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Dario Judzik,
Hector Sala

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Universitat Autònoma de Barcelona

Facultat d'Economia i Empresa

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Departament d'Economia Aplicada
Edifici B
Campus de Bellaterra
08193 Bellaterra

Telèfon: (93) 581 1680
Fax:(93) 581 2292
E-mail: d.econ.aplicada@uab.es
http://www.ecap.uab.es

The determinants of capital intensity in Japan and the U.S.*

Dario Judzik†
Universitat Autònoma de Barcelona

Hector Sala‡
Universitat Autònoma de Barcelona and IZA

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Abstract

We estimate the determinants of capital intensity in Japan and the US, characterized by striking different paths. We augment an otherwise standard Constant Elasticity of Substitution (CES) model with demand-side considerations, which we find especially relevant in the US. In this augmented setting, the elasticity of substitution between capital and labor is placed around 0.85 in Japan, and 0.30 in the US. We also find evidence of biased technical change, which is capital-saving in Japan but labor-saving in the US. These differences help us explain the diverse experience in the capital deepening process of these economies, and lead us to conclude that demand-side drivers may also be relevant to account for different growth experiences. A close look at the nature of technological change is also needed before designing one-size-fits-all industrial, economic growth, and/or labor market policies.

JEL Classification: E22, E24, O33.

Keywords: Capital intensity, Biased technological change, Elasticity of substitution, Capacity utilization rate, Employment.

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†Departament d'Economia Aplicada, Universitat Autònoma de Barcelona, Edifici B, 08193 Bellaterra, Spain; tel: +34-93.581.11.53; email: dariojudzik@gmail.com

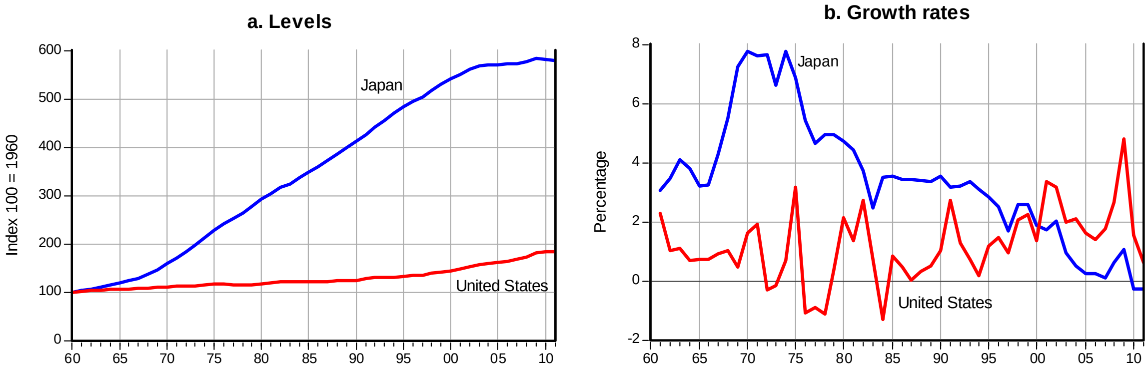
‡Departament d'Economia Aplicada, Universitat Autònoma de Barcelona, Edifici B, 08193 Bellaterra, Spain; tel: +34-93.581.27.79; email: hector.sala@uab.es.

1 Introduction

Although capital intensity, i.e. the ratio of capital stock over employment, plays a central role in economic growth models, it is generally considered as an input variable. No effort is devoted to the empirical assessment of its determinants in spite, for example, of the contrasted trajectory of capital intensity across countries, or in spite of the limitation that this imposes in growth accounting analysis.[1]

This paper intends to fill this void by providing evidence on the determinants of capital intensity in two economies with different trajectories: Japan and the United States. As shown in Figure 1, the different time paths followed by the capital-per-worker ratio is itself calling for an empirical analysis of its causes.

Figure 1. Capital intensity.



Source: Ameco Database.

The progress of capital intensity was especially intense in Japan, where the amount of capital stock per employee grew almost sixfold between 1960 and 2011, in contrast to the US, where it less than doubled (Figure 1a). The origin of these differences lies in the very dynamic process of capital deepening linked to the industrialization process experienced by Japan in the 1960s and 1970s. However, after peaking in the first half of the 1970s, the growth rate of capital intensity has evolved around a steady downward path (Figure 1b). On the contrary, the process of capital deepening in the US accelerated from the mid 1980s until 2009 when the Great Recession caused a sudden fall similar to those occurred in the aftermath of the oil prices shocks.

To investigate on the determinants of capital intensity, we depart from a standard Constant Elasticity of Substitution (CES) model –along the lines, among others, of Antràs (2004) and McAdam and Willman (2013)– and relax the assumptions of perfect competition and perfect information. In this way, we force firms to deal with product demand

[1] Madsen (2010), for example, points out that a problem associated with the traditional growth accounting framework is the lack of information about the factors responsible for the evolution of capital intensity.

uncertainty, which they do by adjusting their degree of factor utilization *ex post,* once investment decisions have already been made. In this context, capital intensity is driven by supply-side factors (i.e., factor costs and technology) as well as by demand-side conditions. The result is a model of capital intensity where the capital-per-worker ratio is explained by the relative factor cost –which is the main supply-side driver–, relative factor utilization –which is the main demand-side driver–, and technological change –which, as standard, is assumed to grow at a constant rate–. Following related literature (e.g., Madsen, 2010; and Hutchinson and Persyn, 2012), additional empirical controls related to the tax system and the degree of exposure to international trade are considered.[2]

In this way, our paper contributes to the literature in three main dimensions. First of all, in considering an extended CES model with demand-side considerations arising from the existence of imperfect competition and imperfect information. Second, in providing an empirical account of the determinants of capital intensity in this wider than usual perspective, including updated estimates of the elasticity of substitution between capital and labor. Third, in identifying the different nature of factor-biased technical change in Japan and the US, in response to the recent 'call for results' by McAdam and Willman (2013, p.698): "... despite renewed interest in models of biased technical change, the corresponding empirical effort to identify (i.e., measure) episodes from macro data has been lacking."

Our estimated models are used to conduct dynamic accounting exercises. In each of them, the time path of capital intensity is evaluated as a result of different counterfactual scenarios that affect each empirical determinant of capital intensity.

As expected, we find relative factor costs to be crucial in explaining the time-path of capital intensity in both countries. But, beyond that, we also find that relative factor utilization accounts for a significant chunk of its progress (or, better, of its lack of progress) in the US. Finally, the different nature of the biased-technological change is shown to exert the opposite influence on the progress of capital intensity. It has contributed to slow it down in Japan, due to its capital-saving nature, while it has boosted it quite intensively in the US because of its labor-saving essence. Our simulations also point to growing openness to trade in Japan as a relevant factor hindering the process of capital intensity.

The rest of this paper is structured as follows. Section 2 presents the analytical framework. Section 3 deals with empirical issues related to the data and the estimated models. Section 4 computes the elasticities of substitution between capital and labor, and evaluates technological change in Japan and the US. Section 5 presents counterfactual

[2] A different way of looking into capital intensity is the one by Hasan *et al.* (2013) in a Hecksher-Ohlin setup. They argue that labor and capital market regulations determine the industry-level capital stock per worker, and claim that restrictive labor laws can curb firms' ability to adjust their labor demand to shocks in demand, technology and trade.

simulations. Finally, section 6 concludes.

2 Analytical framework

We depart from a CES production function from which the factor demand equations are first derived, and then combined into a single expression that accounts for the supply-side determinants of capital intensity. This is along the lines of Antràs (2004) and McAdam and Willman (2013). Then, we add the possibility of product demand uncertainty in the spirit of Andrés *et al.* (1990a, 1990b), Fagnart *et al.* (1999) and Bontempi *et al.* (2010). In this context, when expected demand is not met by its actual value, firms are likely to react by adjusting their use of the production factors either by hiring or firing workers, by changing the rate of capacity utilization, or by using both mechanisms. In other words, the uncertainty on the actual level of product demand creates a transmission channel by which the demand-side conditions affect the investment and hiring/firing decisions of the firms. This explains why capital intensity is likely to depend both on supply-side and demand-side factors.

