for richer interactions at the macro level.[4] In what follows, we propose two alternative strategies to recover country and time specific levels of IT capabilities, θ.

3.1. Calibration Based on Observable Industrial Composition

Our goal is to quantify the extent to which variation in the measured ICT share can be attributed to differences in IT capabilities across countries. In our model, the ICT income share within industry j is given by $\theta\alpha_{i,j}$. In this interpretation, the measured ICT share at the industry level can vary both across countries (e.g., due to variation in θ) and across industries (e.g., due to variation in $\alpha_{i,j}$). However, without further assumptions, we cannot identify θ and $\alpha_{i,j}$ separately.

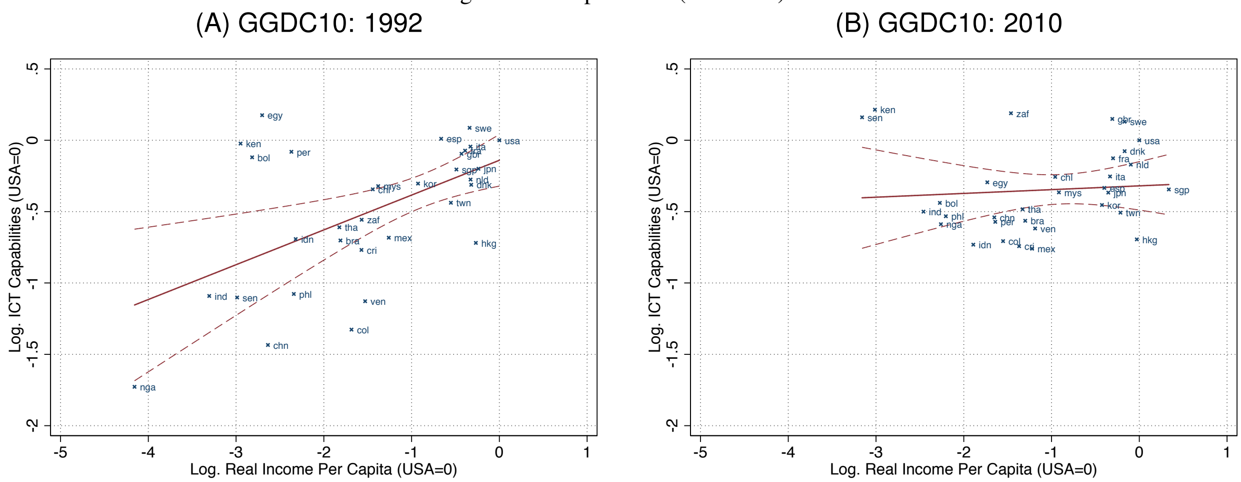
Thus, our first calibration approach builds on the structure in our model, and the assumption that $\alpha_{i,j}$ does not vary across countries. Given $\alpha_{i,j}$, industry-level value added (P_jY_j), and the aggregate ICT income share (s_i), we can infer country and time specific values for θ based on equation (3) using the formula

$$\hat{\theta} = \frac{s_i}{\frac{\sum_j \alpha_{i,j} P_j Y_j}{\sum_k P_k Y_k}} \tag{4}$$

We calibrate the parameters $\alpha_{i,j}$ as follows. Recall that, for a given year and country, the income share of ICT capital in industry j is $\theta\alpha_{i,j}$, regardless of the country's industrial specialization. Thus, normalizing $\theta = 1$ in the US, this implies that $\alpha_{i,j}$ in a given year corresponds to the measured industry-level ICT income share in the U.S. For example, column 2 of Table 1 illustrates these numbers averaged over the period 2010-2015, based on data from the U.S. Bureau of Economic Analysis (BEA) and the methodology in Eden and Gaggl (2018).

[4]To illustrate, consider a simple example of a small open economy with two sectors: one sector that utilizes only low-skilled labor, and another sector that utilizes both ICT capital and skilled labor. In this environment, a decline in the price of ICT will trigger an increase in the production of the ICT-intensive sector, and hence reduce the income share of unskilled labor. Thus, at the macro level, the elasticity of substitution between ICT capital and unskilled labor will be greater than unitary, even though we assume unitary elasticities of substitution at the industry level.

Figure 3: IT capabilities (GGDC10)



Notes: The figure illustrates the relationship between our measure of IT capabilities ($\hat{\theta}$) based on equation (4) and real GDP per capita for the years 1992 and 2010. We use sector value added from the GGDC10 database. In each graph, we normalize IT capabilities in the USA such that $\theta^{USA} = 1$ and analogously real GDP per capita such that $\ln(Y^{USA}) = 0$.

We use data on value added at the industry level from the Groningen Growth and Development Centre's ten sector database (GGDC10, de Vries, Timmer and de Vries, 2014). For the *aggregate* ICT shares (s_i) we could in principle use the estimates in the TED (as plotted in Figure 2). However, the ICT shares in the TED are based on adjusted GDP series (to account for intangible capital and other intellectual property products that are not typically measured in national accounts) which is not consistent with the value added concept in the GGDC10. To circumvent this problem, we construct our own estimates for s_i, based on the methodology in Eden and Gaggl (2018) and data on income from the Penn World Table (PWT), which is consistent with the value added measures in the GGDC10. Our sample (which also overlaps with GGDC10) covers the years 1992-2010 and details on the data construction as well as a comparison with the TED estimates are provided in Appendix A.4. Moreover, a detailed tabulation of the overlap in country coverage between the various datasets used in this analysis is given in Tables A.6 and A.7. In particular, we would like to note that our sample with both ICT share data and industry value added data (GGDC10) consists of 32 countries at various levels of income. Based on the distribution of income per capita (in 2011 PPP) across all 182 countries reported in the PWT9.0 in 2011, our sample contains 11 countries in the fifth quintile (including the U.S.), four countries in the fourth quintile, ten countries in the third quintile, five countries in the second quintile, and two countries in the first quintile (Kenya and Senegal). Using this dataset, Figure 3 displays our results based on equation (4) for the years 1992 and 2010.

If we interpret θ as IT capabilities relative to the US in a given year, then our results suggest that poorer countries had systematically lower levels of IT capabilities in 1992, yet the positive correlation between income and $\ln(\theta)$ has largely vanished by 2010. In particular, notice that the "rotation" of the regression line suggests that poor countries were likely "catching up" to more advanced economies. Column (4) of Table 4 reports the slope coefficients for the regression lines depicted in Figure 3.

An alternative way to investigate this result is to express both sides of equation (3) as a fraction of the corresponding values in the US:

$$\frac{s_i^c}{s_i^{USA}} = \left(\frac{\theta^c}{\theta^{USA}}\right) \frac{\sum_j \alpha_{i,j} \left(\frac{P_j^c Y_j^c}{\sum_j P_j^c Y_j^c}\right)}{\sum_j \alpha_{i,j} \left(\frac{P_j^{USA} Y_j^{USA}}{\sum_j P_j^{USA} Y_j^{USA}}\right)} = \left(\frac{\theta^c}{\theta^{USA}}\right) \left(\frac{\hat{s}_i^c}{\hat{s}_i^{USA}}\right) \tag{5}$$

where c is a country index and we define $\hat{s}_i^c \equiv \sum_j \alpha_{i,j} P_j^c Y_j^c / \sum_j P_j^c Y_j^c$.

It is likely that both terms on the right hand side of equation (5) are increasing in income: θ^c/θ^{US} is increasing in income because richer countries are faster adopters of new technologies, and $\hat{s}_i^c/\hat{s}_i^{US}$ is likely increasing in income because richer countries will likely choose to specialize in more ICT-intensive industries. We therefore write $\ln(\hat{s}_i^c/\hat{s}_i^{US}) = \beta_s \ln(y_c) + \epsilon_c$, and $\ln(\theta^c/\theta^{US}) = \beta_\theta \ln(y_c) + \zeta_c$, where β_s and β_θ are regression coefficients reflecting these correlations with income.[5] Note that the coefficients β_θ and β_s capture statistical relationships rather than causal ones; by construction, the residuals ϵ_c and ζ_c are uncorrelated with income. Our variable of interest is β_θ, which captures the relationship between income and ICT capabilities.

As we do not observe θ directly, we cannot directly estimate β_θ. However, we can re-write equation (5) as follows:

$$\ln\left(\frac{s_i^c}{s_i^{USA}}\right) = \ln\left(\frac{\theta^c}{\theta^{US}}\right) + \ln\left(\frac{\hat{s}_i^c}{\hat{s}_i^{US}}\right) = (\beta_\theta + \beta_s)\ln(y_c) + \epsilon_c + \zeta_c = \beta_\theta \ln(y_c) + \ln\left(\frac{\hat{s}_i^c}{\hat{s}_i^{US}}\right) + \zeta_c \tag{6}$$

As this equation illustrates, a simple regression of log ICT income shares on log income per-capita recovers the sum $\beta_\theta + \beta_s$; as both terms are likely to be positive, this regression coefficient likely overstates the

[5]Note that we omit constants for the ease of exposition but include them in our empirical analysis below.

Table 4: Model Predictions and the Measured ICT Share (GGDC10)

	Log ICT Share Relative to U.S. (USA=1)			$\ln(\hat{\theta})$
	(1)	(2)	(3)	(4)
A. 1992				
Log Real GDP/L	0.373***	0.341***	0.236**	0.244***
	(0.0713)	(0.0885)	(0.0928)	(0.0774)
Log Ind. Pred. (1992)			1.077	
			(0.698)	
Constant	-0.443***	-0.288***	-0.129	-0.140
	(0.0924)	(0.0948)	(0.156)	(0.0886)
Obs.	67	32	32	32
R^2	0.287	0.436	0.477	0.298
Adj. R^2	0.276	0.417	0.441	0.275
B. 2010				
Log Real GDP/L	0.180***	0.0998	0.00173	0.0265
	(0.0598)	(0.0875)	(0.0850)	(0.0733)
Log Ind. Pred. (2010)			1.338***	
			(0.315)	
Constant	-0.527***	-0.512***	-0.254**	-0.319***
	(0.0548)	(0.0897)	(0.0939)	(0.0831)
Obs.	67	32	32	32
R^2	0.198	0.0712	0.298	0.00696
Adj. R^2	0.186	0.0403	0.250	-0.0261

Notes: Column (1) reports cross-country regressions of $\ln(s_i)$ on log income per person. Column (2) restricts the sample to countries in which we have sufficient data to construct "industry predictions" $\hat{s}_i = \ln(\sum_j \alpha_{i,j} P_j Y_j / \sum_k P_k Y_k)$, based on sector value added data from the GGDC10 database. Column (3) adds $\ln(\hat{s}_i)$ as an additional regressor. Finally, column (4) shows regressions of $\ln(\theta)$ on real GDP per capita. For each country, both s_i and $\hat{s}_i$ are expressed as a fraction of the corresponding US value, such that $\ln(s_i) = \ln(\hat{s}_i) = 1$ in the USA. In analogy, we normalize $\theta^{USA} = 1$ in the US. The ICT share is computed using the methodology in Eden and Gaggl (2018) described in Appendix A.4. HAC robust standard errors are reported in parentheses below each coefficient and significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

strength of the relationship between income and IT capabilities (β_θ). However, the final equality in equation (6) suggests that we can estimate β_θ by regressing $\ln\left(s_i^c / s_i^{USA}\right)$ on log income per person while controlling for the industrial composition term, $\ln\left(\hat{s}_i^c / \hat{s}_i^{US}\right)$.

Table 4 summarizes the results from regression analyses based on equations (5) and (6) for the years 1992 and 2010. In Column (1) we regress the log of the ICT share relative to the USA on log income per person within the full sample of 67 countries for which we have estimates of the ICT share. In column (2) we repeat this regression but restrict the sample to countries for which we have industry predictions $\left(\hat{s}_i^c/\hat{s}_i^{USA}\right)$ based on the GGDC10 database. As expected, the slope coefficient is significantly positive in 1992, but much smaller in 2010. Moreover, the sample restriction in column (2) does not change this observation. In column (3) we add the industry predictions $\ln\left(\hat{s}_i^c/\hat{s}_i^{US}\right)$ as an additional regressor, motivated by equation (6). Consistent with our theory, this specification suggests that the inclusion of the industrial composition term reduces the estimated coefficient on income per capita. Moreover, while the relationship with income remains positive in 1992 it effectively vanishes by 2010. Reassuringly, both the "direct" estimate of β_θ in column (4), which is also graphically illustrated in Figure 3, and the "indirect" estimate shown in column (3) are very close for both years. The interpretation of these results is that poorer countries were perhaps lagging behind in terms of IT capabilities in 1992 but have largely caught up by 2010.

The advantage of this approach is that we do not need to assume that industrial composition is optimal; only that, within each industry, ICT capital is paid its marginal product (to guarantee that the industry-level ICT shares are $\theta\alpha_{i,j}$). In addition, the data requirements are quite limited: we do not need data on capital prices or labor endowments, but only data on *aggregate* ICT income shares and value added by industry.

