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Is Misallocation Higher in France than in the United States ?

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Abstract

In this paper, we apply the Hsieh and Klenow (2009) methodology to French microdata on manufacturing firms to quantify the potential extent of intra-industry misallocation in France versus the United States. In contrast to what has been found for developing countries, such as China, India and some countries in Latin America, we do not find any sizeable "efficiency gap" between France and the U.S. in the manufacturing industry. This new evidence is robust to a series of tests addressing both measurement and specification issues. In light of recent advances in the fields of productivity and misallocation, and in particular Bartelsman et al. (2013), we also discuss to what extent our new empirical findings challenge the established view on which continental European economies have higher input and output distortions than the American economy.

Keywords: Misallocation; Productivity, Manufacturing; Firm-level data, France

JEL Classification Codes: O47, O57

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1 Introduction

An increasing number of researchers in the field of productivity analysis are devoting their efforts to analyzing the role of market distortions in shaping international productivity gaps¹. A key contribution in the productivity analysis field is a paper by Hsieh and Klenow (2009) (HK afterwards), which has provided scholars with a new methodology for indirectly inferring the impact of misallocation on total factor productivity (TFP) from longitudinal micro-level databases. Using data on China, India and the U.S., HK showed that moving China and India to "U.S. efficiency" would allow for TFP gains of 30 to 50 percent in China and of 40 to 60 percent in India. Further evidence using the same methodology indicates that large potential aggregate TFP gains due to removing misallocation have been recently accumulated on other developing countries, particularly Latin American ones².

While it is not surprising to find such large efficiency gaps between the U.S. and developing economies, one may wonder whether misallocation is an important source of TFP differences among developed economies. Indeed, because those economies are closer to each other in terms of technological abilities, one may even expect that misallocation explains much of the TFP gap between them.

In this paper, we propose applying the HK methodology on the French economy. France is a good case for study because one would expect to find sizeable misallocation gaps relative to the U.S. economy. First, since the 1990s, France's economy has significantly under-performed compared to the economy of the U.S in terms of aggregate TFP (see Van Ark et al. (2008) and Inklaar and Timmer (2008)). In contrast, resource reallocations have been identified as a key driver of the resurgence of productivity growth in the U.S. economy since the early 19th century (Olley and Pakes (1996), Foster et al. (2001)). Second, similar to most of its European partners, France has a highly regulated market compared to that of the US. (see for instance, Crafts (2006)). These regulations, which concern both input and output markets, have been emphasized as potential key factors driving Europe's low growth performance compared to the U.S. since the 19th century (see in particular Aghion et al. (2007), Arnold et al. (2011)).

The above-mentioned evidence supports the working assumption that misallocation may be key to explaining the under-performance of the French economy compared to the U.S. economy over the last two decades. However, none of the previously mentioned studies allow for a global quantification of the extent of misallocation in France relative to the U.S. economy³. The

¹see Restuccia and Rogerson (2013) for a recent overview.

²References will be detailed in Section 2 *infra*.

³A noticeable exception is a recent paper by Bartelsman et al. (2013)(BHS afterwards), which relies on a slightly different methodology than that of HK to compare the amount of intra-industry misallocation between the U.S. and a set of European countries. In this

present paper attempts to fill in the above-mentioned gap in the literature by offering the first quantification of misallocation in France relative to the U.S., which is directly comparable to the benchmark quantifications that HK derived for the American, Chinese and Indian economies.

For that purpose, we rely on a micro dataset on French manufacturing firms from the French Annual Census of Manufacturers collected by INSEE. Our paper will assess the extent to which the structural differences between our dataset and the ones used by HK cause any specific bias in our relative estimates of misallocation. The paper will also assess whether the HK theoretical framework is relevant for picking up some of the relationship in France between market distortions and misallocation. Finally, we will devote part of the discussion to the current debate on the efficiency gap between the European and the U.S. economies by comparing our new evidence to the evidence recently added to the literature, particularly by Bartelsman et al. (2013), Van Ark et al. (2008), and Rodrik (2013).

The rest of the paper is organized as follows. Section 2 describes the main steps of the HK methodology. Section 3 presents the micro-data on French manufacturing firms used for our analysis. Section 4 displays the comparative results for France. Sections 5 and 6 test, respectively, the robustness of our empirical analysis and the relevance of the HK theoretical framework in the French case. Section 7 provides a general discussion on productivity and misallocation, and our conclusions and perspectives for further work are presented in a final Section.