2.1 Factor demands and capital intensity

Consider an economy with f identical firms that supply a homogeneous good. These firms acquire inputs in competitive markets and face a cost per unit of labor W, and a cost of capital use CC. Each firm has a CES production technology so that:

$$Y_t = \left[\theta(A_t^N N_t)^{-\beta} + (1-\theta)\left(A_t^K K_t\right)^{-\beta}\right]^{-1/\beta}, \tag{1}$$

where Y is output, N is employment, K is capital stock, A^N is an index of labor-augmenting efficiency (proxying Harrod-neutral technological change), and A^K is an index of capital-augmenting efficiency (proxying Solow-neutral technological change); the parameter θ represents the factor share ($0 < \theta < 1$); $\sigma = \frac{1}{1+\beta}$ is the constant elasticity of substitution between capital and labor; and β denotes the degree of substitutability between both factors.

As standard (Antràs, 2004; León-Ledesma *et al.*, 2010), we assume that biased technological progress grows at constant rates denoted, respectively, by λ_N and λ_K. We thus have $A_t^N = A_0^N e^{\lambda_N . t}$ and $A_t^K = A_0^K e^{\lambda_K . t}$, where A_0^N and A_0^K are the initial values of the technological progress parameters, and t is a linear time trend. Note that $\lambda_N = \lambda_K > 0$ would imply Hicks-neutral technical progress; $\lambda_K > 0$ and $\lambda_N = 0$ implies Solow neutrality; $\lambda_N > 0$ and $\lambda_K = 0$ yields Harrod neutrality, while $\lambda_N, \lambda_K > 0$ but $\lambda_N \neq \lambda_K$ is indicative of factor-biased technical change.

Profit maximization in a perfectly competitive environment yields expressions for the factor demands (as a proportion of total output) that log-linearized can be written as

$$\log(K_t/Y_t) = \alpha_K - \sigma \log(CC_t/P_t) - (1-\sigma)\lambda_K t \quad (2)$$

$$\log(N_t/Y_t) = \alpha_N - \sigma \log(W_t/P_t) - (1-\sigma)\lambda_N t, \quad (3)$$

where P is the aggregate product market price; $\alpha_K = \sigma \log(1-\theta) + (\sigma-1)\log A_0^K$ and $\alpha_N = \sigma \log\theta + (\sigma-1)\log A_0^N$ are constants; and $1-\sigma = \frac{\beta}{1+\beta}$. Subtraction of equation (3) from equation (2) yields the following specification for capital intensity:

$$\log(K_t/N_t) = \alpha - \sigma \log(CC_t/W_t) + (1-\sigma)(\lambda_N - \lambda_K)t. \quad (4)$$

where $\alpha = \alpha_K - \alpha_N$.

Equation (4) is standard and corresponds, for example, to equation (3') in Antràs (2004, p. 19) and equation (5) in McAdam and Willman (2013, p. 704). Following this expression, capital intensity depends on two supply-side factors: (i) the relative cost of labor and capital; and (ii) the direction of factor-biased technical change. In other words, there will be more capital intensity whenever real wages grow faster than the user cost of capital, thus making labor relatively more expensive than capital; and whenever labor-efficiency grows faster than capital-efficiency ($\lambda_N > \lambda_K$), provided that labor and capital are gross complements, i.e. $\sigma < 1$.

2.2 Product demand uncertainty

Next, we relax the assumption of perfect competition and perfect information in the product market by assuming that firms hold some market power and are subject to random unexpected shocks. This implies that firms will now maximize profits based on an expectation of the stochastic demand Y^E. Uncertainty about aggregate demand shapes firms' investment decisions (Fagnart *et al.*, 1999; Bond and Jenkinson, 2000; Bontempi *et al.*, 2010) and allows for the inclusion of demand-side considerations.

The sequence of decisions is as follows. Firms maximize profits subject to their expectation of demand in period t. In $t+1$, once the realization of the random (and unexpected) shocks that determine the demand are known, the utilization rate of installed capacity and the corresponding demand for labor are adjusted accordingly.

Along the lines of Fagnart *et al.* (1999) firms use a putty-clay technology. With productive capacity fixed in the short-run, firms adjust the degree of factor utilization, and capital and labor are substitutes *ex ante*. *Ex post*, once capacity choices have been made and idiosyncratic shocks are known, firms' actual demand is faced by adjusting the utilization intensity of the production factors; i.e., by hiring/firing workers, and by deciding on the capacity utilization rate. At this stage, production factors may be thought as complements to achieve a certain level of production. This model, therefore, allows for *ex post* rationing of factor utilization in contrast to the standard maximization problem.

The realization of the demand faced by firms depends on two factors: the price level (chosen by firms) and random shocks. The expected demand that firms consider in their profit maximization problem is the expected value of this realization Y_t^E:

$$Y_t^E = E_{t-1}\left[Y_t(P_t,\varphi)\right], \tag{5}$$

where E is the rational expectations operator, and φ is represents an idiosyncratic (stochastic) shock with zero mean and a constant standard deviation greater than zero. In other words, firms produce (and decide their factor demands) accordingly to their expectation of product demand, which is a function of the the aggregate product market price and the shocks.

Under these assumptions, the profit-maximization problem of the firm corresponds to a standard monopolistic competition case:

$$\begin{aligned}
\max\ \pi\left(K_t,N_t,P_t\right) &= P_tY_t^E - W_tN_t - CC_tK_t \\
\text{subject to } &: \\
Y_t^E &= E_{t_{-1}}\left[\theta(A_0^N e^{\lambda_N.t}N_t)^{-\beta} + (1-\theta)\left(A_0^K e^{\lambda_K.t}K_t\right)^{-\beta}\right]^{-1/\beta}
\end{aligned}$$

where π stands for the firms' profit function.

Operating from the first order conditions of this problem, the optimal levels of factor utilization relative to output are obtained as an inverse relation with respect to each factor's cost:

$$\frac{K_t}{Y_t^E} = (1-\theta)^{\sigma}\left(\frac{CC_t}{P_t}\right)^{-\sigma}(A_0^K e^{\lambda_K.t})^{\frac{-\beta}{1+\beta}} \tag{6}$$

$$\frac{N_t}{Y_t^E} = \theta^{\sigma}\left(\frac{W_t}{P_t}\right)^{-\sigma}(A_0^N e^{\lambda_N.t})^{\frac{-\beta}{1+\beta}} \tag{7}$$

Note that log-linearization of equations (6) and (7) under perfect competition and perfect information would yield equations (2) and (3).

Through aggregation of the f firms, the overall expected demand can be replaced by the potential aggregate demand level ($\hat{Y}$). Further addition of the ratio $\frac{Y_t}{Y_t}$ $(=1)$ to the left-hand side of both equations then yields:

$$\frac{K_t}{Y_t} = (1-\theta)^\sigma \left(\frac{CC_t}{P_t}\right)^{-\sigma} (A_0^K e^{\lambda_K . t})^{\frac{-\beta}{1+\beta}} \frac{\widehat{Y}_t}{Y_t} \tag{8}$$

$$\frac{N_t}{Y_t} = \theta^\sigma \left(\frac{W_t}{P_t}\right)^{-\sigma} (A_0^N e^{\lambda_N . t})^{\frac{-\beta}{1+\beta}} \frac{\widehat{Y}_t}{Y_t}, \tag{9}$$

where the ratio $\frac{\widehat{Y}_t}{Y_t}$ expresses the gap between potential aggregate demand ($\hat{Y}$) and the actual level of aggregate production (Y), once factor demands have been adjusted *ex post.*

2.3 Mind the gap

The $\frac{\widehat{Y}_t}{Y_t}$ ratio is the transmission channel for business cycle effects (Fagnart *et al.*, 1999; Nakajima, 2005; Planas *et al.*, 2013). As such, it is directly related to the gap between total installed production capacity and the rate of capacity utilization of the production factors. However, since $\widehat{Y}_t$ is unobservable, we follow the literature and assume that the degree of factor utilization can be empirically used as a proxy of the ratio $\frac{\widehat{Y}_t}{Y_t}$.

Regarding equation (8), the natural proxy is the standard capacity utilization rate (CUR) variable –see, among others, Graff and Sturm (2012). In this paper, however, we are also interested in equation (9) and require a specific proxy for the demand-pressures affecting the labor factor. For this, we follow the same reasoning than the one normally used for equation (8).[3] Thus, based on the fact that production is responsive to aggregate demand *ex post,* and installed capacity is rigid in the short run, we consider the employment rate ($NR = N/Z$), which reflects the actual use of the labor factor (employment, N) relative to its total potential use (working-age population, Z).