The disadvantage of this approach is that it imposes strong assumptions on the production structure within industries. Unfortunately, for many economies, value added data is available only for broad industry classifications. Thus, this calibration strategy necessitates the assumption of constant $\alpha_{i,j}$ within broad industry categories. For example, we assume a constant ICT income share in services broadly defined. However, as Table 1 suggests, some services, like accommodation, food, and education services have an ICT share of below 2% in the U.S., yet professional and administrative services, finance and insurance, as well as health services have ICT shares well beyond 10%, and above 20% in some industries.

This creates a problem for the interpretation of regression analyses based on equation (6). To see why, it is useful to write the predicted industrial composition term as $\ln(\tilde{s}_i^c/\tilde{s}_i^{US}) = \ln(\hat{s}_i^c/\hat{s}_i^{US}) + \xi_c$, where $\ln(\tilde{s}_i^c/\tilde{s}_i^{US})$ is an observable predictor of the ICT share based on a broad industry classification, while $\ln(\hat{s}_i^c/\hat{s}_i^{US})$ is a more disaggregated measure, which we do not observe. The residual ξ_c is likely to be negatively correlated with IT capabilities and income: countries with better IT capabilities will likely choose to specialize in more IT-intensive sectors. To formalize this scenario, we postulate that $\xi_c = \beta_\xi \ln(y_c) + \xi_c'$, where $\beta_\xi \leq 0$. Together with equation (6), this implies that

$$\begin{aligned}
\ln\left(\frac{s_i^c}{s_i^{USA}}\right) &= \beta_\theta \ln(y_c) + \ln\left(\frac{\hat{s}_i^c}{\hat{s}_i^{US}}\right) + \zeta_c \\
&= \beta_\theta \ln(y_c) + \left[\ln\left(\frac{\tilde{s}_i^c}{\tilde{s}_i^{US}}\right) - \xi_c\right] + \zeta_c \\
&= \beta_\theta \ln(y_c) + \left[\ln\left(\frac{\tilde{s}_i^c}{\tilde{s}_i^{US}}\right) - \beta_\xi \ln(y_c) - \xi_c'\right] + \zeta_c \\
&= (\beta_\theta - \beta_\xi) \ln(y_c) + \ln\left(\frac{\tilde{s}_i^c}{\tilde{s}_i^{US}}\right) + \zeta_c - \xi_c' \qquad (7)
\end{aligned}$$

If indeed $\beta_\xi \leq 0$, then the regression coefficients reported in Table 4 are upward-biased estimates of β_θ. This suggests that the true correlation between income per capita and IT capabilities is likely even weaker than suggested by Figure 3 and reported in column (5) of Table 4. To address this concern, the next section considers an alternative calibration strategy, which explicitly models optimal industrial specialization.

3.2. Calibration Based on Optimal Industrial Composition

Our second calibration strategy imposes stronger assumptions on the production technology, and backs out θ from the model's equilibrium conditions. It considers a model with two sectors: one intensive in both ICT capital and skilled labor and the other intensive only in low skilled labor. This aggregate production framework is similar to Krusell, Ohanian, Ríos-Rull and Violante (2000) and supported by evidence from an extensive literature in labor economics, suggesting that ICT is complementary to high-skill workers/tasks (e.g., Akerman et al., 2015; Gaggl and Wright, 2017) and largely substitutes for less skill-intensive tasks.[6] While it imposes more structure, the benefit of this alternative framework is that we do not need to measure industry specific IT intensity directly and that we explicitly account for the role of skilled labor as a complementary factor.

Production in the "unskilled" sector is governed by the following production function:

$$Y_u = K_{n,u}^{\alpha}(AL_u)^{1-\alpha} \qquad (8)$$

[6] For a review of the broader literature see Acemoglu and Autor (2011).

where $K_{n,u}$ is the NICT capital stock employed in the unskilled sector; L_u is the economy's endowment of unskilled labor; and A is a labor-augmenting productivity parameter.

Production in the skilled sector utilizes ICT capital, K_i, as an additional input. The intensity of ICT use depends on the level of ICT adoption, θ:

$$Y_s = \left[K_{n,s}^{\alpha}(AL_s)^{1-\alpha}\right]^{1-\theta} K_i^{\theta} \tag{9}$$

where $K_{n,s}$ is the NICT capital stock employed in the skilled sector; L_s is the economy's endowment of skilled labor; and K_i is the stock of ICT capital. One can think of this setup as an aggregation in line with the second stylized fact presented in Section 2.

We assume competitive factor markets, in which producers in both sectors take factor prices as given. This implies that both types of capital are paid their respective marginal products, and that marginal products are equalized across industries. In this framework, the relative income shares of labor and NICT capital are constant at $(1-\alpha)/\alpha$, regardless of θ or of the economy's labor endowments. Note further that the same productivity parameter, A, augments both skilled and unskilled labor.[7]

Optimal factor demand in the unskilled sector is pinned down by the following equilibrium condition:

$$MPK_{n,u} = \alpha K_{n,u}^{\alpha-1}(AL_u)^{1-\alpha} = p_n(r+\delta_n) \tag{10}$$

where p_n and δ_n are the price of NICT capital relative to output and the depreciation rate of NICT capital, respectively. Taking L_u and an estimate for $MPK_{n,s} = MPK_{n,u} = MPK_n$ from the data (see Appendix A.5 for details on measurement), and calibrating α based on the labor income share, this equation amounts to a relationship between $K_{n,u}$ and the productivity parameter A. For a given A, we can therefore solve for the equilibrium $K_{n,u}$.

[7]Thus, L_u and L_s are denoted in "efficiency units" here (with equalized wages across sectors) and therefore must be measured in a way that matches the relative income shares of skilled and unskilled labor, implicitly accounting for differences in productivity across the two types of labor inputs. For a more comprehensive discussion of this point see Eden and Gaggl (2018).

Factor demand in the skilled sector is pinned down by the following two equilibrium conditions:

$$MPK_{n,s} = (1-\theta)\alpha K_{n,s}^{\alpha(1-\theta)-1}(AL_s)^{(1-\alpha)(1-\theta)}K_i^{\theta} = p_n(r+\delta_n) \tag{11}$$

$$MPK_i = \theta K_{n,s}^{\alpha(1-\theta)}(AL_s)^{(1-\alpha)(1-\theta)}K_i^{\theta-1} = p_i(r+\delta_i) \tag{12}$$

where p_i and δ_i are the price and depreciation rate of ICT capital. Taking L_s and an estimate for $MPK_{n,s} = MPK_{n,u} = MPK_n$ from the data (see Appendix A.5 for details on measurement), and for a given A and a given θ, these are two equations in two unknowns ($K_{n,s}$ and K_i), which can be solved to obtain equilibrium levels of capital in the skilled sector.

Taken together, the factor demand system (10) – (12) allows us to jointly calibrate A and θ by targeting the measured ICT income share

$$s_i = \theta\frac{Y_s}{Y_s+Y_u} \tag{13}$$

which is given by θ times the income share of the skilled sector in this model, and the aggregate NICT capital stock

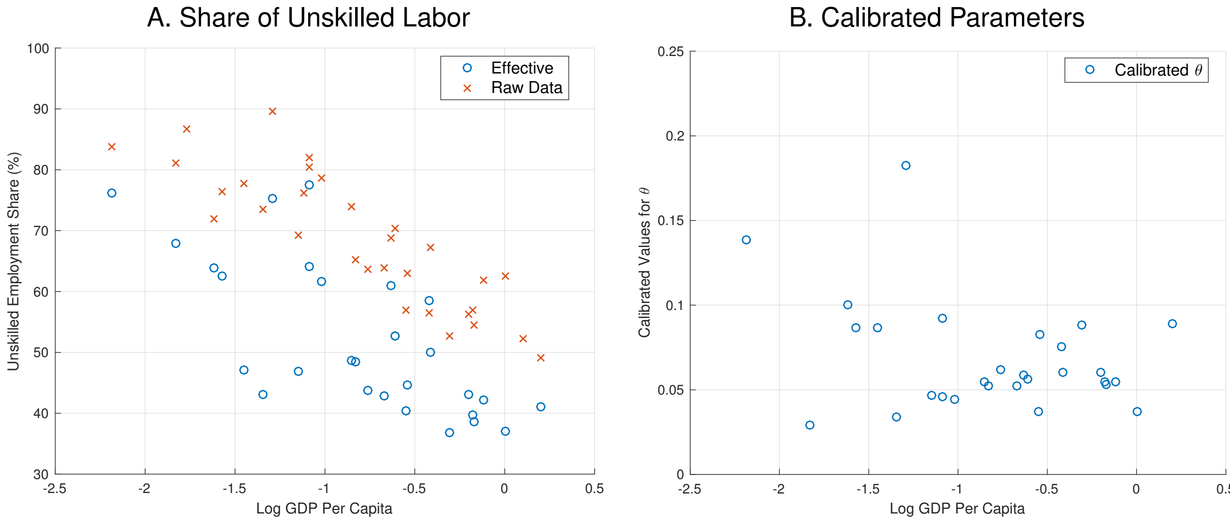
$$K = K_{n,u} + K_{n,s} \tag{14}$$

Intuitively, the parameter A governs the scale of the economy and is disciplined by the aggregate NICT capital stock, K, while the parameter θ is pinned down by matching the ICT share, s_i.

Note that a larger endowment of skilled labor relative to unskilled labor would increase the economy's production in the skilled sector, resulting in a higher equilibrium ICT share (for a given θ). An increase in θ would also result in an equilibrium increase in the ICT share, both because it would absorb a higher fraction of output from the skilled sector, and because it would increase the output in the skilled sector relative to the unskilled sector.

We construct measures of skilled and unskilled labor endowments in efficiency units following the methodology described in Eden and Gaggl (2018) and based on data from the International Labour Organization (ILO). In our framework, the wage rate per efficiency unit needs to equalize across sectors. This implies that the relative labor endowments must equal the relative income shares. The ILO provides data on

Figure 4: Method 2: Calibrated ICT Adoption θ



Notes: Panel A shows the share of unskilled labor both in raw employment counts and "effective units" based on data from the Inernational Labour Organization (ILO). We define high skilled workers as those employed in occupations earning more than half of the best earning occupation. Panel B shows calibrated values for θ based on the calibration strategy described in section 3.2. Both panels are based on data from 2011.

both wages and employment by occupation for a large sample of countries at various levels of development, which allows us to construct occupation-specific aggregate earnings. We then proxy high-skill and low-skill employment by first splitting workers into high- and low-earning occupations and then computing the relative earnings of these two groups following Eden and Gaggl (2018). While the traditional way to classify high- and low-skill workers is by education, we do not have access to earnings data by occupation for poor countries. We therefore resort to sorting workers by occupational earnings as in Autor and Dorn (2013). Panel A of Figure 4 plots the share of unskilled workers against income per capita based on both the ILO's raw employment counts as well as our composition adjusted measure based on relative earnings.

The main challenge with our second calibration strategy is the need for estimates of the real *stocks* of ICT and NICT capital and their prices. While the TED provides estimates for the ICT income share for a large sample of countries (see Figure 2), it does not provide estimates for disaggregated capital stocks. On the flipside, the EU KLEMS (and WORLD KLEMS) dataset does provide estimates of disaggregated capital stocks but it only covers a very limited set of high income countries. We therefore construct our own estimates for disaggregated capital stocks within a sample of 72 countries at various levels of development over the period 1992-2011 and we describe the details of this measurement exercise in Appendix A.3. Moreover, Appendix

Table 5: Alternative Measures of IT Capabilities

Country	Y/L (% of US)	Income Quintile	Employment Share (%) Low Skill	High Skill	$\frac{p_{i,c}}{p_{n,c}}$	IT Capabilities (% of UK) s_i	θ Ver. 1	θ Ver. 2
Hong Kong	97	5	37.00	63.00	1.62	45.71	43.00	41.94
United Kingdom	74	5	36.81	63.19	1.00	100.00	100.00	100.00
Spain	67	5	49.97	50.03	1.08	51.25	61.68	68.57
Korea	65	4	58.50	41.50	1.12	58.32	54.71	84.96
Malaysia	40	4	48.71	51.29	1.46	55.68	59.77	61.44
Venezuela	31	3	77.52	22.48	2.49	32.90	46.42	104.19
Thailand	26	3	75.24	24.76	2.01	51.36	53.11	205.99
Costa Rica	25	3	43.15	56.85	1.63	40.55	41.01	37.96
South Africa	23	3	47.10	52.90	1.80	95.78	104.08	97.63
Peru	19	3	62.58	37.42	1.61	42.62	48.63	98.13
Egypt	18	3	63.98	36.02	1.48	52.29	64.15	113.32
Bolivia	10	2	76.13	23.87	1.23	46.68	55.53	156.54

Notes: The table compares alternative measures of IT capabilities for 2010: the ICT share, θ calibrated as in Section 3.1 (version 1), and θ calibrated as in Section 3.2 (version 2). Moreover, we also report the share of high/low skilled workers as well as the price of ICT relative to NICT. Both the rleative price and the IT measures are expressed as a fraction of the UK. The sample of countries includes the intersection of country coverage across the two calibration methods. The main limiting factor for version 2 is data on high skill employment from the ILO. Countries are sorted by income per person and income quintiles are based on the full set of 182 countries in the PWT9.0.