2 The HK methodology

This section describes the main steps of the methodology by Hsieh and Klenow (2009), incorporating their correction appendix (Hsieh and Klenow (2013)), for revealing the impact of misallocation on aggregate TFP. Basically, HK relies on a Melitz-type model in which firms are assumed to differ not only in their efficiency levels (as in Melitz, 2003) but also in terms of the output and capital distortions they may face.

Specifically, the HK theoretical framework is composed of a closed economy with two primary inputs, labor and capital, as well as S differentiated intermediate goods industries and one single homogeneous final goods industry. The supply side of the economy is vertically integrated in the sense that the primary inputs are only used in the intermediate goods industries, while the final good industry is a "pure assembly" sector that combines the S different sets of differentiated intermediate goods to produce a (homogeneous) final output. On the demand side, final producers compete on a perfectly competitive market to sell their products to a representative final consumer,

paper, a section will be dedicated to comparing the results obtained through the HK and the BHS methodologies.

while intermediate firms compete on monopolistic competitive markets to sell their differentiated outputs to final producers.

These assumed market structures are consistent with the production technologies specified by HK for the homogenous final goods and the differentiated intermediate goods. The production function for the final goods is a Cobb-Douglas aggregator of the S intermediate inputs, each of which is a CES aggregate of the differentiated individual intermediate goods produced in the industry. Within each of the S industries, the production function for the individual intermediate input i is a firm-specific Cobb-Douglas technology that combines primary inputs only. Specifically, the production function of intermediate goods firm i operating in industry s is:

$$Y_{is} = A_{is} K_{is}^{\alpha_s} L_{is}^{1-\alpha_s} \quad (1)$$

where A_{is} is the firm-specific productivity parameter, Y_{is} , K_{is} , and L_{is} are, respectively, the output, capital input and labor input of firm i operating in industry s , and α_s is the industry-specific capital share.⁴

HK introduces idiosyncratic markets distortions in this Melitz-type framework by assuming that firms face different restrictions on both their output and input markets. Denoting τ_{Yis} , the firm-specific distortions that increase the firm's marginal products of capital and labor in the same proportion, and τ_{Kis} , the firm-specific capital distortions that raise the firm's marginal product of capital relative to labor, market distortions manifest in the profit equation of firm i operating in industry s as follows:

$$\pi_{is} = (1 - \tau_{Yis})P_{is}Y_{is} - wL_{is} - (1 + \tau_{Kis})RK_{is} \quad (2)$$

where P_{is} is the output price fixed by the firm, R is the rental price of capital and w is the common wage all firms face.⁵

Using standard profit maximization rules on monopolistic competition markets, and solving for the equilibrium allocation of resources across sectors, HK derives a number of interesting properties about the *physical* productivity and *revenue* productivity of firms operating in intermediate goods sectors.

⁴In the HK model, input shares are supposed to vary across industries but not across firms within the same industry framework. This assumption directly impacts the measure of relative capital distortions in the HK framework and will be discussed later in the paper.

⁵The simplifying assumption that all firms face the same wage means that a labor market distortion will manifest as a low capital market distortion in the HK framework. In such a case, the idiosyncratic input distortion would *lower* the firm's marginal product of capital with respect to labor.

Let us denote $TFPQ_{is} \equiv A_{is}$ the physical productivity of firm i operating in industry s , and $TFPR_{is} \equiv (P_{is}Y_{is})/K_{is}^{\alpha_s}L_{is}^{(1-\alpha_s)}$ to its revenue productivity. HK shows that the TFPR would not vary across firms within a same industry unless firms face capital and/or output distortions⁶. Intuitively, in the absence of distortions, more capital and labor would be allocated to firms with higher TFPQ to the point where their higher output results in a lower price and the same TFPR as that found for smaller firms. In contrast, in the presence of distortions, a high TFPR is a sign that the firm confronts barriers that raise its capital and labor, rendering the size of the firm less than optimal.

At the aggregate level, the presence of firm distortions translates into a lower industry TFP. This can be illustrated by comparing the expression for industry TFP in the absence of distortions with the corresponding expression in the presence of distortions. First, in the absence of distortions, the "efficient" industry TFP is straightforwardly given by the CES aggregate of each individual firm TFPQ operating in the industry:

$$TFP_s^{\text{"efficient"}} \equiv A_{ms} = \left[\sum_{i=1}^{M_s} A_{is}^{\sigma-1} \right]^{1/(\sigma-1)} \quad (3)$$

where σ is the elasticity of substitution of any pair on intermediate inputs produced in industry s , M_s is the total number of individual firms producing differentiated goods in industry s , A_{si} is the physical productivity (i.e., TFPQ) of the individual firm i operating in industry s , and A_{ms} is the aggregate and average physical productivity in industry s .