Accordingly, we re-write the factor demand equations as:

$$\frac{K_t}{Y_t} = (1-\theta)^\sigma \left(\frac{CC_t}{P_t}\right)^{-\sigma} (A_0^K e^{\lambda_K . t})^{\frac{-\beta}{1+\beta}} \; h(CUR_t) \tag{10}$$

$$\frac{N_t}{Y_t} = \theta^\sigma \left(\frac{W_t}{P_t}\right)^{-\sigma} (A_0^N e^{\lambda_N . t})^{\frac{-\beta}{1+\beta}} \; h(NR_t), \tag{11}$$

where $h(\cdot)$ are monotonically increasing functions of CUR_t and NR_t (see Andrés *et al.*, 1990a, p. 88).

Log-linearization of equations (10) and (11), and subtraction of the second one from

[3] Although firms invest in capacity following their expectation on potential demand, they end up using it based on the actual demand they face (this is the idea of *ex post* rationing) determining, in this way, their degree of capacity utilization (or capacity utilization rate).

the first one yields an expression for capital intensity and its determinants:[4]

$$\log\left(\frac{K_t}{N_t}\right) = \alpha - \sigma\left[\log\left(\frac{CC_t}{P_t}\right) - \log\left(\frac{W_t}{P_t}\right)\right] + (1-\sigma)(\lambda_N - \lambda_K)t$$
$$+ (\gamma_K - \gamma_N)\left[\log(CUR_t) - \log(NR_t)\right]. \quad (12)$$

Note that the only difference with respect to equation (4) is the last term, which results from the assumption of stochastic behavior of aggregate product demand allowing for *ex post* rationing of factor utilization.

2.4 Factor-biased technical change

The empirical measurement of factor-biased technological change is a critical issue –see, among many others, Antràs (2004), León-Ledesma *et al.* (2010, 2013), and McAdam and Willman (2013). In this context, making *a priori* assumptions about the form of technical progress (e.g. assuming Hicks neutrality) is likely to misguide the insights on the effect of technical progress, for example, on capital intensity. This is the reason why it is worth paying close attention to the second term in the right-hand-side of equation (12).

Achieving a balanced growth path (BGP) in standard models of economic growth implies that the main macro variables converge to a common growth rate, the underlying ratios (factor income shares and factor to GDP ratios) remain constant –as described by Kaldor (1961)–, and technical change is solely labor augmenting (i.e., Harrod neutral). Acemoglu (2003) and McAdam and Willman (2013) suggest that although technical progress is labor-augmenting along the BGP, it can be capital-augmenting in medium-run transitions away from the BGP. With an elasticity of substitution between labor and capital different from unity, this pattern allows for long-run asymptotic stability of factor shares and, also, for a non-stationary evolution in the medium-run, which we actually observe in reality.

In the context of our model, let us consider a situation in which the elasticity of substitution between labor and capital is below unity (and the production factors are gross complements). As shown by McAdam and Willman (2013, p. 703), this implies that capital intensity grows with a relatively higher growth of labor-augmenting technical change:

$$\frac{\partial(K/N)}{\partial(A^N/A^K)} > 0 \quad \text{if} \quad \sigma < 1 \quad (13)$$

[4] Consistently with the rest of the variables, we assume that the log-linearization of $h(\cdot)$ yields a linear function of the logs of CUR and NR as presented in (12).

which, in terms of equations (4) and (12), takes place whenever $\lambda_N > \lambda_K$. On the contrary, with $\sigma < 1$ and $\lambda_N < \lambda_K$, there is a fall in capital intensity.

This situation of $\sigma < 1$ is empirically endorsed in the works of Antràs (2004), Chirinko (2008), Chirinko *et al.* (2011), León-Ledesma *et al.* (2010), Klump *et al.* (2012), and McAdam and Willman (2013).

3 Empirical issues

3.1 Estimated models

We augment the base-run equation (12) with two sets of control variables related to capital intensity: the degree of exposure to international trade and the fiscal system. Since capital intensity, the degree of substitution between capital and labor, and globalization are deeply intertwined (Hutchinson and Persyn, 2012), inclusion of the degree of trade openness (op) is a must. Regarding the fiscal system, a key variable for firm's decisions is direct taxes on business, which is crucial in defining, for example, investment decisions. This has been studied in Bond and Jenkinson (2000), Edgerton (2010) and Madsen (2010), where the decelerating effect of corporate taxation on capital deepening is explained as a disincentive to firm-level investment. Because we originally have one expression per production factor, we consider both direct taxes on business $\left(\tau^b\right)$ and direct taxes on households $\left(\tau^h\right)$ to capture, if any, the specific impact of taxes on each factor. Of course, payroll taxes is another crucial element of the tax system, but its relevance is more related to the wage bargaining process between firms and workers. Since this is implicitly taken into account through the wage variable in the user cost of capital (total compensation, which includes social security contributions), no further control is required.

Following this reasoning, the first model we estimate is a straightforward augmented version of equation (12):

$$kn_t = \beta_0 + \beta_1(cc_t - w_t) + \beta_2(cur_t - nr_t) + \beta_3 t + \beta_4 op_t + \beta_5 \tau^b + \beta_6 \tau^h + u_{1t}, \qquad (14)$$

where $kn_t = \log(K_t/N_t)$, $cc_t = \log(CC_t/P_t)$, $w_t = \log(W_t/P_t)$, $cur_t = \log(CUR_t)$, $nr_t = \log(NR_t)$ and u_{1t} represents a standard error term with zero mean and constant standard deviation. This is called Model 1 in Tables 2 to 5. Note, also, that detailed definitions of the additional controls, op, τ^b,and τ^h (and also of the rest of the variables) are given in Table 1.

We consider a second model because the choice of demand-side drivers in factor demand equations is still an open issue, and we want to know how robust their inclusion is. This is the reason why, on top of the relative degree of factor utilization $\log(CUR_t) - \log(NR_t)$, we follow Añón-Higón (2007) and consider the variation in worked hours per employee as an alternative aggregate proxy of demand-side pressures (we take the growth rate because this proxies the business cycle in terms of time-varying demand-side pressures). The reasoning behind this choice is that worked hours per employee reflect simultaneously the increase in the usage intensity in both capital stock and labor. Moreover, the average annual amount of hours worked per employee is likely to avoid the endogeneity problems that would entail considering variations in output (since the dependent variable is indeed made of capital and labor), which is the natural alternative in the literature.

Following this reasoning, in Model 2 we substitute relative factor utilization, $cur_t - nr_t$, by the change in worked hours per employee (Δhr):

$$kn_t = \gamma_0 + \gamma_1(cc_t - w_t) + \gamma_2 \Delta hr_{t-1} + \gamma_3 t + \gamma_4 op_t + \gamma_5 \tau^b + \gamma_6 \tau^h + u_{2t}, \tag{15}$$

where u_{2t} represents a standard error term with zero mean and constant standard deviation. Note that the coefficient on hours is lagged once to help avoiding endogeneity problems. In contrast, the term capturing demand-side pressures in equation (14) is not lagged to maintain coherence with respect to the theoretical model. We have assumed a putty-clay technology and argued that short-run capital stock adjustments take place through changes in the degree of capacity utilization. This implies that demand changes foreseen in $t-1$ are accommodated through changes in investment, not through changes cur which can only respond in period t.

A crucial remark is that these empirical models are estimated as dynamic equations to take into account the adjustment costs potentially surrounding all variables involved in the analysis (endogenous and exogenous). The lagged structure of the estimated relationships is therefore a strict empirical matter.

The coefficients β_1/γ_1 are associated to the relative cost of production factors, and a negative sign is expected. As the wedge between the cost of factors $(cc - w)$ increases, capital becomes relatively more costly than labor, and a deceleration in the growth capital intensity is expected.[5] The crucial feature of these coefficients is their correspondence with the constant elasticity of substitution between capital and labor (σ).

The coefficients β_2/γ_2 are associated to the role of demand-side pressures, and a positive sign is expected. A rise in the wedge between the relative intensity in factor

[5] Decisions to invest in new capacity are influenced by the cost and availability of capital and the target rates of return sought by firms and financial institutions. The dependence on bank loans is an important factor limiting expansion and the user cost of capital is a crucial factor in the expected net return to investment by firms.

utilization $(cur - nr)$ implies that tightness in the capital side is larger than in the labor side. Firms, therefore, are expected to react by investing more intensively than embarking in new hirings. As a consequence, capital intensity is expected to accelerate.