A.5 shows how we use these capital stock estimates to construct estimates for MPK_i and MPK_n. Figure A.12 displays the resulting estimates for all required data inputs within the subset of countries that also have the relevant data on skill-group specific employment and wages from the ILO.

Panel B of Figure 4 shows our calibration results based on data for 2011. The results are perhaps even more striking than those based on our first calibration strategy, as they suggest that, in 2011, there is no systematic relationship between θ and income per capita. This calibration then suggests that cross-country heterogeneity in ICT capital is likely driven by industrial specialization, with the patterns of specialization driven in part by cross-country differences in high-skill labor endowments.

4. Country-Level Analysis

While our main goal is to assess the relationship between income per capita and IT capabilities, our analysis can also be used for country-level analysis. Table 5 presents our calibration results for several countries.

Our calibration approach suggests that the ICT income share is a downward-biased estimate of the technological capabilities of low-income countries. For example, in Egypt, the ICT income share is about half of that of the UK. However, after accounting for differences in industrial composition, its technological capabilities are estimated at 64% of the UK. After differences in skill endowments are taken into account, its technological capabilities are estimated to be comparable to the UK.

While these patterns are consistent with most countries in our sample, there are some exceptions. For example, for Hong Kong—a country with a similar skill mix and a similar industrial composition as the UK—the ICT income share is roughly equal to the calibrated value of θ.

5. Concluding Remarks

This paper begins by documenting the evolution of ICT capital income shares across countries and across time. Consistent with the findings of Comin and Mestieri (2017), our analysis suggests that, even though there has been substantial cross-country convergence in ICT capital use, the intensity of ICT capital use remains positively correlated with income per capita.

We proceed by studying the extent to which this regularity can be accounted for by cross-country differences in industrial composition. We propose a simple structural framework in which an economy's industrial composition is jointly determined by its IT capabilities and its endowments of other factors of production. Using the same structural framework, we pursue two approaches for backing out the country's level of IT capabilities. The first approach uses data on industry-level value added and the second approach uses data on the abundance of complementary factors of production. Both approaches suggest that IT capabilities have mostly converged across countries by 2011, and that remaining gaps are due primarily to other forces impacting countries' industrial specialization patterns.

Compared to previous approaches, our methodology takes into account differences in industrial composition which may be driven by country characteristics that are independent from its level of technology adoption. While, in this paper, we use this methodology to assess the degree of IT adoption, we hope that it can be used more broadly to assess the degree of technological differences across countries for other technologies as well.

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Appendix A. Data Construction

This appendix lays out our procedure for estimating stocks and income shares for ICT and non-ICT (NICT) capital within a sample of 67 countries at various levels of development. We start by constructing ICT stocks in a way that is conceptually consistent with standard datasets, such as the Penn World Table (PWT) or the Total Economy Database (TED). We then use the methodology described by Eden and Gaggl (2018) in order to decompose total income (as measured by GDP in the PWT) into the portions that goes to labor, ICT capital, and NICT capital, respectively. For our two alternative structural approaches to gauge IT capabilities across countries, we further merge industry level data on value added from the Groningen Gorwth and Develpment Centre's 10 Sector Database (GGDC10) as well as wage and employment data from the International Labor Organization (ILO). Tables A.6 and A.7 give an overview of the country coverage and sample overlap.

Appendix A.1. Nominal ICT Investment

We start with estimating the stock of ICT and NICT capital for 72 countries at various levels of development, largely following the conceptual procedure in the PWT (and the TED). We use data on ICT

Table A.6: Data Summary (Part 1)

Country	Code	Y/L	Inc. Perc.	Number of Years with Data: 1992-2011				
				PWT+WITSA+ITU+ICP	TED	GGDC10	ILO Occ. Wages	ILO Occ. Emp.
Total No. of Countries				67	62	32	28	31
Kuwait	KWT	150	5	20	20			
Singapore	SGP	144	5	20	19	20		
Norway	NOR	122	5	20	20		1	1
Switzerland	CHE	110	5	20	20			1
Saudi Arabia	SAU	102	5	20	20			
United States	USA	100	5	20	20	19		
Hong Kong	HKG	100	5	20	20	20	1	1
Netherlands	NLD	92	5	20	20	20		
Ireland	IRL	90	5	20	20			
Austria	AUT	89	5	20	20		1	1
Australia	AUS	88	5	20	20			
Sweden	SWE	87	5	20	20	20		
Germany	DEU	86	5	20	20		1	1
Denmark	DNK	86	5	20	20	20		
Belgium	BEL	84	5	20	20		1	1
Canada	CAN	83	5	20	20			
Finland	FIN	81	5	20	20		1	1
Taiwan	TWN	81	5	20	20	20		
France	FRA	76	5	20	20	20		
United Kingdom	GBR	73	5	20	20	20	1	1
Italy	ITA	72	5	20	20	20		
Japan	JPN	69	5	20	20	20		
Spain	ESP	66	4	20	20	20	1	1
Korea	KOR	65	4	20	20	20	1	1
New Zealand	NZL	64	4	20	20			
Israel	ISR	63	4	20	20			
Czech Republic	CZE	58	4	20	20		1	1
Slovenia	SVN	57	4	20	20		1	1
Portugal	PRT	54	4	20	20		1	1
Greece	GRC	53	4	20	20		1	1
Slovakia	SVK	51	4	20	20		1	1
Hungary	HUN	46	4	20	19		1	1
Russia	RUS	46	4	20	16			
Poland	POL	45	4	20	19		1	1
Malaysia	MYS	42	4	20	20	20	1	1
Chile	CHL	41	4	20	20	20		
Uruguay	URY	36	4	20	17		1	1
Turkey	TUR	35	4	20	19		1	1

Notes: Tables A.6 and A.7 combined summarize the total number of countries (first line) and the years of data per country within the various data sources used in this paper. The countries are sorted by GDP per capita (expressed as % of USA) and grouped into five quintiles, based on the full 182 countries in the Penn World Tables (PWT) in 2011. The underlying data sources are PWT, the World Information Technology and Services Alliance (WITSA), the International Telecommunication Union (ITU), the World Bank's International Comparison Program (ICP), the Groningen Gorwth and Develpment Centre's 10 Sector Database (GGDC10), and the International Labor Organization (ILO).

spending from the World Information Technology and Services Alliance (WITSA) as well as the International Telecommunication Union (ITU). WITSA is currently the most widely used source for data on ICT

Table A.7: Data Summary (Part 2)

Country	Code	Y/L	Inc. Perc.	Number of Years with Data: 1992-2011				
				PWT+WITSA+ITU+ICP	TED	GGDC10	ILO Occ. Wages	ILO Occ. Emp.
Venezuela	VEN	34	3	20	20	20	1	1
Panama	PAN	33	3	20				1
Bulgaria	BGR	32	3	20	20		1	1
Mexico	MEX	31	3	20	20	20		
Brazil	BRA	30	3	20	17	20		
Thailand	THA	27	3	20	20	20	1	1
Costa Rica	CRI	26	3	20	20	20	1	1
South Africa	ZAF	24	3	20	20	20	1	1
Colombia	COL	23	3	20	19	20		
Peru	PER	21	3	20		20	1	1
Jordan	JOR	21	3	20	11			
China	CHN	20	3	20	20	20		
Tunisia	TUN	20	3	20	20			
Ukraine	UKR	20	3	20	11			
Egypt	EGY	20	3	20	20	20	1	1
Ecuador	ECU	20	3	20	20			1
Indonesia	IDN	18	2	20	19	20		
Sri Lanka	LKA	17	2	20	10		1	1
Jamaica	JAM	15	2	20	20			
Morocco	MAR	14	2	20	20			
Philippines	PHL	12	2	20	20	20		
Bolivia	BOL	11	2	20	20	20	1	1
Nigeria	NGA	10	2	20		20		
India	IND	9	2	20	20	20		
Honduras	HND	9	2	20				
Kenya	KEN	5	1	20	11	20		
Cameroon	CMR	5	1	20	20			
Senegal	SEN	4	1	20		19		
Zimbabwe	ZWE	3	1	20	11			

Notes: Tables A.6 and A.7 combined summarize the total number of countries (first line) and the years of data per country within the various data sources used in this paper. The countries are sorted by GDP per capita (expressed as % of USA) and grouped into five quintiles, based on the full 182 countries in the Penn World Tables (PWT) in 2011. The underlying data sources are PWT, the World Information Technology and Services Alliance (WITSA), the International Telecommunication Union (ITU), the World Bank's International Comparison Program (ICP), the Groningen Gorwth and Develpment Centre's 10 Sector Database (GGDC10), and the International Labor Organization (ILO).

spending on a global scale and is assembled using a combination of various surveys, vendor supply analysis and other statistics.[8] Specifically, WITSA reports ICT spending for four categories: (1) computer hardware, (2) computer software, (3) computer services, and (4) communications. The sum of these four categories gives a fairly comprehensive picture of ICT *expenditure* around the world. However, as we are interested in constructing measures of the physical *stock* of ICT capital, it is important to notice that, conceptually, some

[8]For instance, both the Penn World Table (PWT) and the Conference Board's Total Economy Database (TED) use WITSA as the main source for information on ICT spending.

of these WITSA spending measures represent investment spending but others consist primarily of rental fees. For example, while spending on internet subscriptions or telecommunication fees may comprise a substantial amount of ICT spending, it does not constitute investment: from a macro perspective, these are transfers between users of ICT capital and owners of ICT capital, more appropriately viewed as rental fees. From an aggregate perspective, an internet subscription does not require the sacrifice of resources today for the purpose of increasing aggregate production capacity tomorrow, which is the defining characteristic of investment.

More specifically, of the four WITSA spending categories, computer services is in fact the only category that consists primarily of true aggregate investment spending, taking the form of custom software development and equipment maintenance. This category also includes some services that may be more appropriately viewed as rental payments, such as web hosting, but these likely represent a small share of spending in this category.

The categories of computer hardware and computer software include the total value of purchases and leases. Ideally, one would like to count hardware and software investment as the purchase of new machinery or software. However, the WITSA measure includes secondary markets as well, as it takes into account the value of leases. Bluntly, if a computer is purchased and then leased, it is double counted. We therefore adopt an approach similar to Vu (2005) and assume that hardware investment is 0.57 times computer hardware spending, which is roughly the coefficient of proportionality in US data.[9] The coefficient of proportionality for software is greater than one, suggesting that software spending is lower than software investment in the United States. This is probably due to the omission of computer services spending, which includes some forms of software investment. Since we include computer services in our ICT investment measure, we assume that the remaining software investment is equal to WITSA software spending.