Second, in the presence of firm distortions, industry TFP is itself distorted, as it depends both on the firms' absolute physical productivities and on their relative revenue productivities. Indeed, high-productivity firms that confront distortions (i.e., firms characterized by both high TFPQ and high TFPR), will be less than optimal. In contrast, low-productivity firms that benefit from distortions (i.e., firms characterized by both low TFPQ and low TFPR), will be more than optimal. In this context, "inefficient" industry TFP is given by:

$$TFP_s = \left[\sum_{i=1}^{M_s} \left(A_{is} \frac{TFPR_{ms}}{TFPR_{is}} \right)^{\sigma-1} \right]^{1/(\sigma-1)} \quad (4)$$

⁶For a demonstration, see Hsieh and Klenow (2009, page 1,410) and their correction appendix (Hsieh and Klenow (2013))

where $TFPR_{is}$ is the revenue productivity of the individual firm i operating in industry s , and $TFPR_{ms}$ is the average revenue productivity in industry s .

Intuitively, equation (4) implies a negative relationship between the degree of dispersion of firms' TFPR within an industry and the degree of inefficiency in the industry TFP. This property can be fully established in a special case in which output distortions prevail and the distributions of firms' TFPQ and TFPR are jointly log-normal

$$\log TFP_s = \frac{1}{\sigma - 1} \log \left(\sum_{i=1}^{M_s} A_{is}^{\sigma-1} \right) - \frac{\sigma}{2} \text{var}(\log TFPR_{is}) \quad (5)$$

meaning that the negative effect of distortions on aggregate TFP can be summarized by the variance of log TFPR, which reveals the extent of misallocation due to the dispersion of marginal products⁷.

The next step of the HK methodology is choosing a benchmark value for the dispersion of TFPR in order to accurately evaluate the extent of misallocation in any given country. Obviously, if the HK model did not omit any factors (other than modeled market distortions) susceptible to generating gaps in marginal products, and if firm-level data sets were not subject to measurement errors, the accurate benchmark value for the variance of TFPR would be zero. However, because the presence of omitted factors and measurement errors are both likely, the choice of a relevant benchmark becomes critical.

HK solves this issue by choosing as a benchmark the dispersion of TFPR observed in the U.S. economy. HK's basic idea is that if omitted factors and measurement errors do not differ much across countries, then a positive deviation of the dispersion of TFPR between any given country and the U.S. can be interpreted as a sign of greater market distortions in that country's economy compared to the U.S. economy.

Implementing Equation (4) for India and China using the U.S. as a benchmark, HK found that moving to "U.S. efficiency" would increase TFP at by 30 to 50 percent in China and by 40 to 60 percent in India. Applying the HK methodology to other developing countries, the recent literature has consistently found sizeable potential aggregate TFP gains by removing misallocation in a variety of Latin American countries. For example, these studies found that both Bolivia and Uruguay could increase their manufacturing TFP by approximately 10 to 15 percent by equalizing the marginal products of capital and labor of their respective firms to the

⁷For more complex formulae in the general case in which both input and output distortions prevail, see Hsieh and Klenow (2013)

extent of the U.S. plants in 1997 (see Machicado and Birbuet (2012) for Bolivia and Casacuberta and Gandelman (2012) for Bolivia). Camacho and Conover (2010) and Neumeyer and Sandleris (2010) found fewer efficiency gains for Colombia and Argentina. Specifically, both studies found potential TFP gains relative to the U.S. of approximately 6 to 8 percent. However, both studies acknowledged some potential downward bias in their estimates of the TFPR dispersion⁸.

What should we expect when applying for the first time the HK methodology to a developed country, in this case, France? On the one hand, we must note that the efficiency gap between France and the U.S. is much smaller than the efficiency gap between China or India (or some Latin American countries) and the U.S. (as France can be seen as relatively undistorted compared to these developing countries). On the other hand, as the issue of omitted factors and measurement errors is likely to be less severe in the case of a comparison between similarly developed economies, we should be more confident in the fact that a revealed "efficiency gap" would indeed reflect differences in market distortions rather than differences in measurement errors or omitted factors.

The next section presents the dataset we used for France to quantify the extent of misallocation along the lines of the HK methodology.