Firm's decisions to expand capacity through investment are based to a large extent on their assessment of their future sales, which we assumed to be uncertain. Managers are naturally cautious about overestimating future sales, as the penalty for doing so tends to be much greater than for losing potential business by failing to expand (Smith, 1996). In our model, the capacity utilization rate is a proxy for the perception of the firm of the economic reality, which reflects on its expectations on aggregate demand. Since the expansion of capacity drives investment, we expect a positive effect on capital intensity when the wedge between a higher degree of capacity utilization rate and a higher employment rate widens.

Given the assumption of constant rates of technical progress, the coefficients $\beta_3/\gamma_3 = (1-\sigma)(\lambda_N - \lambda_K)$ measure an asymmetric progress in the efficiency of each production factor. If $\hat{\beta}_3/\hat{\gamma}_3 > 0$ and $\hat{\sigma} < 1$, there is evidence that labor-augmenting efficiency grows faster than capital-augmenting efficiency (the same holds in case of opposite signs in both estimates). If, on the contrary, the $\hat{\beta}_3/\hat{\gamma}_3 > 0$ are positive and $\hat{\sigma} > 1$, the conclusion is that capital-augmenting efficiency grows faster than labor-augmenting efficiency. In both cases, therefore, there is evidence of biased technological change, something that in the standard Cobb-Douglas framework, where $\hat{\sigma} = 1$, cannot be measured.

3.2 Data

We use annual data obtained from various sources. From the European Commission's Ameco database we take long-time series on net capital stock.[6] Data on the capacity utilization rate is obtained from Ministry of Economy, Trade and Industry for Japan, and from the Board of Governors of the Federal Reserve System for the U.S. The rest of the variables is gathered from the OECD Economic Outlook.

Table 1 provides the concrete definitions of the empirical variables used. All of them are standard and the only clarification refers to the definition of the user cost of capital, which is constructed as $\frac{p^i}{p}(i + \delta - \Delta p^i)$ assuming a constant depreciation rate, δ, equal to 0.1. All variables will be used in logs so as to allow an unambiguous interpretation of the estimated coefficients as elasticities.

[6] The net capital stock at constant prices is computed as $OKNDt = OKND_{t-1} + [OIGTt - (UKCTt : PIGTt) * 100]$, where OIGT = Gross fixed capital formation at constant prices; UKCT = Consumption of fixed capital at current prices; and PIGT = Price deflator gross fixed capital formation; and OIGT = Gross fixed capital formation at constant prices in construction; equipment; products of agriculture, forestry, fisheries and aquaculture; and other procucts.

Table 1. Definitions of variables.

k	real net capital stock	p	GDP deflator
n	employment	p^i	investment deflator
kn	capital intensity $(= k - n)$	δ	depreciation rate
z	working-age population	i	nominal interest rate
nr	employment rate $(= n - z)$	cc	real user cost of capital
cur	capacity utilization rate		$= \frac{p^i}{p}(i + \delta - \Delta p^i)$
w	real compensation per employee	T	direct taxes on business
hr	hours of work per employee	τ^b	direct taxes on business (TB) as % GDP
Y	GDP		$= \log(TB/Y)$
X	exports of goods and services	τ^h	direct taxes on households (TH) as % GDP
M	imports of goods and services		$= \log(TH/Y)$
op	trade openness	t	linear time trend
	$= \log([X + M]/Y)$	Δ	difference operator
c	constant		

Note: All variables used in the econometric analysis are expressed in logs.

3.3 Estimation procedure

Time series estimates need to ensure that the long-run estimated relationships between capital intensity and its determinants are non-spurious. Of course, if k, n, cc, w, cur, z, T, and Y certainly behaved as $I(1)$ variables we could argue, since we work with these variables in ratios $(kn, cc - w, cur - nr, (X + M)/Y$ and $T/Y)$, that we end up dealing with $I(0)$ variables and cointegration issues are of no concern.

However, unit root tests show that some of these ratios behave as $I(1)$ variables (see Table A1 in the Appendix for the tests results). This is why our estimation is conducted following the bounds testing approach, or ARDL (AutoRegressive Distributed Lag) approach, which yields consistent short- and long-run estimates irrespective of whether the regressors are $I(1)$ or $I(0)$. This approach, which was developed by Pesaran and Shin (1999) and Pesaran, Shin and Smith (2001), provides an alternative econometric tool to the standard Johansen maximum likelihood, and the Phillips-Hansen semi-parametric fully-modified Ordinary Least Squares (OLS) procedures. The main advantage of the bounds testing approach is the possibility of avoiding the pretesting problem implicit in the standard cointegration techniques. It also yields consistent long-run estimates of the equation parameters even for small size samples and under potential endogeneity of some of the regressors (see Harris and Sollis, 2003).

We proceed as follows. We first estimate our models by OLS, and select equations that are dynamically stable and satisfy the conditions of linearity, structural stability, no serial correlation, homoscedasticity, and normality of the residuals. Then, among the models that meet these requirements, we select the dynamic specification of each equation by relying on the optimal lag-length algorithm of the Schwartz information criterion (Table A2 in the Appendix shows that these standard diagnostic tests are all passed at conventional significance levels). Then, to make sure that we have obtained non-spurious relationships between potential non-stationary variables, we verify that the residuals resulting from our estimated models are indeed stationary (see Table 4 below).

Finally, we estimate the selected specifications by Two Stages Least Squares (TSLS) so as to control for potential endogeneity biases in the estimated effect of the relative factor costs ($cc - w$), in relative factor utilization ($cur - nr$) or hours, and in direct taxes on business. The instruments are statistically significant and we find the OLS and the TSLS results to be relatively alike, thus supporting the robustness of the estimated relationships.[7]

4 Results

4.1 Estimated equations

We present the estimation results for equations (14) and (15) in Table 2, for Japan, and Table 3, for the US.

Japan's estimation includes three dummy variables d^{9102}, d^{83}, and d^{97}, which take value one, respectively, in 1991-2002, 1983, and 1997. They account for the lost decade, and specific events such as the East-Asian crisis, and help to achieve better results in terms of the misspecification tests (displayed in Table A2).

The estimated coefficient associated to the first lag of capital intensity is large in all estimated equations. This high persistence is to be expected since productive capacity is not easily changed in the short run. Relative factor costs in Japan are highly significant and with the expected negative sign in both models. Regarding the demand-side proxies, hours worked in Model 2 have greater statistical significance than the employment rate in Model 1. Direct taxes, both on businesses and households, exert the expected decelerating effect on capital intensity in the two models, as also does the degree of openness to international trade.

Finally, the estimated coefficient associated to the time trend is negative. Combined with a lower-than-one elasticity of substitution, this is indicative that capital-associated

[7] Although, the Durbin-Wu-Hausman test of exogeneity is rejected by a short margin in Model 2 for Japan, this is not affecting our empirical conclusions because our simulation exercises are based on Model's 1 estimates.

efficiency grows at a higher rate than labor-associated efficiency (a detailed discussion on this issue is provided in Section 4.2).

Table 2. Japan, 1980-2011.