It is perhaps worth noting that the distinction between software leases and software investment is somewhat blurred. The software spending category consists of the total value of purchased or leased packaged software. While purchasing software is investment from the firm's perspective, from a macro perspective this is perhaps more appropriately viewed as a rental fee. The creation of new software is similar to investment in research and development (R&D). The returns to writing new software are the dividends from

[9] See the Appendix of Vu (2005) for year-by-year estimates of this factor of proportionality.

selling or leasing the rights to use that software. From a timing perspective, the value of the initial investment is the costs of programmers and associated capital costs for producing new software. The returns to the investment are the sales of software licenses, either permanent (purchases) or temporary (leases). From a macroeconomic perspective, software investment should be counted as the costs associated with developing new software (similar to R&D investment). However, given that this data is not available, we stick with the commonly adopted micro perspective and assume that software investment is software purchases and leases.[10]

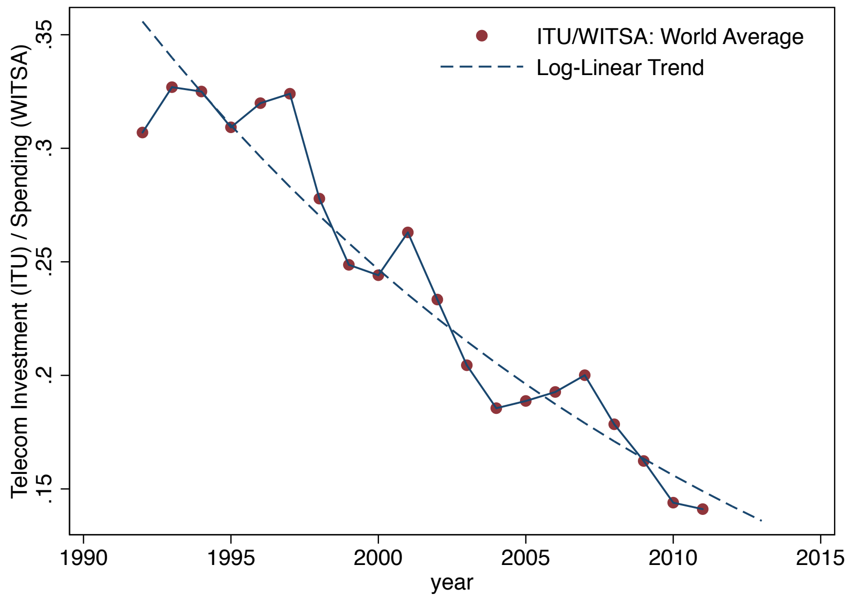
WITSA produced seven publicly available reports (Digital Planet 1998, 2000, 2002, 2004, 2006, 2008, 2010) that provide data on the four ICT spending categories over the period 1992 to 2011. The number of (WITSA member) countries varies across the reports (55-75 countries) and WITSA draws on data provided by the International Data Corporation (for reports 1998, 2000, 2004) and Global Insights, Inc. (for reports 2004, 2006, 2008, 2010) and further details are provided at http://www.witsa.org. In order to construct continuous time series for the four ICT spending categories mentioned above, we use the 1998, 2002, 2004, 2006, and 2010 reports. The reason why we use the information in all of these reports (rather than just the 2010 report) is that each report covers different years (with some overlap). We make the assumption that the most recent reports contain the most up-do-date information and adjust the level of spending in older reports, such that the level in an overlapping "anchor year" aligns but growth rates are maintained as observed in the older reports.

The fourth WITSA category, communication technology (CT), is defined as the total value of voice and data communication services and equipment. Conceptually, communication services (such as internet subscriptions or payments for phone usage) represent rental fees for communication infrastructure, rather than investment. Since we are interested in a pure investment measure, we substitute this category with a direct measure of CT investment from ITU. ITU publishes the World Telecommunication/ICT Indicators database covering data on 150 telecommunication/ICT statistics from 1975 to 2013 for over 200 countries and further information is provided at http://www.itu.int/en/ITU-D/Statistics/Pages/publications/wtid.aspx.

While we think that the ITU investment measures are the preferred estimate of TC investment, the ITU's

[10] Note that the high depreciation rate of software implies that there is no big difference between permanent purchases and temporary leases. Generally, most attempts to construct capital stocks take this perspective. The BEA's computations for the NIPA tables are one example. See the official NIPA documentation for details: http://www.bea.gov/national/pdf/chapter6.pdf.

Figure A.5: ITU TC Investment vs. WITSA TC Spending



Notes: The Figure presents the wolrd avarage ratio of telecommunication (TC) investment from ITU relative to WITSA TC spending.

data coverage varies widely across countries. In some countries, we have a continuous data series going back to 1975, while other countries only have a handful of data points. In order to construct a TC investment series for the full sample of 1992-2013 we estimate a smooth trend in the ratio of TC investment (ITU) to spending (WITSA) for years where ITU and WITSA overlap. Figure A.5 illustrates the smooth trend in the World average of these investment/spending ratios. We use country specific versions of the trend in this ratio, to interpolate missing ITU data based on WITSA TC spending. For countries that don't have a sufficiently long time series with overlap between ITU and WITSA to estimate a country specific trend line, we use the World average as displayed in Figure A.5.

Taken together, our final measure of nominal ICT investment at current cost in USD is the sum of TC investment (ITU), computer services spending (WITSA), adjusted computer hardware spending (WITSA), and computer software spending (WITSA). This procedure results in a sample or 51 countries with a complete time series from 1992-2013 for all ICT investment series (TC, Hardware, Non-Hardware), 20 countries with 14 years of data, 3 countries with 13 years of data, and one country with only 4 years of data for all

ICT investment categories (Panama only has 4 years of TC data but 14 years of IT investment data). For the countries that do not have a full sample we extrapolate backward and forward in proportion to an aggregate of investment in machinery and "other assets" (excluding transportation equipment and structures) from the PWT capital detail files. This leaves us with a balanced sample of 75 countries with IT and TC investment data over the period 1992-2013.

Appendix A.2. The Price of ICT

Ideally, we would like to use our WITSA-ITU TC and IT investment series to construct the number of internationally comparable ICT units within each country. However, to construct an ICT index that is comparable across countries, we need country and time specific prices for ICT and non-ICT goods. Unfortunately, we do not have direct access to such data for a representative sample of countries at all levels of development.[11]

However, we do have access to two waves of item-level price data from the World Bank's International Comparison Program (ICP, 2005 and 2011), which allow us to construct country-level measures for the relative price of ICT and NICT capital goods in 2005 and 2011. We then combine this static measure of cross-country variation in the price of ICT with estimates of the US ICT price from Eden and Gaggl (2018) as well as differential trends in the GDP deflator across countries (to account for general cross country time trends in prices). Specifically, we model the price of asset j (either ICT or NICT) as

$$p_{j,c,t} = p_{j,c} \cdot p_{j,us,t} \cdot p_{c,t} \tag{A.1}$$

where $p_{j,c}$ ia a time invariant price of asset j in country c relative to ICT goods in the US, $p_{j,us,t}$ is the BEA based price deflator for asset j at time t as in Eden and Gaggl (2018), and $p_{c,t}$ is the GDP deflator in country c relative to the GDP deflator in the US, readily available from the PWT.

To estimate the time invariant "ICT price premium", $p_{j,c}$, we start with manually classifying items as ICT and NICT investment goods (as well as other asset classes, such as consumption goods) in line with

[11]While the construction of the PWT aggregate capital stock in part builds on such data (Feenstra, Inklaar and Timmer, 2015; Inklaar and Timmer, 2013), we were not able to obtain access to the detailed unlerying micro data, and the PWT only publishes four aggregate categories: structures, machineary, transportation equipment, other assets.

the usual definitions of ICT. This allows us to estimate a price index for "asset type" j, based on the relative price of each item k in country c, relative to the price of the same item in a reference country (e.g., the US), using a country specific sample of available items $I_{j,c}$. Specifically, we compute

$$p_{j,c} = E_{k \in I_{j,c}} \frac{p_{k,c}}{p_{k,US}} \tag{A.2}$$

where $p_{k,c}$ denotes the price of item k in country c, with $c = US$ indicating the US. We compute the expected value E as an expenditure weighted geometric average, with ICP expenditure weights from the reference country (e.g., the US).

This measure uses prices in the reference country as a benchmark, and compares prices of ICT and NICT items relative to this reference country. We use the US as a benchmark because, due to limited data availability, we cannot construct ICT and NICT investment bundles that are comparable across countries. The role of the comparison with the US is to remove item fixed effects. To see the importance of this, consider a hypothetical scenario in which there are two countries. In country 1, we have data on the price of computers (an ICT item) and a sewing machine (a NICT item). In country 2, we have data on the price of computers but we do not have data on the price of a sewing machine; instead, we have data on the price of a vehicle (a larger NICT item). It would be meaningless to compare the ratio of the computer price to the NICT item, because the vehicle represents a more expensive item. However, if we compare the price of computers relative to a benchmark country to the price of the NICT item relative to a benchmark country (where we use the US as a benchmark), we are capturing some notion of whether there is a premium associated with ICT items, on average.

Table A.8 summarizes the sample of ICT and NICT items as well as country coverage in the two ICP waves, while Figure A.6 illustrates our ICP based price measures.[12] Panel A plots the prices of ICT, NICT, and overall capital goods relative to consumption goods against real income per capita. That is, we are plotting $p_{ICT,c}/p_{C,c}$, $p_{NICT,c}/p_{C,c}$, and $p_{K,c}/p_{C,c}$, where $p_{C,c}$ is the price of consumption goods in country c relative to the US based on equation (A.2). By construction, all three measures are equal to 1 in the reference country (the US) and we normalize log real income per capita such that it is 0 in the US. The

[12] Appendix C tabulates country and item coverage in more detail.

Table A.8: ICP Price Data: Summary

Country	Consumption	Materials (incl. labor)	Structures	ICT	NICT
	Number of Items				
A. 2005 ICP Wave					
Average	403	49	29	27	106
Std. Dev.	57	8	5	9	31
Min.	283	36	19	10	49
Max.	504	61	36	40	159
# Countries	18	18	18	18	18
B. 2011 ICP Wave					
Average	343	58	28	34	85
Std. Dev.	107	33	8	14	32
Min.	97	5	4	7	25
Max.	654	100	44	77	188
# Countries	175	175	175	175	175

Notes: The table summarizes the number of items per country for which prices are available in five categories of "assets": consumption goods; materials including labor inputs; residential and non-residential structures; ICT assets; non-ICT assets. See Appendix C for more detailed tabulations.

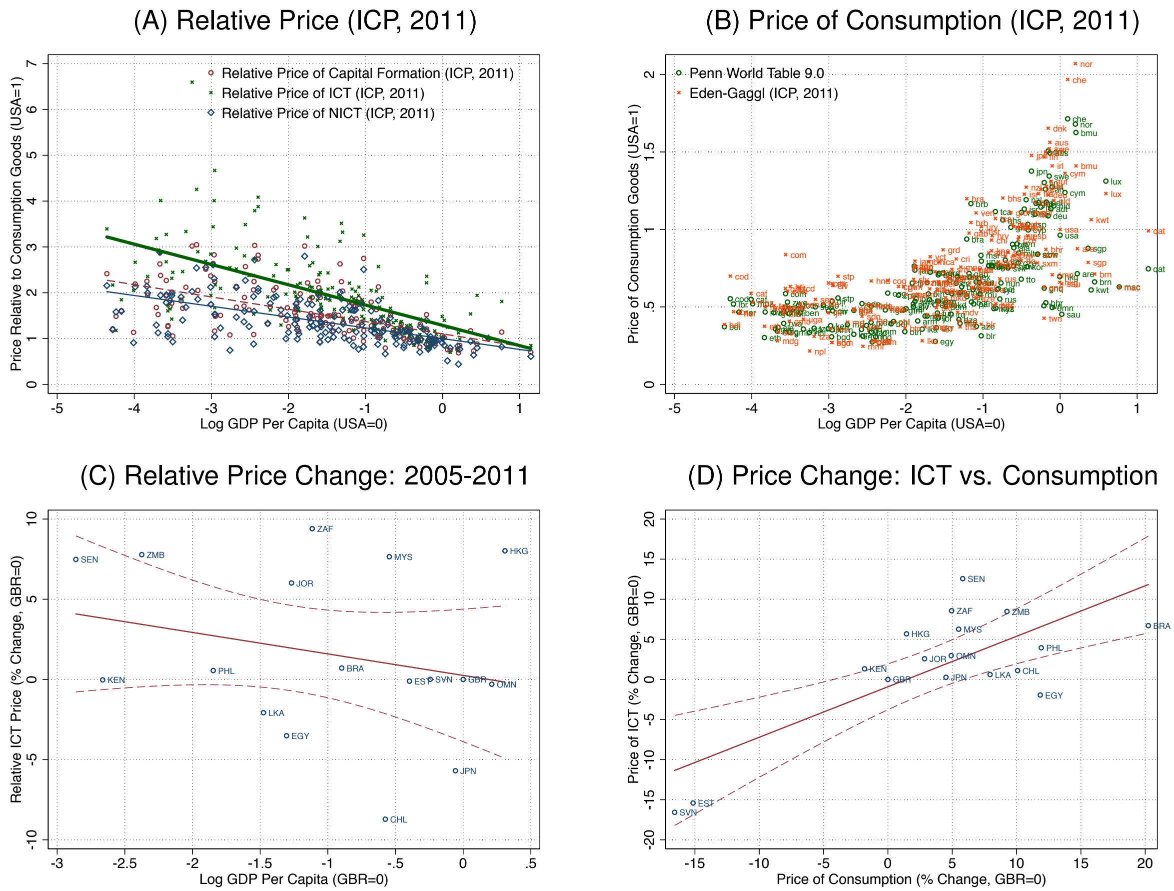
figure illustrates that ICT goods are relatively more expensive than non-ICT goods in general, but this ICT premium is larger for poorer countries.

In order to gauge the comparability of these price measures with other datasets, panel B of Figure A.6 contrasts our price of consumption goods ($p_{C,c}$) with the PPP adjusted consumption deflator from the PWT 9.0 (PWT variable `pl_c`). Our measure for the consumption price lines up quite well with the one constructed in the PWT. While we cannot directly compare our ICT and NICT prices to those in the PWT (since the PWT does not publish ICT or NICT prices), we hope that the strong similarity in consumption prices suggests that our ICT prices are likely to accurately reflect the differences in the price of ICT across countries in 2011.