3 French data

Our main source for French data is the confidential *Enquete Annuelle d'Entreprises (EAE)*, an annual survey conducted by the French National Statistical Office (INSEE) that gathers information from the financial statements and balance sheets of all individual manufacturing firms with at least 20 employees. The firms surveyed account for approximately 25% of the total number of French manufacturing firms and approximately 85% of total value added in manufacturing. The raw data consist of approximately 20,000 firms in each year over the period 1990 to 2007. In comparison, the main source for U.S. data used by HK is the quinquennial Census of Manufactures (CM) conducted by the U.S. Bureau of the Census from 1977 to 1997. This survey covers all manufacturing *plants* (but not firms), for more than 160,000 plants in each year after dropping the smallest units with limited production data (Administrative records).

At first glance, the French and the U.S. data do not appear comparable. They differ in the unit of observation (plant versus firm), the number of observations (on average, 8 times larger in the U.S.) and in the period of coverage. While these caveats call for attention⁹, they apply to the compara-

⁸In the Argentinean case, the authors show that misallocation increased substantially (to a peak of 12 percent) after the crisis of 2001-2.

⁹and will be addressed in a dedicated robustness checks section.

tive exercise initially performed by HK on the Chinese, Indian and American economies. Specifically, HK drew their data on China from a *firm*-level annual survey conducted between 1998 and 2005 that included approximately 100,000 state and non-state firms in 1998, a number that grew to 200,000 in 2005. HK drew the data for India from an annual *plant*-level census conducted between 1987 and 1995 covering all individual manufacturing plants with at least 50 workers, and a random one-third sample of registered plants with more than 10 workers. This raw data consisted of approximately 40,000 plants in each year. Compared to the Chinese and Indian data, the French data do not appear less suitable for comparison with the U.S. data.

Let us now describe the main firm-level variables that we used. We use the firm's industry (at the four-digit level, as in the HK paper), labor compensation, value-added (excluding taxes), capital stock and age (based on first entry into the EAE survey¹⁰). For the U.S. data, we compute labor compensation as wages plus benefits. Concerning capital stocks, the EAE reports information on investment flows by firms. We can then estimate real capital stocks using a permanent inventory methodology (PIM) based on past firm-level investment series and industry-level investment price indexes¹¹.

Finally, let us present the data we used for the industry-level variables. As required by the HK methodology, we must choose values for the following set of industry parameters: The elasticity of substitution of manufactures σ , the rental price of capital R , and the elasticity of output with respect to capital α . (This third industry parameter should be the one to prevail if France's economy was to be liberalized to the extent to which the U.S. economy is). For each of these parameters, we follow as closely as possible the HK original paper. In all industries, we set R to the value of 10%, which corresponds to a rough 5% real interest rate added to a rough 5% depreciation rate, and σ to the value of 3 which corresponds to the lower bound value found by Broda and Weinstein (2006) in their estimates of the substitutability of competing manufactures in a variety of manufacturing industries.

For the elasticity of output with respect to capital, we follow HK in relying on the NBER-CES Manufacturing Industry database, which provides industry capital shares computed as 1 minus the labor share in the corresponding industry in the U.S. However, because of a lack of concordance across the U.S. industrial classification (US-SIC) and the French classifica-

¹⁰Similar to the U.S. Census, the EAE data do not provide information on the birth date of the firm. Thus, we use the date of the firm's first entry into the EAE data (starting in 1984) to identify the firm's birth year. Specifically, we follow HK in assuming that the birth date is the year the plant first appeared in the survey, minus three years

¹¹We can alternatively take the average of the net book value of fixed capital at the beginning and end of the year, as HK did. However, this estimation method would reduce the number of observations in the early period of our coverage because book values of tangible assets were not available in the EAE dataset for firms under 100 employees until 1994. We reserve this alternative measure for a robustness check.

tion (NAF rev 1 2003), we rely on the U.S. capital shares at the three-digit level instead of at the four-digit level, as HK did¹² Finally, we use as industry output shares the French industry value added shares computed from the EAE database.

On the basis of these industry parameters and firm data, we can estimate the distortions and productivity for each French firm in each year. We can then use those estimates to infer potential gains from reallocation in the French economy. The results of these computations are presented in the next section.