	Model 1			Model 2*	
	OLS	TSLS		OLS	TSLS
c	0.005 [0.983]	0.084 [0.759]	c	−0.020 [0.907]	−0.008 [0.969]
kn_{t-1}	0.964 [0.000]	0.954 [0.000]	kn_{t-1}	0.966 [0.000]	0.960 [0.000]
$cc_t - w_t$	−0.033 [0.000]	−0.038 [0.001]	$cc_t - w_t$	−0.034 [0.000]	−0.036 [0.062]
$\Delta(cc_t - w_t)$	0.020 [0.001]	0.019 [0.003]	$\Delta(cc_t - w_t)$	0.021 [0.000]	0.031 [0.030]
$\Delta(cc_{t-1} - w_{t-1})$	0.015 [0.002]	0.016 [0.005]	$\Delta(cc_{t-1} - w_{t-1})$	0.021 [0.001]	0.025 [0.004]
$cur_t - nr_t$	0.005 [0.625]	0.003 [0.813]	Δhr_{t-1}	0.076 [0.106]	0.111 [0.070]
$\Delta(cur_t - nr_t)$	0.015 [0.188]	0.019 [0.175]			
$\Delta\tau_t^b$	−0.015 [0.001]	−0.014 [0.012]	$\Delta\tau_t^b$	−0.014 [0.001]	−0.007 [0.573]
$\Delta\tau_{t-1}^h$	−0.007 [0.329]	−0.006 [0.426]	$\Delta\tau_{t-1}^h$	−0.009 [0.149]	−0.010 [0.200]
op_t	−0.030 [0.003]	−0.035 [0.008]	op_t	−0.035 [0.001]	−0.056 [0.002]
D^{9102}	0.005 [0.005]	0.005 [0.024]	D^{9102}	0.004 [0.005]	0.003 [0.039]
D^{83}	−0.014 [0.000]	−0.013 [0.000]	D^{83}	−0.014 [0.000]	−0.014 [0.000]
D^{97}	−0.010 [0.000]	−0.011 [0.000]	D^{97}	−0.010 [0.000]	−0.009 [0.034]
t	−0.001 [0.030]	−0.001 [0.145]	t	−0.001 [0.016]	−0.0003 [0.605]
LL	167.6			167.33	
Obs	32	32		32	32

Notes: LL = Log-likelihood; p-values in brackets; Instruments: kn_{t-1} cc_{t-1} w_{t-1} Δcc_{t-1} Δw_{t-1} cur_{t-1} nr_{t-1} op_{t-1} $\Delta\tau_{t-1}^h$ $\Delta\tau_t^b$ $\Delta\tau_{t-1}^b$ D_{9102} D_{83} D_{97} t Δhr_{t-1} Δhr_{t-2}.

Durbin-Wu-Hausman test [prob]: Model 1 [0.95]; Model 2 [0.04].

As for the US, the coefficients associated to relative factor cost are also negative and significant. And, in contrast to Japan, not only Δhr_{t-1} presents statistical significance, but also the relative factor utilization. Direct taxes and openness are also detrimental for capital intensity, with the latter entering the equation in differences. This implies a long-run elasticity of capital intensity with respect to the level of openness cannot be computed. We interpret this as a reflection of a more conjunctural than structural type of influence in a context of a closed economy, in contrast to Japan.

The estimated coefficient associated to the time trend is positive. Taking into account that the estimated elasticity of substitution for the US is lower than unity, this is indicative of labor-saving biased technical change resulting from faster growth rates of labor-efficiency than those of capital-efficiency (details in Section 4.2).

Table 3. US, 1970-2011.

	Model 1			**Model 2***	
	OLS	TSLS		OLS	TSLS
c	0.345 [0.401]	0.327 [0.516]	c	0.136 [0.772]	0.286 [0.582]
kn_{t-1}	0.951 [0.000]	0.941 [0.000]	kn_{t-1}	0.973 [0.000]	0.965 [0.000]
Δkn_{t-1}	0.292 [0.015]	0.308 [0.038]	Δkn_{t-1}	0.215 [0.241]	0.288 [0.176]
$cc_t - w_t$	−0.010 [0.094]	−0.016 [0.132]	$cc_t - w_t$	−0.013 [0.058]	−0.011 [0.443]
$cur_t - nr_t$	0.083 [0.139]	0.126 [0.192]	Δhr_{t-1}	−0.310 [0.317]	−0.204 [0.572]
$\Delta (cur_t - nr_t)$	−0.182 [0.000]	−0.170 [0.001]	Δhr_{t-2}	0.526 [0.027]	0.547 [0.026]
τ_t^b	−0.019 [0.069]	−0.035 [0.114]	τ_t^b	−0.018 [0.115]	−0.008 [0.699]
τ_t^h	−0.002 [0.899]	0.003 [0.862]	τ_t^h	0.014 [0.366]	0.011 [0.535]
Δop_t	−0.099 [0.024]	−0.069 [0.382]	Δop_t	−0.149 [0.002]	−0.206 [0.002]
t	0.001 [0.079]	0.001 [0.191]	t	0.0002 [0.655]	0.0004 [0.492]
LL	161.2			155.5	
$Obs.$	42	42		42	42

Notes: LL = Log-likelihood; p-values in brackets; Instruments: kn_{t-1} Δkn_{t-1} cc_{t-1} w_{t-1} cur_{t-1} nr_{t-1} Δcur_{t-1} Δnr_{t-1} τ_t^b τ_{t-1}^b τ_t^h τ_{t-1}^h Δop_{t-1} t Δhr_{t-1} Δhr_{t-2}

Durbin-Wu-Hausman test [prob]: Model 1 [0.92]; Model 2 [0.73].

Beyond the use of the ARDL methodology, we further ensure the validity of the estimated long-run relationships (with the key ones presented in Table 5) by testing for the existence of unit roots in the residuals of the estimated equations. For this, we use the Augmented Dickey-Fuller test (ADF, with the null hypothesis of non-stationarity) and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS, with the null hypothesis of stationarity). The results of these tests are presented Table 4 and reject, in all cases and by large, the existence of a unit root in the ADF test, and fail to reject the hypothesis of stationarity in the KPSS test. We thus conclude that the residuals are stationary and we can safely compute the key long-run relationships.

Table 4. Unit root tests on the residuals of equations (14) and (15)

	ADF test				KPSS test			
	Model 1 (u_{1t})		Model 2 (u_{2t})		Model 1 (u_{1t})		Model 2 (u_{2t})	
	OLS	TSLS	OLS	TSLS	OLS	TSLS	OLS	TSLS
Japan	−5.84	−5.32	−5.47	−6.61	0.054	0.045	0.447	0.500
U.S.	−4.17	−6.18	−6.41	−6.89	0.054	0.042	0.081	0.083

Note: ADF test critical value is -3.60 at the 1% level.

KPSS test critical values are 0.739 at the 1% level, and 0.463 at the 5% level.

4.2 Elasticities of substitution and technological change

Directed technical change is a consequence of a production factor becoming relatively more scarce, more expensive, or both. Innovation is then directed towards technologies that would save on the relatively more expensive factor. The bias in technical change may have a saving effect on one factor and an augmenting effect on the other one. The degree of substitutability between labor and capital is closely related to this phenomenon. They are, together, key variables in economic growth models, with special influence in medium-run dynamics as explained in McAdam and Willman (2013).

Table 5 shows the elasticity of substitution between factors implied by our empirical models ($\hat{\sigma}$), together with the long-run impact on capital intensity of the constant rate of technological progress $\left(\varepsilon^{LR}_{kn-trend}\right)$. Given that the estimated models are dynamic, the elasticity of substitution is computed as the long-run elasticity of kn with respect to $(cc - w)$. Taking the example of Japan using Model 1, we have $0.038/(1-0.954) = 0.83 = \hat{\sigma}$. In turn, $\varepsilon^{LR}_{kn-trend} = (-0.001/(1-0.954)) * 100 = -2.2\%$.

These two values are used to compute the implied rate of biased technological change following equations (4) or (12). More precisely, in case of Model's 1 estimates for Japan, we use $\hat{\sigma} = 0.83$ and $\varepsilon^{LR}_{kn-trend} = -2.2\%$ to compute the value of $(\lambda_K - \lambda_N)$ using:

$$\begin{aligned} -2.2\% &= (1-0.83)(\lambda_N - \lambda_K) \\ &\implies (\lambda_K - \lambda_N) = 12.5\% \end{aligned}$$

This result implies that there is factor-biased technical change in Japan ($\lambda_K - \lambda_N > 0$, that is, $\lambda_K \neq \lambda_N$) and the direction, in this case, is capital saving.

Table 5 shows the calculations for both countries using the instrumental variables estimation of Models 1 and 2.

Table 5. Elasticities of substitution and technological change.

	Model 1				**Model 2**			
			Technical progress				Technical progress	
	$\hat{\sigma}$	$\varepsilon^{LR}_{kn-trend}$	Type	Rate	$\hat{\sigma}$	$\varepsilon^{LR}_{kn-trend}$	Type	Rate
Japan	0.83	-2.2%	Capital saving	12.5%	0.90	-0.7%	Capital saving	7.5%
US	0.27	1.7%	Labor saving	2.3%	0.31	1.1%	Labor saving	1.7%

Notes: $\varepsilon^{LR}_{kd-trend}$ denotes the long-run elasticity of capital intensity with respect to constant technical change; technical change is capital saving whenever $\lambda_K > \lambda_N$ and labor saving whenever $\lambda_N > \lambda_K$.