Although we have access to detailed item level price data in both the 2005 and 2011 ICP waves, these data are only available for a small number of countries in 2005 (for example, not including the US), which makes the construction of time trends difficult (see Table C.9 for a detailed summary of country and item coverage in the 2005 ICP wave). To illustrate, panels C and D of Figure A.6 draw on the sample of 17 countries with overlap between the 2005 and 2011 wave and an acceptable number of ICT items.[13] Since

[13] We drop Cameroon from this analysis, as it only has 10 ICT items in the 2005 ICP wave and produces a massive outlier for the price of ICT.

Figure A.6: The Relative Price of ICT and NICT Goods



Notes: Panel A plots our estimates of PPP adjusted relative prices $p_{j,c}/p_{C,c}$ for ICT assets, NICT assets, and all investment goods, relative to consumption goods ($j = C$) in all countries c. Panel B compares our estimate for $p_{C,c}$ based on the ICP ($p_{C,US} = 1$) and compares it to the price of consumption reported in the PWT 9.0 (pl_c), which is also based on the ICP 2011 wave. Panel C plots annualized changes in the ICT price based on the 2005 and 2011 ICP waves, with UK as the reference country. Panel D plots changes in the ICT price against changes in the price of consumption, again using the 2005 and 2011 waves with the UK as the reference country.

the US is not in the 2005 ICP sample, we construct all relative prices with the UK as the reference country instead. Panel C of Figure A.6 plots the annualized precent change in the relative price of ICT (as displayed in panel A except with the UK as the reference country) against log GDP per capita. Panel D plots the change in the ICT price against that of the price of consumption.

Given the lack of data, it is hard to draw strong conclusions from this analysis, but one suggestive result is that there is no strong systematic relationship between the relative price of ICT and income, and that the price of ICT largely moves in lockstep with consumption prices. This provides one source of suggestive evidence for a key assumption made in equation (A.1), namely that time variation in country-specific ICT price premia relative to the US are proxied by differential trends in the GDP deflator across countries, denoted $p_{c,t}$ in equation (A.1). We note that both the PWT and the TED make the same assumption to proxy for differential ICT price trends across countries.

Appendix A.3. ICT and NICT Capital Stocks

Equipped with the investment series for ICT and NICT from Appendix A.1 and the price indexes from Appendix A.2, we use the standard perpetual inventory method (PIM) to construct estimates for the stock of ICT.[14] For each asset, we take the investment series in current cost USD and deflate it using the price indexes constructed in Appendix A.2, resulting in a series that is measured at constant 2011 prices in the US, denoted $I_{c,t}$. For example, investment in IT assets is then denoted in units of 2011 IT assets in the US. We note that we use the ICT price deflator from Appendix A.2 for both IT and TC assets.

Our first year with IT and TC investment data is 1992. In order to construct an initial capital stock, we apply a two-step procedure: we first extrapolate each investment series backward in proportion to investment in machinery and "other assets" from the PWT capital detail.[15] We stop the extrapolation in the first year of available investment data in the PWT capital detail. In a second step, we use a version of the standard (Solow) steady state condition, $K_{c,0} = \frac{I_{c,0}}{\bar{g}_c} + \delta$, to estimate an initial value $K_{c,0}$ for the first year of PWT investment data, $I_{c,0}$, where $\bar{g}_c$ represents country specific investment growth, and δ is the depreciation rate in the initial period. We have experimented with various alternatives (e.g., initializing all values in 1992 with the Solow steady state assumption, or initializing all data series with zero in the initial year of PWT investment data, etc.) but did not find these choices to have notable effects on our results for the period 2000-2011, which is the most relevant sample for our main analyses. However, in order to ensure estimates that are as accurate as possible at the beginning of our sample in 1992, we use as much information from the PWT capital detail as possible.

Based on these initial capital stocks we then use the perpetual inventory method separately for IT, TC,

[14]Note that both the PWT and TED also use the standard PIM to construct ICT stocks.

[15]Specifically, we compute the in sample time series for the ratio of ICT investment (our measure) to investment in machinery and other assets (the PWT measure). We then extrapolate this ratio backward using a log linear trend. Finally, we use the out of sample predicted values of this ratio and multiply them with PWT investment in machineary and other assets for all availalbe years of data in the PWT.

and NICT capital, where we compute a series for NICT investment by taking the difference between aggregate, current cost investment reported in the PWT and the sum of our series for IT and TC investment. We then deflate the resulting nominal NICT investment series with the NICT price index from Appendix A.2.

For each of the three asset groups, we then iterate on the standard neoclassical law of motion for the capital stock:

$$K_{c,t+1} = I_{c,t} + (1 - \delta_{c,t})K_{c,t} \tag{A.3}$$

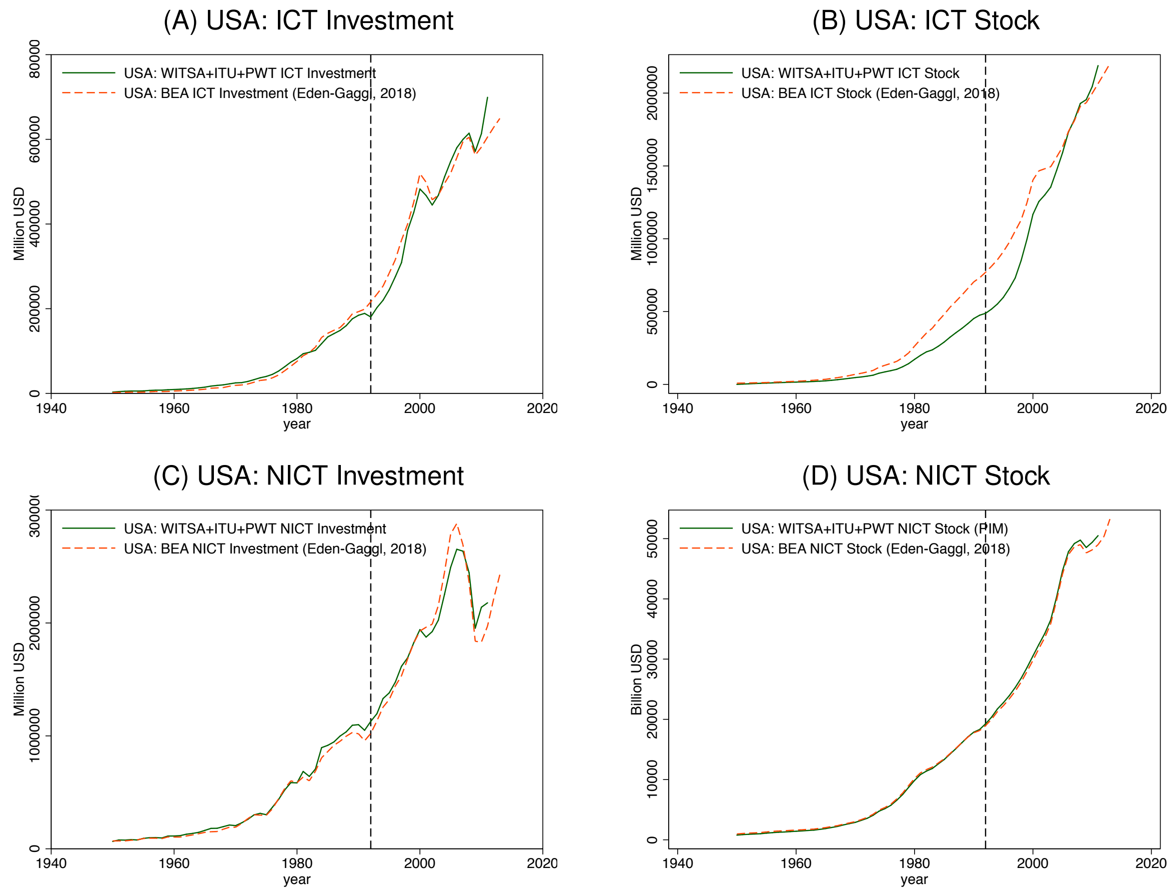
where we assume the following depreciation rates: 31.5% for IT, 11.5% for TC (see Inklaar and Timmer, 2013), which implies an average value of ICT depreciation of 18.9%, and 3.59% for NICT (based on data in Eden and Gaggl (2018)).

In order to gauge the quality of our estimates for ICT and NICT stocks, we compare our estimates for the US to those by Eden and Gaggl (2018), which are a direct aggregation of the BEA's estimates by detailed asset. Figure A.7 reports this comparison in current cost USD. Notice that the investment series for both ICT and NICT are virtually identical, perhaps with the largest discrepancy in ICT investments at the very end of the sample. The resulting stock estimates for NICT also match almost perfectly, while the estimates for ICT show a notable difference in 1992, despite the virtually identical investment series and initial value in 1950.

This discrepancy in the 1992 estimate for the ICT stock is mostly due to different assumptions about the rate of depreciation. The BEA uses fixed depreciation rates at a very disaggregated level and therefore the changing composition of ICT investments leads to a much lower rate of depreciation in earlier years. We took the depreciation rates for IT (31.5%) and TC (11.5%) from the PWT documentation (which is also consistent with the assumptions made in the TED). To illustrate, Panel A of Figure A.8 plots the depreciation rates based on these assumptions and also plots the time varying implied depreciation rate for ICT (a stock value weighted average of the two depreciation rates). One can clearly see that the general time pattern of ICT depreciation is similar to the BEA estimates in Eden and Gaggl (2018) but that the BEA level is substantially lower, particularly in the earlier part of the sample.

Panel B of Figure A.8 shows the resulting ICT depreciation rate for an alternative set of assumptions, which matches the implied ICT depreciation rate for the US very well. As with the assumptions in the PWT and TED, the numbers are based on Fraumeni (1997), who reports the official, asset specific depreci-

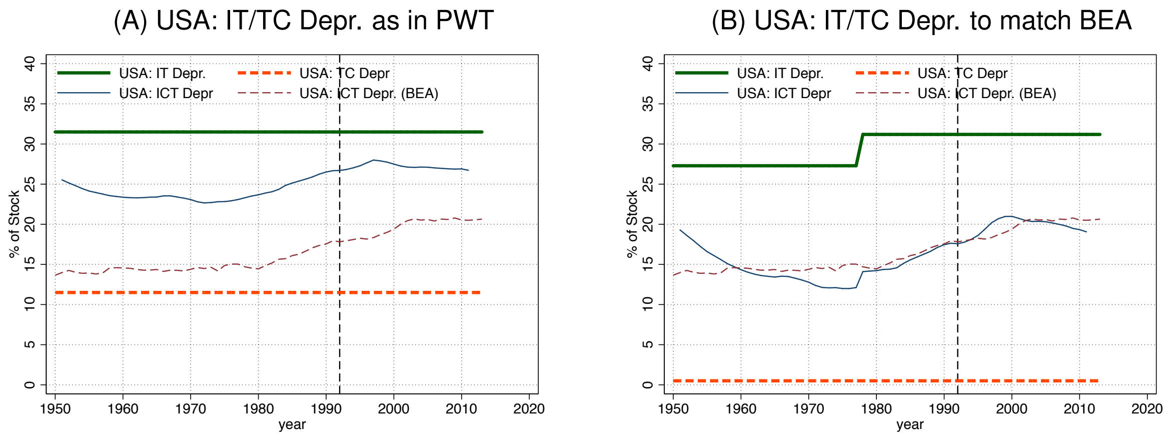
Figure A.7: ICT/NICT Investment & Stocks: BEA vs. WITSA-ITU-PWT



Notes: The graphs plot ICT and NICT investment and stocks for the USA. We compare our series based on WITSA, ITU, and PWT data to the series constructed by Eden and Gaggl (2018), which are a direct aggregation of the BEA's estimates in the detailed fixed asset accounts. Panels A and B plot ICT investment and stocks, while panels C and D illustrate NICT investment and stocks. The vertical dashed lines indicate 1992, which is the first year of WITSA ICT spending data.