4 French manufacturing misallocation in international perspective

According to our methodology, *revenue* productivity and *physical* productivity for each firm can be inferred from the following equations:

$$TFPR_{is} \equiv \frac{P_{is}Y_{is}}{K_{is}^{\alpha_s} L_{is}^{1-\alpha_s}} \quad (6)$$

$$TFPQ_{is} \equiv A_{is} \equiv \frac{Y_{is}}{K_{is}^{\alpha_s} L_{is}^{1-\alpha_s}} = k_s \frac{(P_{is}Y_{is})^{\frac{\sigma}{\sigma-1}}}{K_{is}^{\alpha_s} L_{is}^{1-\alpha_s}} \quad (7)$$

with k_s a scalar of unobservable variables, which can be set equal to 1 without affecting relative productivities (and consequently, reallocation gains).

Equations (6) and (7) show how, in the HK framework, real output Y_{si} can be inferred from the observed nominal output ($P_{si}Y_{si}$) simply by assuming an elasticity of demand. This is what makes this framework so suitable for distinguishing a firm *revenue* and *physical* productivities despite the lack of information on firm output prices.

We estimate both equations (in log) using (the log of) our previously defined firm-level data, particularly the firm value added as the nominal output, $P_{si}Y_{si}$ and the firm capital stock as the capital input K_{si} . However, for the labor input, we follow HK's empirical strategy of using the wage bill

¹²Camacho and Conover (2010) perform this exercise in their paper on Colombia. They show how the estimated extent of misallocation substantially varies depending on the assumed capital shares. In particular, they show that the estimated TFP gains (from equalizing TFPR within industries) are significantly smaller when U.S. capital shares are used instead of Colombian capital shares. On average, those TFP gains are approximately 48% in Colombia when computed using U.S. capital shares (at the 3-digit level in lieu of the 4-digit level, due to industrial classification correspondence issues), and approximately 77% when computed using Colombian capital shares (at the 4 digit level).

Table 1: Dispersion of TFPQ

France	1998	2001	2005	China	1998	2001	2005
S.D.	0.90	0.94	0.93	S.D.	1.06	0.99	0.95
75-25	0.99	1.03	1.03	75-25	1.41	1.34	1.28
90-10	1.92	2.06	2.05	90-10	2.72	2.54	2.44
N	18,438	18,057	16,250	N	95,980	108,702	211,304
U.S.A.	1977	1987	1997	India	1987	1991	1992
S.D.	0.85	0.79	0.84	S.D.	1.16	1.17	1.23
75-25	1.22	1.09	1.17	75-25	1.55	1.53	1.60
90-10	2.22	2.05	2.18	90-10	2.97	3.01	3.11
N	164,971	173,651	194,669	N	31,602	37,520	41,006

Notes. The statistics are for deviations of $\log(\text{TFPQ})$ from industry means. S.D. is the standard deviation, 75-25 is the difference between the 75th and the 25th percentiles, and 90-10 is the difference between the 90th and the 10th percentiles. Industries are weighted by their value-added shares. N is the number of firms. Values for the U.S., China, and India are from Hsieh and Klenow (2009). Values for France are from the authors' calculations.

instead of the employment level to estimate L_{si} in order to (crudely) control for differences in human capital and worked hours across firms. Finally, we trim the 1% tails of both firm productivities to make the results robust to outliers, as HK does.

The dispersions in French firms ($\log$) TFPQ and TFPR are analyzed in Tables 1 and 2, respectively. Each table displays the standard deviation (S.D.), the ratio of the 75th minus the 25th percentiles, and the ratio of the 90th minus the 10th percentiles of the productivity distribution. In each table, the values for the French economy are compared with the corresponding values for the U.S. economy, drawn from HK. Moreover, to broaden the international comparative perspective, the HK values for China and India are also reported in a dedicated section of each table.

Obviously, the figures reported for France in Table 1 and 2 are similar to the values reported for the U.S. and are significantly below the values found for China and India. The U.S. standard deviation of the $\log$ TFPQ is slightly lower than the corresponding French figure. However, the ratios of 75th to 25th and of 90th to 10th are higher. The presence of more extreme values of the distribution of TFPQ in the U.S. economy compared to the French economy may be because the U.S. data encompass small units, while the French data cover only units comprised of more than 20 employees. Turning to the dispersion of firm ($\log$) TFPR, we found a similar picture. French data reveal a firm TFPR dispersion close to that of the U.S. economy and below the economies of China and India. Finally, in each country, the