As noted, we find the elasticity of substitution between capital and labor to be below 1 in Japan. This value is larger than in other studies, which place it between 0.2 and 0.4 (Rowthorn 1999, Klump *et al.* 2012). However, neither the sample period nor the methodology is common to the one followed here.

We find the long-run impact of technological change to be between -0.7% and -2.2%. This implies that a rise in the rate of technological progress is translated, in the long-run and *ceteris paribus*, to a fall in capital intensity. This result is critical to understand the deceleration in the process of capital deepening experienced by Japan since the mid 1970s. Together with the estimated elasticity of substitution, it provides evidence of a substantial bias in technological change, which is capital saving, and evolves at a rate between 7.5% and 12.5%. The capital-saving effect comes from the fact that a higher rate of capital related efficiency growth (i.e., $\lambda_K > \lambda_N$) reduces the pace of capital stock growth. This is consistent with the path followed by the process of capital deepening in Japan, with a huge increase in capital accumulation in the expansionary decades of 1960 and 1970, and a steep and continuous decrease in the 1980s, 1990s and 2000s. On this account, let us recall that our sample period for Japan starts in 1980. Not only this prevents us to have noise from the structural break occurred in the Japanese economic growth model, but it also allows us to capture more precisely this extraordinary long period of continuous deterioration in the ratio of capital stock to employment.

Regarding the US, our analysis yields an elasticity of substitution between capital and labor around 0.3, a value in the lower range of the estimates provided by the literature. In particular, although Chirinko (2008) finds a σ between 0.4 and 0.6, and León-Ledesma *et al.* (2010) and Klump *et al.* (2007) present values in the 0.5-0.7 range, it is important to emphasize Chirinko's *et al.* (2011) indication that the use of time series data at annual frequencies may lower the estimation of σ.[8] Chirinko *et al.* (1999), for example, provide an estimation of the elasticity of substitution rather low for the US of around 0.25.

We also find a long-run impact of technological change on capital intensity between 1% and 2%. This implies that a rise of 1 percentage point in the rate of technological progress is translated, in the long-run, in at least a 1% increase in capital intensity. In terms of biased technological change, we find consistent evidence (since Models 1 and 2 yield similar results) of a labor-saving bias (i.e., labor-related efficiency grows at a faster rate in the U.S., $\lambda_K < \lambda_N$). This may contribute to explain the secular process of industrial firms' delocalization of the US economy including the growing relevance of phenomena such as offshoring and outsourcing.

It is important to remark that our estimates between 1.7% and 2.5% of biased technological change in the US are fully aligned with those supplied by the literature and summarized in Klump *et al.* (2012), Table 1. The reported range of values obtained from many studies is placed between 0.27% and 2.2%, with the exception of Antràs (2004) where it is placed slightly above 3%.

5 Counterfactual simulations

Takahashi *et al.* (2012) show that capital intensity has been crucial in Japan and other OECD economies' postwar growth. Few efforts, however, have been made to assess the determinants of the economies's capital intensity in such long-run perspective. To contribute to such important matter, we now use our estimated models to perform dynamic accounting exercises.

For each country, the estimated Model 1 is solved in two scenarios. The first one is a baseline scenario in which all exogenous variables take their actual values. In the second scenario, each of the exogenous variables (one at a time) is kept constant at its

[8] Chirinko *et al.* (2011) argue that time series variations of investment spending largely reflect adjustments to transitory shocks; then, because firms respond less to temporary than to permanent shocks, an elasticity estimated with time series data will tend to be lower than the "true" long-run elasticity.

value at the beginning of the sample period (1980 for Japan, 1970 for the US). We call this a counterfactual simulation because the difference between the fitted values of capital intensity obtained with the actual and the simulated values of the explanatory variables reveals how much of its actual trajectory can be explained by the factor kept constant in the simulation.

Note we are not claiming that the fitted values from the simulated scenarios are the true values that capital intensity would have taken had some particular variable remained constant. It is just a dynamic accounting exercise to assess which have been the main driving forces of capital intensity in the two examined economies.

Figure 2 plots the results. The scale in all graphs is based on a 100 index for the first year of the sample period. To evaluate these results it is helpful to take into account the evolution of the exogenous variables which is plotted in Figures A1 and A2 in the Appendix.

The actual path of capital intensity is represented by the continuous line. With a 98.9% growth, it almost doubled in Japan between 1980 and 2011, while in the US it grew by 65.9% over the 1970 to 2011 period.

Following our simulations, had relative factor costs ($cc - w$) remained unchanged at the beginning of the sample, these growth rates would have been around 40% (38.4% in Japan and 40.2% in the US). This is the outcome of the decline in the relative cost of factors that both countries have experienced in last decades. This implies that the fall in the relative factor costs, with capital becoming secularly cheaper, has been a relevant source of capital accumulation and, thus, of progress in capital intensity. This is specially so in Japan, where the difference between the two scenarios amounts to 50 percentage points of growth, half the actual progress in capital intensity.

In contrast to Japan, in the US it is the evolution of relative factor utilization what explains most of the progress. This is the outcome of the estimated coefficients –recall that the demand-side drivers had a stronger explanatory power in the US than in Japan–, but also of the trajectories of the variable $cur - nr$ (depicted in Figures A1 and A2). In Japan its has an oscillatory evolution, with a fall in the 1990s and a steep rise over the 2000s whereas in the US it is more homogeneous, with a downward trend over the sample period that ends up explaining a significant portion of the evolution of capital intensity. In the absence of this downward trend, capital intensity would have grown by 176.8% rather than by 65.9% (Figure 2b). This means that steady demand-side pressures may be notably influential in the process of economic growth. Therefore, the fact that pressures on the rate of capacity utilization have been systematically less binding than pressures on the employment rate (as uncovered by the steady fall in the relative factor utilization variable $cur - nr$) appears as a clear-cut disincentive for US firms to keep investment at the same path than the Japanese firms, where this was not occurring.

Another interesting result arises when technology is not allowed to progress. The outcome of this simulation clearly uncovers the dramatic opposite influence of a factor-biased technological change that is capital saving in Japan, but labor-saving in the US (Figure 2c). This implies that capital intensity has been hindered by technical progress in Japan –had it not been there, capital intensity would have grown by 162.3%, rather than by 98.9%–, and has been boosted in the US, where in the absence of labor-saving progress in technology would have left capital intensity virtually unchanged.

Figure 2: Simulation results.