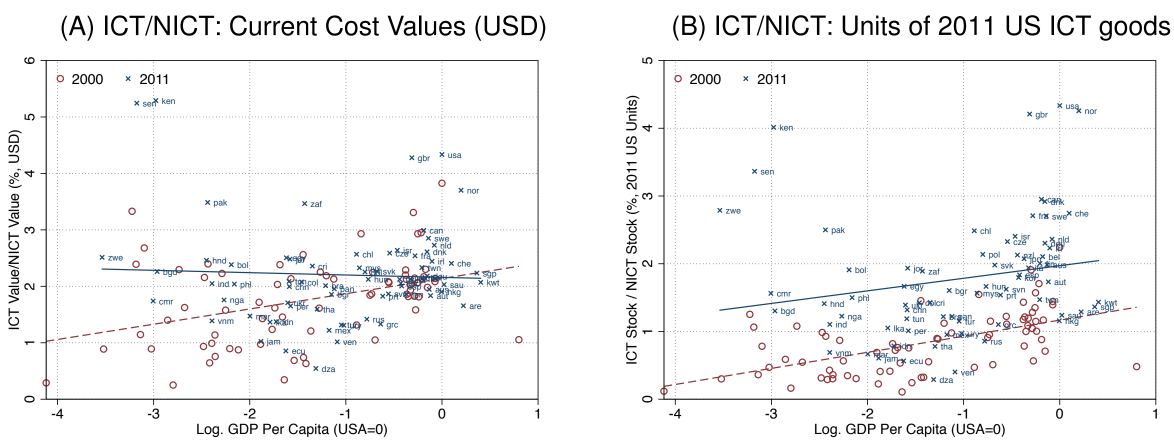
ation rates used by the BEA. Here, we took the values for "Office, computing, and accounting machinery" (27.29% before 1978 and 31.19% after 1978) to proxy for IT and "Electrical transmission, distribution, and industrial apparatus" (0.5%) to proxy for TC from Table 3 in Fraumeni (1997). The same table reports "Communications equipment" (15% for business services, and 11% for other industries), which are the numbers used by the PWT and TED. Our alternative specification implicitly assumes that investment in telecommunications equipment (as reported by ITU) represents largely physical transmission lines, cell phone towers, etc., which have very low depreciation rates. It turns out that this assumption matches the BEA value for ICT depreciation much better than the assumptions made in the PWT and TED. That said,

Figure A.8: ICT Depreciation Rate



Notes: The graphs plot depreciation rates for IT and TC, as well as the implied depreciation rate for ICT. As a reference, we plot the ICT depreciation rate based on BEA estimates for the US, as reported by Eden and Gaggl (2018).

Figure A.9: ICT/NICT Stocks & Income Per Person



Notes: The graphs plot the ratio of ICT to NICT capital in percent. Panel A reports current cost values while panel B illustrates internationally comparably constant cost units. In order to minimize the influence of the initial values in 1992, the figure reports these ratios for the years 2000 and 2011, where 2011 is both our final year in the sample and the year in which we have detailed item level ICP data to compute the relative prices of ICT and NICT (see Appendix A.2)

the resulting stocks don't differ dramatically (though they match the US series from Eden and Gaggl (2018) better), so to stay consistent with other datasets, we conduct our main analyses using the same assumptions on depreciation as in the PWT and TED.

To illustrate the cross country variation in ICT and NICT capital stocks, Figure A.9 plots the ratio of

ICT to NICT capital in percent. Panel A reports current cost values while panel B illustrates internationally comparably constant cost units. In order to minimize the influence of the initial values in 1992, the figure reports these ratios for the years 2000 and 2011, where 2011 is both our final year in the sample and the year in which we have detailed item level ICP data to compute the relative prices of ICT and NICT (see Appendix A.2).

The Figure suggests that the amount of ICT relative to NICT (both in values and internationally comparable units) shows a positive correlation with income per capita in 2000. However, in 2011, this correlation has largely disappeared in current cost values but is still almost unchanged when measured in units of 2011 constant cost values in the US. This difference in 2011 suggests that relative prices play an important role for this relationship. That is, the fact that ICT goods are relatively more expensive in poorer countries can make the comparison in current cost values misleading.[16]

Appendix A.4. ICT and NICT Income Shares

We measure the ICT and NICT income shares following the methodology of Eden and Gaggl (2018), which builds on two identifying assumptions: first, constant returns to scale in the aggregate, which implies that GDP is split among factor inputs; second, the return to investing in different assets (ICT and NICT) must equalize across assets. Formally, these assumptions can be summarized by the following two conditions:

$$s_{K,t} P_t Y_t = \sum_{j \in J} R_{j,t} K_{j,t} \tag{A.4}$$

$$\frac{R_{i,t}}{P_{i,t}} + (1-\delta_{i,t}) \frac{P_{i,t+1}}{P_{i,t}} = \frac{R_{n,t}}{P_{n,t}} + (1-\delta_{n,t}) \frac{P_{n,t+1}}{P_{n,t}} \quad \text{for all} i, n \in J \tag{A.5}$$

where $s_{K,t}$ is capital's share in aggregate income $P_t Y_t$, with P_t the GDP deflator. The set of available assets is denoted J, with $P_{j,t}$, $\delta_{j,t}$, and $K_{j,t}$, respectively, indicating the price, depreciation rate, and stock of asset j, measured in internationally comparable units. $R_{i,t}$ indicates the nominal rental rate of asset j.

Focusing on the two asset case with i = ICT and n = NICT, we can solve the above system of equations

[16] We note that Kenya and Senegal are perhaps outliers, at least in 2011. When we fit the regression line for 2011 without thse two countries, there is still a mild positive relationship, however markedly flatter than in 2000.

for the relative price adjusted nominal rental rate for each asset:[17]

$$\frac{R_{i,t}}{P_{i,t}} = [CG_{n,t} - CG_{i,t}]\frac{P_{n,t}K_{n,t}}{P_{K,t}K_t} + (1+\pi_{n,t})s_{K,t}\frac{P_tY_t}{P_{K,t}K_t} \tag{A.6}$$

$$\frac{R_{n,t}}{P_{n,t}} = [CG_{i,t} - CG_{n,t}]\frac{P_{i,t}K_{i,t}}{P_{K,t}K_t} + (1+\pi_{i,t})s_{K,t}\frac{P_tY_t}{P_{K,t}K_t} \tag{A.7}$$

where $P_{K,t}K_t = P_{i,t}K_{i,t} + P_{n,t}K_{n,t}$ denotes the current cost aggregate capital stock and $CG_{j,t} = (1 - \delta_{j,t})(1 + \pi_{j,t})$ asset specific capital gains net of depreciation, with $1 + \pi_{j,t} = P_{j,t+1}/P_{j,t}$. Thus, the data inputs to compute the right hand side of both expressions are: (1) asset specific price inflation and depreciation; (2) current cost values for the stock of both assets; (3) current cost GDP; and (4) an estimate of the capital share, $s_{K,t}$.

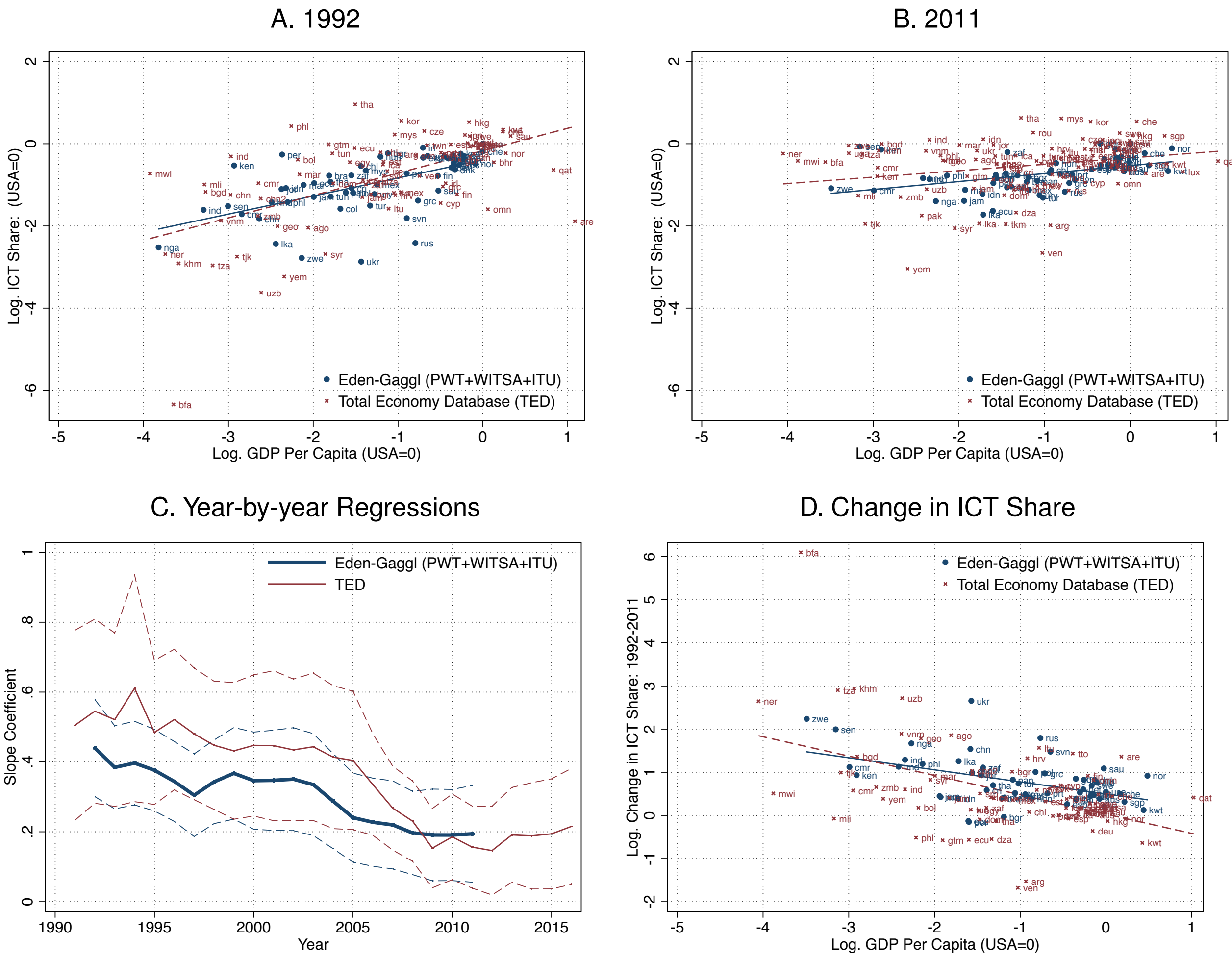
We take the current cost values and price deflators from Appendix A.3, nominal GDP from the PWT, and estimate the capital share based on the labor share reported in the PWT as $s_{K,t} = 1 - s_{L,t}$. The income share of each asset can then be obtained by multiplying $R_{j,t}/P_{j,t}$ from equations (A.6) and (A.7) with the value of asset j in total GDP, requiring no additional data inputs:

$$s_{j,t} = \frac{R_{j,t}}{P_{j,t}}\frac{P_{j,t}K_{j,t}}{P_tY_t} = \frac{R_{j,t}K_{j,t}}{P_tY_t} \tag{A.8}$$

We would like to highlight two important measurement assumptions, which are treated differently in the TED. First, we attempt to explicitly construct ICT stocks that are measured in internationally comparable units. While both the TED and the PWT account for differential trends in the price of ICT, using country specific GDP deflators, they do not adjust for cross-country differences in the relative price of ICT in the base year (2011 in our case). Second, the TED measures GDP differently from what is reported in the national accounts for many countries. Among other things, they try to account for changes in the price of intellectual property products and intangible capital, which they argue is mismeasured in the traditional national accounts estimates.

[17] We note that the notation presented here is slightly different from Eden and Gaggl (2018), based on an implicit assumption about the timing of investment returns. If the rental rate $R_{i,t}$ is paid "today" then there is no need for additional adjustments due to changes in the relative asset prices. If $R_{i,t}$ is paid "tomorrow", then the formulas need to be adjusted for asset specific inflation as in Eden and Gaggl (2018). This assumption about the timing of rental payments has no effect on the results in this paper and we therefore choose this simplified exposition.

Figure A.10: ICT Share and Income: TED vs. PWT+WITSA+ITU



Notes: Panels A and B plot $\ln(s_{ICT})$ against log output per capita for the years 1992 and 2011 (the first and last year in our WITSA-ITU based sample). Log GDP per capita is normalized so that the US is zero and drawn from the respective data source (Eden-Gaggl and TED). Panel C plots the slope coefficient for the regression lines displayed in panels A and B for all years between 1991-2016. Panel D plots the change in $\ln(s_{ICT})$ between 1992-2011 (the difference between panel A and panel B) against log GDP per capita, normalized such that $\ln(Y_{US}/L_{US})$=0.

In light of these differences in measurement assumptions, panels A and B of Figure A.10 plot the ICT share for both data sources against log real GDP per capita within the respective data source, for the years 1992 and 2011, respectively (the first and last year in our dataset). That is, we plot our measures of the ICT share against the PWT measure of real income, while we plot the TED measures of the ICT share against the TED measure of income. As a result, the data points do not line up perfectly along both dimensions.

However, while the estimates for the ICT share in the two data sources do not align perfectly, they broadly agree on the relationship between ICT intensity and income. Importantly, panel A suggests that in the early 1990s, there was a clear positive relationship between the ICT share and real income per person. However, by 2011 this relationship has mostly vanished. Panel C highlights this finding, by plotting the slope coefficient of regression lines like the ones displayed in panels A and D, separately for each year throughout the sample. Again, while the two data sources don't agree perfectly, the broad patterns are the same. Finally, panel D plots the change in the ICT share between 1992 and 2011, illustrating that the gradual disappearance of this positive relationship is likely driven by the fact that poor countries were systematically catching up with rich countries. While the slope toward the end of the sample in panel C is still positive, it is only marginally significant.