Table 2: Dispersion of TFPR

France	1998	2001	2005	China	1998	2001	2005
S.D.	0,45	0,48	0,48	S.D.	0.74	0.68	0.63
75-25	0,45	0,48	0,47	75-25	0.97	0.88	0.82
90-10	0,92	1,00	1,00	90-10	1.87	1.71	1.59
N	18,438	18,057	16,250	N	95,980	108,702	211,304
U.S.A	1977	1987	1997	India	1987	1991	1992
S.D.	0.45	0.41	0.49	S.D.	0.69	0.67	0.67
75-25	0.46	0.41	0.53	75-25	0.79	0.81	0.81
90-10	1.04	1.01	1.19	90-10	1.13	1.64	1.60
N	164,971	173,651	194,669	N	31,602	37,520	41,006

Notes. The statistics are for deviations of log (TFPR) from industry means. S.D. is the standard deviation, 75-25 is the difference between the 75th and the 25th percentiles, and 90-10 is the difference between the 90th and the 10th percentiles. Industries are weighted by their value-added shares. N is the number of firms. Values for the U.S., China, and India are from Hsieh and Klenow (2009). The values for France are from the authors' calculations.

dispersions of TFPR are lower than the ones of TFPQ, which is consistent with (and imposed by) the underlying theoretical model.

All in all, these figures are consistent with the idea that developing countries suffer more from resource misallocation than developed countries such as France and the U.S. However, these figures are not consistent with the idea that the U.S. economy faces less misallocation than a typical continental European economy such as France. According to the index of TFPR dispersion, resource misallocation within manufacturing industries does not appear more severe in France than it does in the U.S.

To rigorously assess the point, we proceed to the next step of the HK empirical methodology, which entails properly estimating the TFP gains that would accrue to a given country if the country fully equalized marginal products across firms in each industry. This step first requires estimating the ratio of actual TFP for each industry, as given by equation (4), to the "efficient" level of TFP, as given by equation (3). The ratio must then be aggregated across sectors using a Cobb-Douglas aggregator, with the industry value added shares as weights. Specifically, we compute:

$$\frac{Y}{Y_{efficient}} = \prod_{s=1}^S \left[\sum_{i=1}^{M_s} \left(\frac{A_{is}}{A_{ms}} \frac{TFPR_{ms}}{TFPR_{is}} \right)^{\sigma-1} \right]^{\theta_s/(\sigma-1)} \quad (8)$$

where θ_s are the value-added shares of the industries. The results of this exercise are reported in Table 3, along with the corresponding HK values

for the U.S., China and India.

Table 3: TFP gains resulting from Equalizing TFPR within Industries

France	1998	2001	2005	China	1998	2001	2005
%	30.5	27.5	30.5	%	115.1	95.8	86.6
U.S.A.	1977	1987	1997	India	1987	1991	1992
%	36.1	30.7	42.9	%	100.4	102.1	127.5

Notes: Entries are $100(Y_{efficient}/Y - 1)$.

Values for the U.S., China, and India are from Hsieh and Klenow (2009).

Values for France are from the authors' calculations.

As expected, in Table 3, the French figures are similar to the American ones. Both countries exhibit values of misallocation gains far below the corresponding values for developing countries such as China and India. Furthermore, France exhibits lower TFP gains due to misallocation than does the U.S.

Finally, we perform the last step in the HK methodology, which entails expressing the percentage of TFP gains in each country relative to those in the U.S. This step allows us to assess to what extent TFP in a country would hypothetically increase if the country moved to the "U.S. efficiency" level. In Table 4, we report the results of this exercise for France using as a benchmark either the 1997 TFP gains in the U.S. (as in the original HK paper) or the 1987 TFP gains in the U.S., which corresponds to the conservative choice in our case ¹³.

Table 4: French TFP gains derived from Equalizing TFPR relative to U.S. Gains

	1998	2001	2005
Benchmark U.S. 1997	-4.4%	-2.4%	-8.7%
Benchmark U.S. 1987	-0.2%	-2.4%	-0.2%

Notes: Entries are the ratio of $Y/Y_{efficient}$ for France to the benchmark U.S. ratio minus 1, multiplied by 100. The benchmark U.S. ratio is computed either as the 1997 ratio (first row) or as the 1987 ratio (second row).