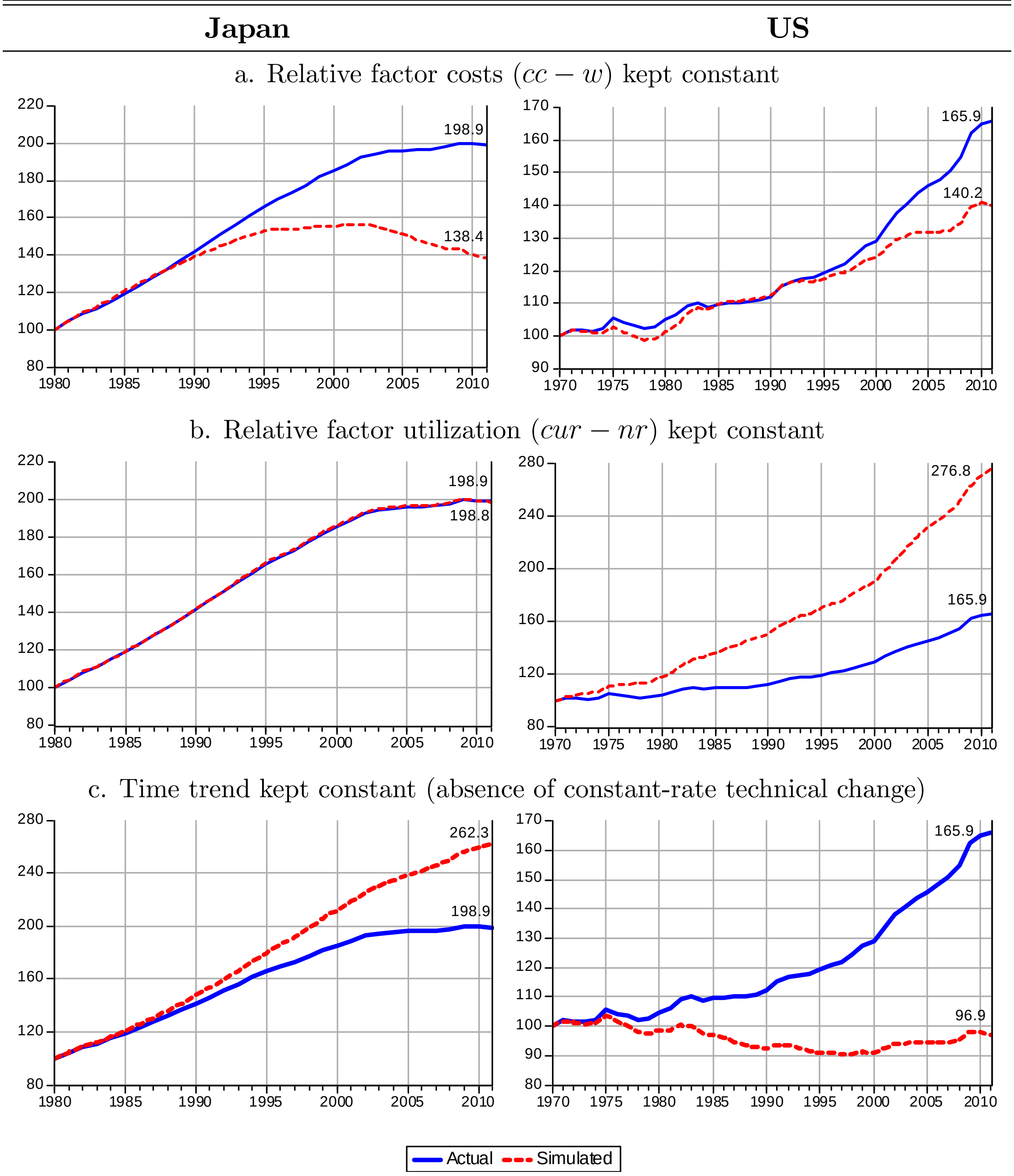
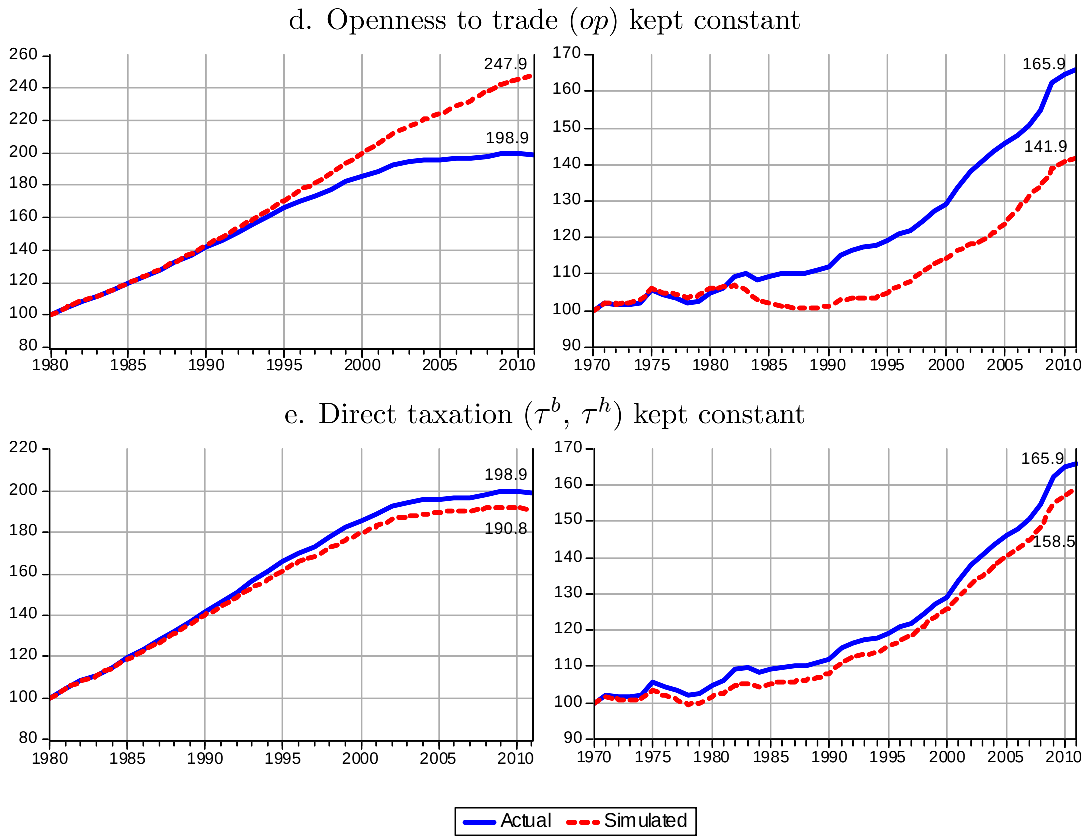


Figure 2 *(cont.)*

Japan **U.S.**



One of the critical changes experienced by the Japanese economy in last decades has been a globalization process by which the degree of openness to trade, which had already increased in the 1960s and 1970s, doubled between 1980 and 2011. Our simulations show that this process has been as influential as the evolution of relative costs in shaping the trajectory of capital intensity during this period, but in the opposite sense (Figure 2d): in the absence of such opening process, capital intensity in Japan would have progressed by almost 150% (instead of close to 100%). The results for the US are not comparable, since they are based on keeping the growth rate of openness at its large 1970 value (6.5%) relative to an average growth rate of 2.8% during the sample period. The result from this simulation is that had the exposure to international trade kept growing so rapidly, capital intensity would have been lower. Thus, the negative impact of trade on capital intensity is a common feature of Japan and the US.

Finally, direct taxation has negative effect on the evolution of capital per worker. As shown in Figures A1 and A2, taxes have not grown in last decades. Had they stayed at their 1970 and 1980 values, capital intensity would have grown around 8 percentage points less in each country (i.e., 91% in Japan, rather than 99%, and 58% in the US, rather than

66%).

6 Concluding remarks

This paper focuses on a generally unattended issue: the determination of capital intensity. The capital-per-worker ratio is usually considered as an input in growth accounting, and the empirical assessment of its determinants has been a rather neglected topic.

We develop an analytical setting that extends, with demand-side considerations, the models in Antràs (2004) and McAdam and Willman (2013). In this setting, we estimate empirical models for capital intensity that include supply- and demand-side determinants, technology, and relevant controls related to international trade and the tax system.

We confirm the relative cost of production factors as a main supply-side driver of capital intensity yielding, also, plausible estimates of the elasticity of substitution between capital and labor. The two proxies accounting for the demand-side pressures are also found relevant in the US, and partly so in the case of Japan. This calls for a wider than usual approach when working with production factor demands and, as we have done in this study, when examining the determinants of capital intensity.

Along the lines of recent works stressing the relevance factor-specific efficiency growth –Acemoglu (2003), Klump et al. (2012), McAdam and Willman (2013)–, the different nature of technological change in Japan and the US has been also uncovered. As we have argued, this difference provides an explanation of the contrasted evolution of capital intensity in these economies, and even of their diverse growth models; Japan having been, traditionally, one of the great world net exporters and the US having been, and being, one of the greatest net importing economies.

Policywise, our results warn about a simplistic design of policies exclusively based on supply-side considerations. On the supply-side, our findings call for a careful design of policies affecting firms' decisions on investment and hiring. The reason is that these policies crucially affect the procyclical behavior of the ratio between the rates of capacity utilization and (the use of) employment, since in economic expansions the capacity utilization rate tends to increase proportionally more than the employment rate, probably because in the very short run it is less costly to use already installed capacity than to hire new workers. From this point of view, the design and implementation of labor market reforms should be closely connected to investment policies, a conclusion already obtained in Sala and Silva (2013) in their analysis of labor productivity.

In general, demand-side forces are not included in economic growth models. Nonetheless, our results reveal the incidence of demand-side pressures on the evolution of capital intensity, specially in the US, where the growth path of capital intensity could have been much steeper without the fall in the relative factor utilization rate. Considering that capital intensity is a key growth driver, this result has important policy implications in the fields of economic growth and development.

To conclude, there are three sources of potential improvements in this analysis. The first one is the introduction of imperfect competition in factor markets. There is work done regarding the labor market (Raurich *et al.* 2012), but financial markets, and the associated mark-up over the marginal product of capital, should simultaneously be evaluated. The second one, as explained in León-Ledesma *et al.* (2010), is to block potential identification problems by moving from single-equation estimates of the elasticity of substitution to multi-equation systems in which output and all factor demands are modeled. The third avenue for improvement is to relax the assumptions on technological change and devote further effort in modeling efficiency progress by explicitly considering R&D and innovation. Future research will have to face these compelling challenges.