In sum, while there are a number of differences in the details of the data construction, both our data and the TED convey the same general patterns in the cross-country variation of ICT and NICT shares. The two main benefits of our dataset are: (1) we have also constructed ICT and NICT stocks that are internally consistent with our measures of disaggregated capital shares; (2) our estimates for the ICT share are conceptually consistent with the measures of value added from the GGDC10; (3) our dataset allows us to directly estimate the marginal product of capital in internationally comparable units of ICT and NICT, a data input we need for our second calibration strategy.

Appendix A.5. Capital Data for Two-Sector Calibration

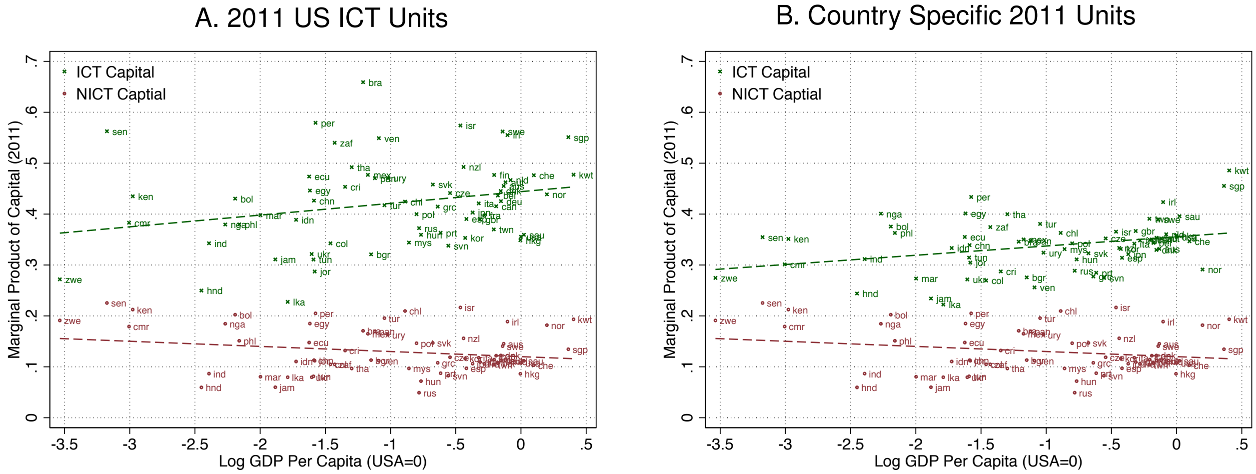
Aside from the data on labor inputs discussed in Sections 2 and 3.2 our second calibration strategy requires estimates of both the marginal product of capital for ICT and NICT as well as a measure of the stock of NICT capital. We note that it is important that these quantities are measured in internationally comparable units, to allow a meaningful interpretation of the resulting estimate of IT capabilities (θ).

In our competitive framework, the rental rate must equal the nominal marginal product of capital $R_{j,t} = P_t MPK_{j,t}$. Using this relationship, we can estimate the real marginal product by multiplying the relative price adjusted rental rates from equations (A.6) and (A.7) with the relative price of asset j, $P_{j,t}/P_t$:

$$MPK_{j,t} = \frac{P_t MPK_{j,t}}{P_{j,t}} \frac{P_{j,t}}{P_t} = \left(\frac{R_{j,t}}{P_{j,t}}\right) \frac{P_{j,t}}{P_t} \tag{A.9}$$

where the expression in parentheses can be computed using equations (A.6) and (A.7). Thus, in our measurement, $MPK_{i,t}$ measures the amount of additional output in a given country in return to investing into

Figure A.11: Marginal Product of Capital



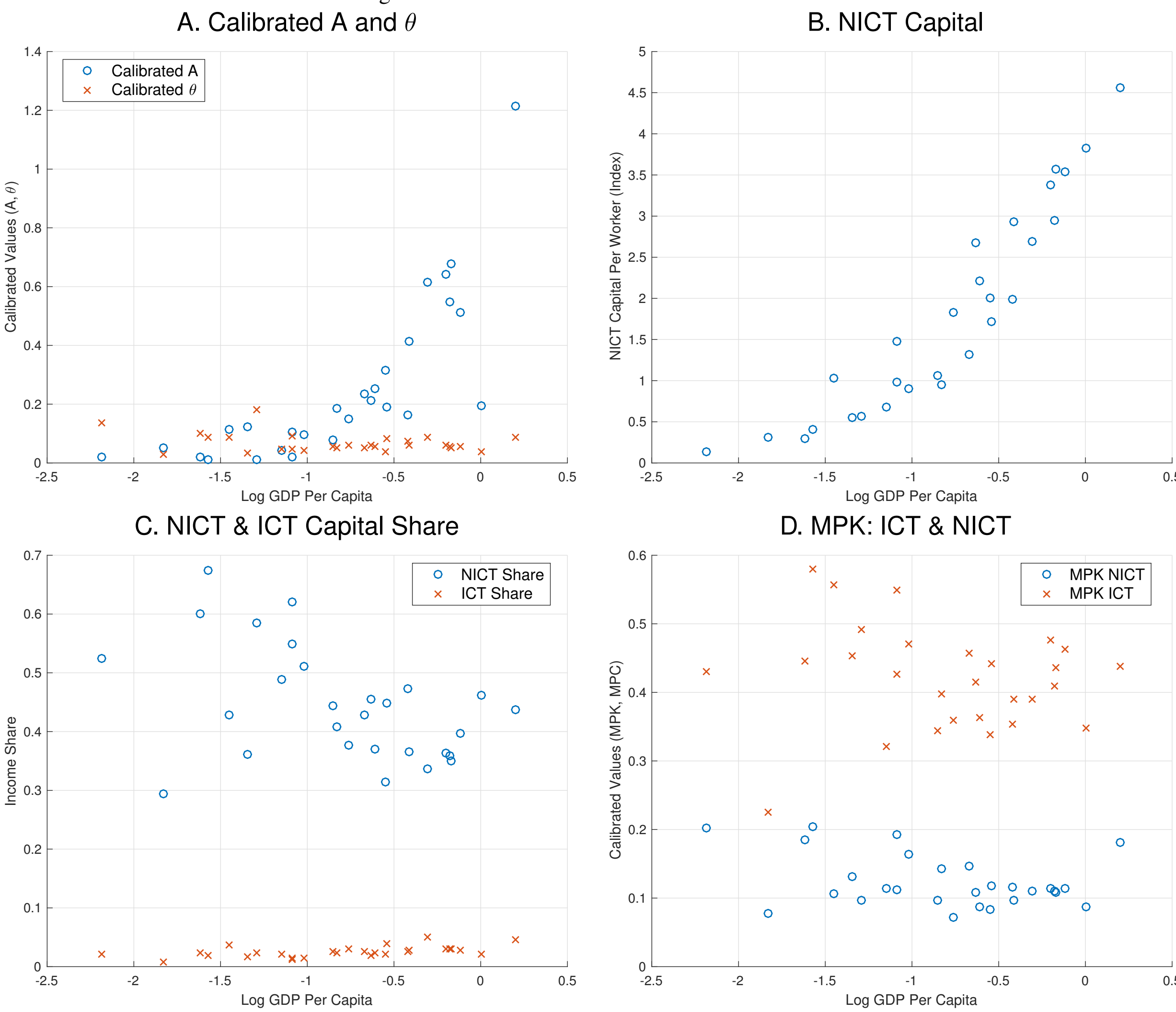
Notes: Panels A and B plot $MPK_{j,t}$ as defined in equation (A.9) against log GDP per capita, normalized such that $\ln(Y^{USA})$=0. Panel A measures ICT and NICT in 2011 US units, whereas panel B does not account for level differences in the relative price of ICT across countries in 2011 (i.e., $p_{c,j} = 1$ for all c).

an extra unit of ICT (measured in *internationally comparable* units of ICT). Note that we use our ICP based price of ICT in 2011, in order to account for the fact that same unit of ICT has a different price in different countries. Figure A.11 illustrates this point. Panel A reports our estimates in internationally comparable units, while panel B is based on a version in which ICT and NICT prices are constructed as in the TED and PWT. That is, in panel B we assume that $p_{c,j}$ is one for all countries and assets. The biggest effect of our price measurement is that the marginal product of ICT is markedly higher, on average.

Figure A.12 reports both our calibrated values for A and θ, alongside the data inputs for the calibration of our two-sector model, restricted to the sample of countries that also have the detailed labor input data reported in Figure 4 in Section 3.2. Panel B reports our index of NICT capital per worker, measured in internationally comparable units. As mentioned in Section 3.2, the distribution of NICT across countries closely tracks our estimates of A, essentially governing the scale of each economy.

Consistent with panel A of Figure 1, panel C illustrates that the ICT share in 2011 shows almost no relationship with income per capita. Finally, panel D shows the implied marginal product of ICT and NICT. Equipped with these data series, together with our estimates of high/low skilled labor in effective units (panel A of Figure 4), we can use equations (10) through (14) to solve for A and θ (plotted in panel A of figure Figure A.12). Again, the sample of countries in Figure A.12 is restricted to the countries with all necessary

Figure A.12: Method 2: Calibration & Data in 2011



Notes: Panel A shows calibrated values for A and θ using "method 2". Panels B-E show the country-specific data inputs for the calibration for the year 2011.

data for our calibration described in Section 3.2.

Appendix B. Comparison With Existing Datasets

It is perhaps useful to compare our measurement strategy with existing datasets that include measures of ICT capital. There are two main datasets containing ICT capital measures: (a) the Groningen Growth and Development Center's KLEMS datasets, and (b) the Conference Board's Total Economy Database (TED).

The key difference with the KLEMS datasets is country coverage. The EU KLEMS covers 27 high income countries between 1970-2013 (O'Mahony and Timmer, 2009) and the WORLD KLEMS database provides additional ICT/NICT data for Canada (Gu, 2012) and Russia (Voskoboynikov, 2012). In contrast, our dataset on ICT/NICT capital stocks covers 67 countries at various levels of development and is—to the best of our knowledge—the most comprehensive account of ICT and NICT *stocks* at this point. That said, there are currently numerous WORLD KLEMS projects under construction to expand converge. The TED, on the other hand, has very comprehensive country coverage, yet it only contains measures of the growth in ICT capital services for the period 1990-2014 and does not specifically attempt to measure ICT capital stocks.

While our measurement efforts are clearly complementary to Jorgenson and Vu (2005), who also use WITSA and ITU data to estimate ICT, there are some differences. Specifically, they assume that ICT investment is proportional to ICT spending, while we try to construct an investment measure directly. Furthermore, most previous work does not count the category of "capital services" as an investment category, and rather focuses on projected values of hardware, software and telecommunications spending on hardware, software and telecommunications investment. Since the services category consists of some software investment (such as custom software or website design), the ratio of software spending and software investment in the US is above two (Vu, 2005). Our view is that the category "ICT services" represents pure investment spending and should be counted as such. Another important difference is that the data provided in his paper is data on ICT capital growth rather than on the stock of ICT.

Finally, we keep our methodology conceptually close to that of the PWT (Feenstra et al., 2015; Inklaar and Timmer, 2013). Note that, starting with version 8.0, the PWT constructs aggregate capital stocks by adding estimated capital stocks of six different asset types, among them computers, communication equipment and software.[18] These are also based on the PIM, run separately for these categories, with depreciation rates that are similar for computers and software (31.5%) but substantially lower for communications (11.5%). As mentioned in Appendix A.3, we also adopt these assumptions.

[18] Note that, unfortunately, PWT does not make their disaggregated investment series publicly available and we were not able to gain access to these data.

Appendix C. ICP Price Data: Detailed Country Coverage

Table C.9: ICP Wave 2005: Items Per Country

Country	Y/L	Inc. Perc.	Number of Items: Consumption	Materials (incl. labor)	Structures	ICT	NICT
China, Hong Kong SAR	44.499	94	424	54	36	36	134
United Kingdom	**38.251**	**89**	**454**	**56**	**24**	**40**	**159**
Japan	34.221	84	283	38	23	28	87
Oman	27.373	76	448	58	30	27	126
Slovenia	26.447	76	399	48	19	40	154
Estonia	17.808	70	442	56	28	40	141
Malaysia	16.179	66	504	60	32	32	120
Chile	13.623	63	355	45	27	18	82
South Africa	10.245	55	344	40	21	19	66
Brazil	8.732	49	336	40	27	18	74
Jordan	5.342	40	351	38	33	16	93
Egypt	5.308	39	458	55	32	28	134
Sri Lanka	4.831	36	361	48	36	27	106
Philippines	4.062	31	417	47	30	32	111
Cameroon	2.305	21	410	41	34	10	72
Senegal	1.936	18	465	61	35	26	100
Kenya	1.885	16	423	57	35	30	106
Zambia	1.585	13	374	36	26	25	49
Average			402.667	48.778	29.333	27.333	106.333
Std. Dev.			56.517	8.496	5.269	8.704	31.339
Min.			283	36	19	10	49
Max.			504	61	36	40	159
# Countries			18	18	18	18	18

Notes: The table summarizes the number of items per country for which prices are available in five categories of "assets": consumption goods; materials including labor inputs; residential and non-residential structures; ICT assets; non-ICT assets. Our reference country is highlighted. Countries are sorted by precentiles of real GDP per capita based on all countries available in the PWT.