¹³In the original HK paper, the choice of the year 1997 as the benchmark year would be seen as conservative because 1997 is the year for which the potential U.S. TFP gains derived from the removal of misallocation are the highest. Consequently, this choice would minimize the TFP gains for China and India relative to those for the U.S. However, in comparing France and the U.S., the conservative choice consists in using 1987 as the benchmark year (when U.S. TFP gains were the lowest)

According to the figures in Table 4, hypothetically moving France to the "U.S. efficiency level of 1997" may *decrease* (rather than increase) TFP by approximately 5 percent. However, looking at the conservative case, the average efficiency gap between France from 1998 to 2005 and the U.S. in 1987 is less than 1 percent. We thus cautiously conclude that the HK methodology does not allow for comparison of the allocative efficiency of the French and American manufacturing industries.

5 Measurement issues

Our results on the reallocation gains in France relative to the U.S. may be biased due to differences between the French and U.S. data. In this section, we check for the robustness of our results to some expected downward biases in our estimates of French TFPR dispersions.

Analysis of the TFPR variance

Our first concern is whether the difference in the sample structure of French and U.S. data can induce a downward bias in the French TFPR dispersions. To shed some light on this issue, we compute how much of the within-year and industry TFPR dispersion in France is due to differences in firm size, firm age and firm structure (i.e., mono- versus multi-plants).

The results of this exercise are reported in Table 5. Specifically, columns 1 and 2 provide, respectively, the coefficients and the standard errors of a linear regression of the intra-industry variance of log of firm TFPR on firm size, firm age, and firm structure. The regression also includes a full set of year dummies, which are all significant but whose coefficients and standard errors are not reported (to save space). Column 3 provides the percentage of the intra-industry variance of TFPR (within-year), which is explained by the age, size and multi-plant structure of firms. The cumulated contribution of these three variables to the variance is reported in the last row of the table.

Table 5: Analysis of the French intra-industry TFPR dispersion

	Size	Age	Multi-plant	total
% of the variance	1.00%	4.95%	0.05%	6,01%

Notes. The dependent variable is the variance of the deviation of the firm log TFPR from its industry average. The explicative variables are size quartiles, age quartiles, and a dummy variable, which takes the value 1 for firms with more than one plant and the value 0 for mono-plant firms. The regression includes a full set of year dummies (not reported in the table).

Table 5 shows that the variance of log TFPR is weakly impacted by

firm-level variables. In particular, the variance of intra-industry, intra-year log TFPR is larger within the sub-groups of smaller firms, younger firms, and multi-plant firms. The U.S. dataset includes more numerous small firms than the French dataset (which covers only firms of more than 20 employees), which can introduce a downward bias in the estimated TFPR dispersion of French firms relative to U.S. firms. However, the fact that the French dataset covers *firms* while the U.S. dataset covers *plants* is not likely to introduce any bias in the estimated firm TFP dispersion. Indeed, the plant structure of French firms (mono- versus multi-plants) has only a weak impact on the variance of log TFPR (approximately 0.05%). Moreover, dispersion across multi-plant firms is larger than dispersion across mono-plant firms. Interestingly, the firm-level variable, which has the strongest impact on the French TFPR dispersion, is the age of the firm (not its size). The former variable (age) explains almost 5% of the intra-industry variance of log TFPR, while the latter (size) explains only 1% of it. However, the firm-level variables do not explain much more than 6% of the intra-industry variance of log TFPR. Thus, it is unlikely that the differences between the French and U.S. data regarding the unit surveyed affect the estimated TFPR dispersions.

Trends in Misallocation

A second issue is whether the TFPR dispersion in France exhibits a decreasing trend over the period of coverage, which could introduce a downward bias in the estimated intra-industry variance of log TFPR. If such a trend existed, this could partly explain why we do not find an efficiency gap between the French manufacturing data between 1998 and 2005 and the U.S. manufacturing data between 1977 and 1997.

In Figure 1 above, we then trace the evolution of TFPR dispersion over our period of coverage: 1990-2007. The values reported in Figure 1 correspond to the weighted sum across industries of the variance of the deviation of the firm log TFPR to its industry average. Figure 1 shows an *increasing* trend in the intra-industry TFPR dispersion, decreasing the likelihood of a downward bias in firm TFPR dispersion in France due to a difference in the period of coverage between French and U.S. data.

Alternative measure of capital stocks

We may also want to check to what extent our results are sensitive to alternative measures of key firm-level and industry-level variables. Here, our main concern is the way we estimated firm capital stocks. We relied on real capital stocks inferred from the past investment series of firms¹⁴ following a traditional perpetual inventory method (PIM). Specifically, we computed:

¹⁴Actually, we are able to trace firm investments back to 1984 or, for firms started after 1984, back to their date of entry in the dataset.