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Appendix

Table A1. Unit root tests of main variables.

	Japan					US				
	ki	$cc-w$	$cur-nr$	op	Δhrs	ki	$cc-w$	$cur-nr$	op	Δhrs
ADF	0.33 $I(1)$	0.71 $I(1)$	−1.11 $I(1)$	0.03 $I(1)$	−4.80 $I(0)$	3.18 $I(1)$	−0.94 $I(1)$	−2.45 $I(1)$	−0.25 $I(1)$	−4.95 $I(0)$
KPSS	0.72 $I(1)$	0.70 $I(1)$	0.20 $I(0)$	0.61 $I(1)$	0.13 $I(0)$	0.78 $I(1)$	0.54 $I(1)$	0.75 $I(1)$	0.81 $I(1)$	0.23 $I(0)$
Result	$I(1)$	$I(1)$	—	$I(1)$	$I(1)$	$I(1)$	$I(1)$	$I(1)$	$I(1)$	$I(1)$

ADF = Augmented Dickey-Fuller Test. Hypothesis of unit root.

1% and 5% critical values = -3.66 and -2.96 respectively.

KPSS = Kwiatkowski-Phillips-Schmidt-Shin Test. Hypothesis of stationarity.

1% and 5% critical values = 0.739 and 0.463 respectively.

Table A2. Misspecification tests.

	Japan				US			
	Model 1		Model 2		Model 1		Model 2	
	OLS	TSLS	OLS	TSLS	OLS	TSLS	OLS	TSLS
SC [$\chi^2(1)$]	0.01 [0.931]	0.08 [0.772]	1.53 [0.216]	0.64 [0.425]	0.52 [0.470]	0.003 [0.960]	0.01 [0.916]	2.17 [0.141]
HET [$\chi^2(a)$]	9.83 [0.364]	7.55 [0.580]	8.05 [0.529]	8.04 [0.530]	10.9 [0.615]	9.98 [0.696]	10.2 [0.602]	9.03 [0.700]
ARCH [$\chi^2(1)$]	0.52 [0.470]	1.88 [0.170]	0.09 [0.770]	0.04 [0.853]	1.95 [0.163]	1.61 [0.204]	0.16 [0.693]	0.06 [0.801]
NOR [JB]	1.57 [0.457]	1.87 [0.392]	1.46 [0.481]	0.93 [0.627]	0.47 [0.791]	1.62 [0.445]	0.45 [0.799]	1.25 [0.534]

Notes: *p-values* in brackets.

SC = Lagrange multiplier test for serial correlation of residuals;

HET = White test for Heteroscedasticity; NOR = Jarque-Bera test for Normality

ARCH = Autoregressive Conditional Heteroscedasticity; a = number of coefficients in estimated equation (intercept not included).

Figure A1: Actual evolution of the main variables in Japan. Index 100 in 1980.

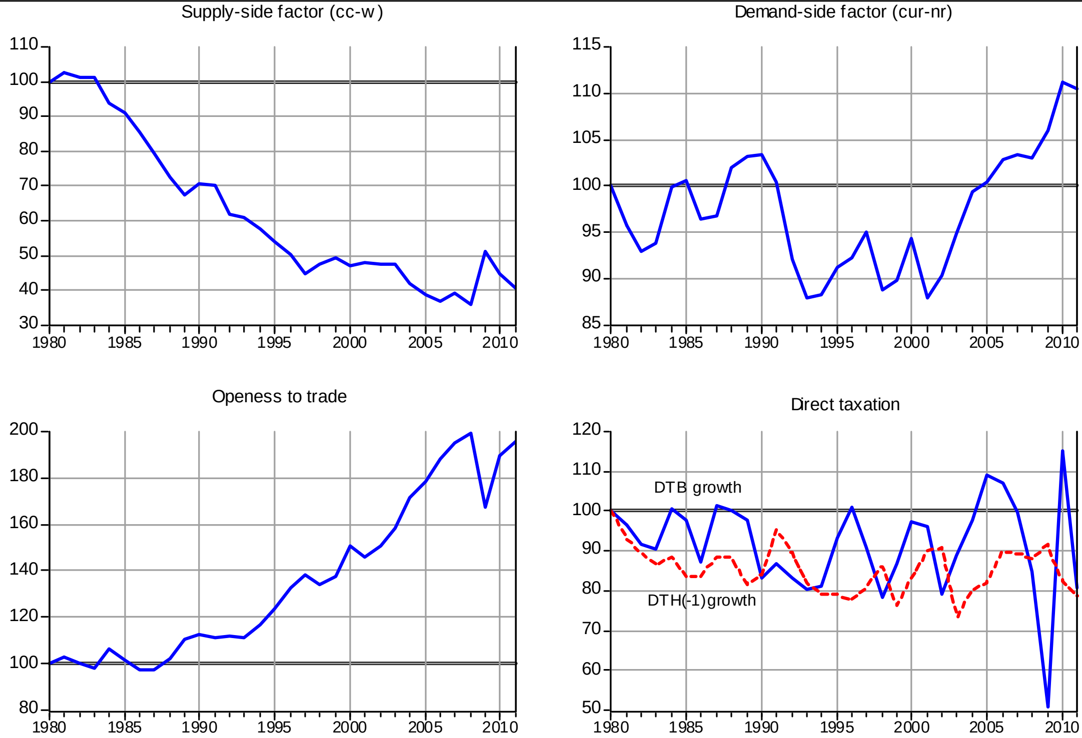
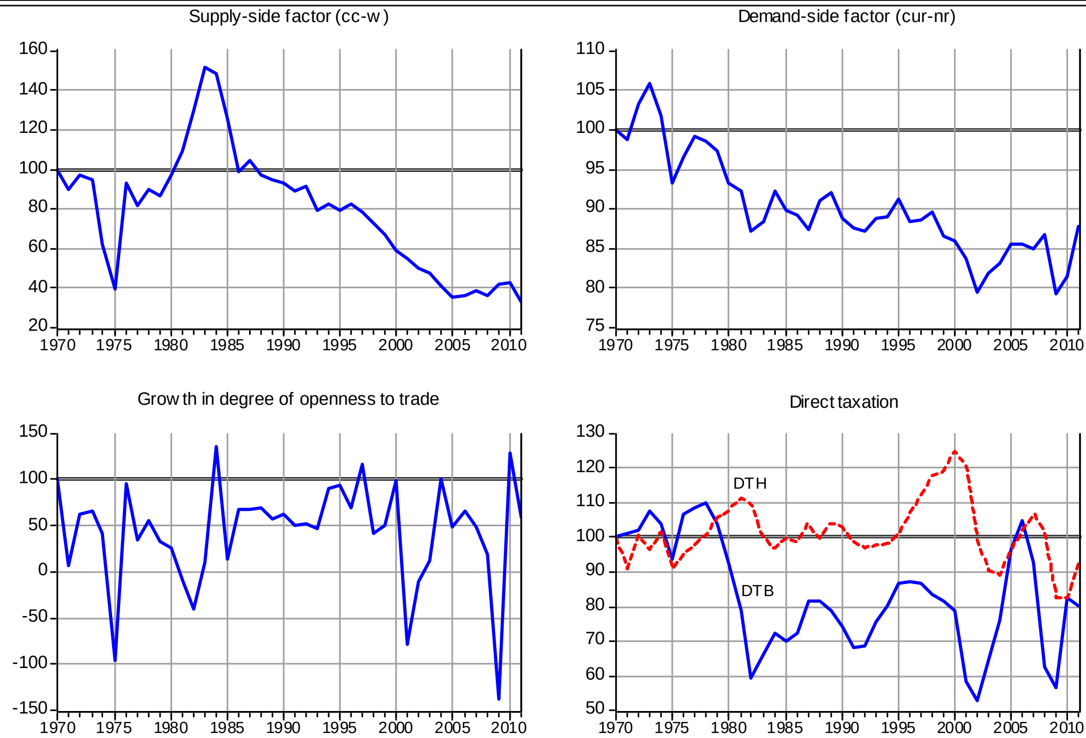


Figure A2: Actual evolution of the main variables in the US. Index 100 in 1970.



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