Table C.10: ICP Wave 2011: Items Per Country (Part 1)

Country	Y/L	Inc. Perc.	Number of Items				
			Consumption	Materials (incl. labor)	Structures	ICT	NICT
Qatar	156.909	100	540	80	44	65	155
China, Macao SAR	107.6	99	292	65	23	30	49
Luxembourg	90.445	99	276	12	23	29	68
Brunei Darussalam	78.131	98	269	54	17	13	61
Kuwait	74.705	98	615	99	44	66	168
Singapore	71.79	97	280	73	24	39	65
United Arab Emirates	62.388	97	640	82	44	77	188
Bermuda	61.338	96	293	70	26	32	70
Norway	60.882	96	257	12	23	24	61
Switzerland	55.081	95	274	12	23	29	81
Cayman Islands	53.188	94	343	63	29	35	77
Saudi Arabia	51.05	94	637	100	44	74	182
United States	49.909	93	244	90	23	41	101
China, Hong Kong SAR	49.693	93	288	78	24	33	84
Netherlands	46.09	92	282	90	25	32	113
Oman	45.085	92	524	91	37	60	149
Ireland	45.014	91	297	12	25	24	70
Austria	44.33	91	282	12	21	35	82
Australia	43.716	90	275	92	25	17	88
Sweden	43.353	90	272	11	20	29	58
Germany	42.815	89	280	12	22	35	73
Denmark	42.747	88	277	95	21	36	79
Belgium	41.795	88	279	9	24	32	88
Bahrain	41.517	87	588	82	42	59	137
Canada	41.273	87	245	64	20	40	93
Finland	40.636	86	269	93	22	20	80
Equatorial Guinea	40.615	86	113	74	11	7	29
Taiwan	40.508	85	303	72	19	25	86
Iceland	38.896	85	258	10	22	24	70
France	37.709	84	297	12	24	21	72
Aruba	37.393	83	307	14	25	19	49
Sint Maarten (Dutch part)	37.18	83	284	62	26	22	52
United Kingdom	**36.483**	**82**	**299**	**94**	**23**	**38**	**138**
Italy	36.095	82	316	13	26	22	67
Japan	34.451	81	227	9	21	20	44
Cyprus	33.027	81	299	11	23	22	74
Spain	32.844	80	307	13	25	37	87
Republic of Korea	32.543	80	268	13	19	21	55
New Zealand	32.142	79	234	11	12	18	37
Israel	31.371	79	287	11	22	23	74
British Virgin Islands	30.296	78	198	6	21	7	25
Trinidad and Tobago	30.159	77	347	64	30	44	87
Malta	29.213	77	299	11	26	27	59
Czech Republic	28.976	76	293	13	26	26	93
Slovenia	28.604	76	298	13	25	29	92
Anguilla	27.386	75	317	53	29	42	59
Curaao	27.352	75	323	89	29	44	75
Portugal	26.951	74	308	96	22	41	133
Greece	26.36	74	307	12	23	22	68
Slovakia	25.389	73	282	13	25	29	84

Notes: Tables C.10 through C.13 combined summarize the number of items per country for which prices are available in five categories of “assets”: consumption goods; materials including labor inputs; residential and non-residential structures; ICT assets; non-ICT assets. Countries are sorted by the number of ICT assets. Our reference country is highlighted. Countries are sorted by precentiles of real GDP per capita based on all countries available in the PWT.

Table C.11: ICP Wave 2011: Items Per Country (Part 2)

Country	Y/L	Inc. Perc.	Number of Items: Consumption	Materials (incl. labor)	Structures	ICT	NICT
Estonia	24.529	72	277	12	24	29	84
Bahamas	23.738	72	253	76	25	37	70
Hungary	23.19	71	295	94	26	18	82
Russian Federation	22.847	71	270	80	25	34	108
Lithuania	22.491	70	294	12	22	27	85
Poland	22.412	70	295	13	25	28	84
Seychelles	22.062	69	358	84	37	36	71
Kazakhstan	21.701	69	391	18	38	54	123
Turks and Caicos Islands	21.559	68	223	11	23	16	27
Malaysia	21.139	68	349	82	26	55	125
Croatia	20.672	67	304	13	25	34	100
Chile	20.521	66	270	12	20	32	70
Saint Kitts and Nevis	20.51	66	272	15	25	17	44
Latvia	19.802	65	281	13	22	29	83
Antigua and Barbuda	19.767	64	235	62	12	20	36
Uruguay	17.983	63	276	86	31	59	125
Belarus	17.938	63	331	16	36	46	102
Montserrat	17.885	62	269	54	25	18	39
Romania	17.639	61	291	13	25	35	77
Turkey	17.525	61	302	11	23	26	79
Azerbaijan	16.853	60	383	15	40	44	96
Venezuela (Bolivarian Republic of)	16.785	60	291	70	24	54	74
Panama	16.28	59	279	92	11	52	116
Mauritius	16.132	58	539	67	36	49	119
Bulgaria	15.816	58	300	12	25	34	96
Barbados	15.704	57	311	78	30	44	76
Mexico	15.43	56	294	9	20	24	69
Gabon	15.321	55	359	62	39	19	65
Suriname	14.901	55	300	76	30	31	70
Brazil	14.874	54	326	74	35	55	130
Botswana	13.939	54	421	94	27	36	83
Montenegro	13.748	53	274	11	23	28	67
Thailand	13.632	53	322	76	25	39	96
Algeria	13.44	52	553	83	38	52	118
Maldives	13.201	52	206	70	23	34	44
Costa Rica	12.958	51	307	66	30	60	123
Serbia	12.263	51	302	11	24	31	99
Iraq	12.121	50	580	94	43	60	156
South Africa	11.961	49	476	88	18	39	90
Colombia	11.583	49	214	43	14	32	75
TFYR of Macedonia	11.291	48	265	11	26	18	75
Dominican Republic	11.289	48	258	74	17	53	117
Grenada	10.937	47	326	71	27	30	73
Saint Lucia	10.373	47	301	58	16	32	66
Peru	10.329	46	314	80	29	56	115
Dominica	10.274	46	224	66	22	16	33
Jordan	10.262	45	634	100	44	68	184
China	10.205	44	358	84	25	55	161
Tunisia	10.168	44	319	77	35	18	71
Ukraine	10.029	43	375	16	38	61	118

Notes: Tables C.10 through C.13 combined summarize the number of items per country for which prices are available in five categories of “assets”: consumption goods; materials including labor inputs; residential and non-residential structures; ICT assets; non-ICT assets. Countries are sorted by the number of ICT assets. Our reference country is highlighted. Countries are sorted by precentiles of real GDP per capita based on all countries available in the PWT.

Table C.12: ICP Wave 2011: Items Per Country (Part 3)

Country	Y/L	Inc. Perc.	Number of Items: Consumption	Materials (incl. labor)	Structures	ICT	NICT
Egypt	9.891	43	519	92	44	57	147
Ecuador	9.836	42	248	81	16	59	142
St. Vincent and the Grenadines	9.261	42	274	64	23	27	59
Albania	9.197	41	281	12	22	31	78
Bosnia and Herzegovina	9.044	41	287	12	25	25	69
Indonesia	8.897	40	366	77	23	39	129
Namibia	8.893	40	533	97	38	42	112
Mongolia	8.657	39	300	81	22	38	94
Sri Lanka	8.342	38	308	73	17	24	72
Armenia	7.876	37	359	18	34	37	73
Belize	7.733	37	246	13	21	13	30
Swaziland	7.598	36	479	93	37	35	108
Jamaica	7.588	36	360	76	31	41	83
Angola	7.528	35	139	5	11	23	63
El Salvador	7.459	35	242	10	19	24	50
Paraguay	7.434	34	304	12	32	35	76
Fiji	7.33	33	261	66	21	36	132
Morocco	6.771	32	463	95	40	41	110
Bhutan	6.661	32	217	62	19	16	53
Guatemala	6.545	31	276	55	26	44	80
Cabo Verde	6.133	31	369	52	35	20	55
Philippines	5.755	30	340	73	27	42	103
Bolivia (Plurinational State of)	5.576	29	308	81	22	60	129
Congo	5.339	29	395	83	39	22	66
Nigeria	5.169	28	414	98	39	21	90
India	4.562	27	334	73	27	51	104
Viet Nam	4.559	27	342	79	24	32	96
Pakistan	4.359	26	276	74	26	34	86
State of Palestine	4.352	26	654	98	44	51	165
Lao People's DR	4.326	25	241	58	16	31	64
Honduras	4.305	25	261	60	15	22	66
Republic of Moldova	4.295	24	367	16	37	47	119
Nicaragua	4.055	24	307	76	22	47	81
Myanmar	3.864	23	278	73	19	27	62
Sudan (Former)	3.82	22	551	78	35	53	155
Yemen	3.797	22	581	85	36	42	133
Ghana	3.44	21	575	88	39	28	93
Kyrgyzstan	3.437	21	343	16	34	26	63
Zambia	3.394	20	391	71	32	33	91
Mauritania	3.164	20	285	11	31	28	40
Sao Tome and Principe	2.797	19	293	68	39	28	73
Cte d'Ivoire	2.615	19	519	98	35	19	78
Cambodia	2.595	18	293	83	22	26	78
Djibouti	2.595	18	321	78	7	23	30
Bangladesh	2.578	17	344	73	24	30	94
Kenya	2.543	16	458	93	34	44	91
Cameroon	2.472	16	463	98	39	35	110
Tajikistan	2.464	15	337	13	36	37	79
Lesotho	2.312	15	417	57	35	41	95
Senegal	2.086	14	479	91	40	39	94

Notes: Tables C.10 through C.13 combined summarize the number of items per country for which prices are available in five categories of "assets": consumption goods; materials including labor inputs; residential and non-residential structures; ICT assets; non-ICT assets. Countries are sorted by the number of ICT assets. Our reference country is highlighted. Countries are sorted by precentiles of real GDP per capita based on all countries available in the PWT.

Table C.13: ICP Wave 2011: Items Per Country (Part 4)

Country	Y/L	Inc. Perc.	Number of Items: Consumption	Materials (incl. labor)	Structures	ICT	NICT
U.R. of Tanzania: Mainland	2.052	14	540	92	37	52	97
Nepal	1.936	13	251	64	22	18	49
Uganda	1.787	13	489	76	36	51	104
Benin	1.712	12	324	81	15	25	60
Chad	1.679	11	240	78	32	15	56
Haiti	1.507	11	97	58	4	9	59
Mali	1.489	10	539	93	38	30	89
Gambia	1.487	10	402	100	38	21	63
Zimbabwe	1.453	9	412	62	38	33	60
Comoros	1.417	9	279	73	34	27	54
Guinea-Bissau	1.414	8	416	11	39	20	42
Burkina Faso	1.386	8	441	90	30	32	76
Rwanda	1.384	7	334	86	39	41	83
Sierra Leone	1.286	7	490	81	29	35	75
Madagascar	1.275	6	562	55	40	25	64
Guinea	1.245	5	428	82	28	29	60
Togo	1.217	5	374	79	39	32	78
Malawi	1.087	4	517	86	35	28	74
Ethiopia	1.077	4	299	89	31	30	113
Mozambique	.925	3	373	85	33	46	94
Central African Republic	.906	3	400	78	32	20	39
Niger	.774	2	471	89	21	12	59
Liberia	.722	2	369	84	37	21	50
D.R. of the Congo	.691	1	356	94	34	24	64
Burundi	.641	1	418	82	35	34	90
Average			342.6	57.623	27.686	33.977	85.217
Std. Dev.			106.572	32.692	8.347	13.722	32.329
Min.			97	5	4	7	25
Max.			654	100	44	77	188
# Countries			175	175	175	175	175

Notes: Tables C.10 through C.13 combined summarize the number of items per country for which prices are available in five categories of "assets": consumption goods; materials including labor inputs; residential and non-residential structures; ICT assets; non-ICT assets. Countries are sorted by the number of ICT assets. Our reference country is highlighted. Countries are sorted by precentiles of real GDP per capita based on all countries available in the PWT.