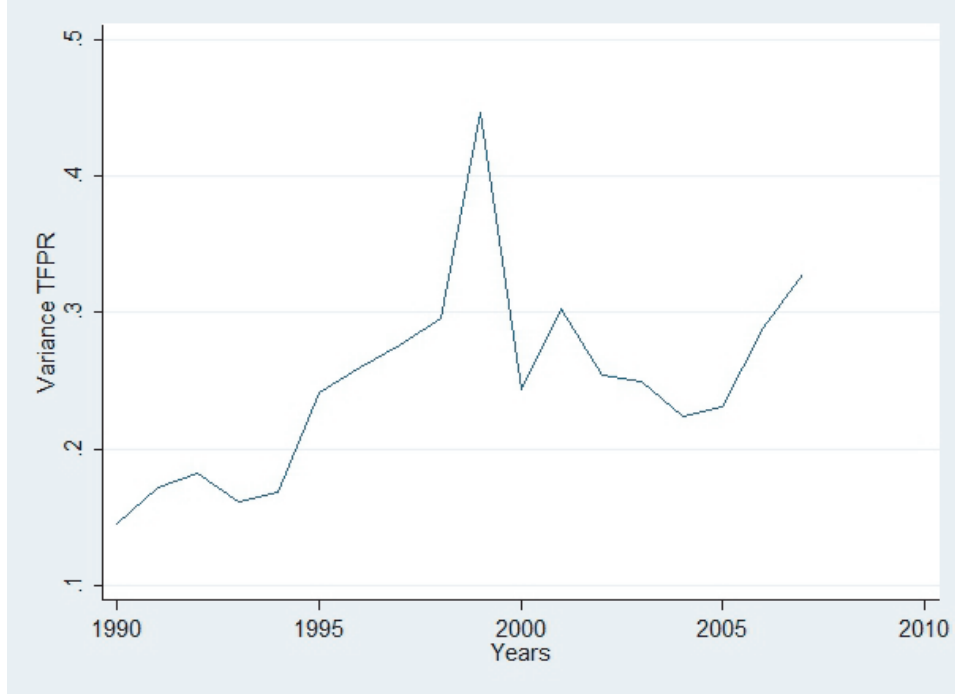


Figure 1: Evolution of the Dispersion of TFPR.

$K_{i,t} = (1 - \delta_{S,t-1})K_{i,t-1} + I_{i,t}/P_{I,S,t}$ where $K_{i,t}$ is the capital stock of firm i at date t , $\delta_{S,t-1}$ is the depreciation rate at the date $t-1$ in industry S , $I_{i,t}$ is the nominal amount invested by firm i at date t , and $P_{I,S,t}$ is the price index of investment in industry S at time t . Both investment price indexes and depreciation rates are defined at the 2-digit industrial classification level. While this methodology is known to provide more reliable estimates of firm real capital stocks than the current book values of capital method (as HK did), it may have introduced a downward bias into our French TFPR dispersion relative to what has been observed by HK for the U.S. economy. Indeed, if real capital stocks are a less noisy variable than current book values, it could partially explain why the French TFPR dispersion does not appear to be higher and may even be slightly lower than the U.S. TFPR dispersion. In that respect, it is noticeable that Camacho and Conover (2010), which also used a PIM methodology to compute real capital stocks, found a much lower TFPR dispersion in Colombia compared to other developing countries, such as India and China. To check for this potential bias, we re-estimate our TFPR indexes using the current book value of tangible assets instead of the real capital stocks as our firm capital input variables.

The results, presented in Table 6, show that our estimates for the dispersions of TFPR in France are not significantly affected by the way we measure firm capital inputs. Both the standard deviations and the ratios of

Table 6: French dispersion of TFPR with alternative Capital Stock estimates.

Year	1998	2001	2005
S.D.	0.41	0.45	0.49
75-25	0.46	0.51	0.52
90-10	0.94	1.04	1.07
N	17420	17030	14951

Notes. As in Table 2, statistics are for deviations of $\log(\text{TFPR})$ from industry means. TFPR_{is} is still defined as $Y_{is}/(K_{is}^{\alpha_s} L_{is}^{1-\alpha_s})$ but K_{is} is now directly inferred from book values of tangible assets. S.D. is the standard deviation, 75-25 is the difference between the 75th and the 25th percentiles, and 90-10 is the difference between the 90th and the 10th percentiles. Industries are weighted by their value-added shares. N is the number of firms.

percentiles are close to the ones reported in Table 2.

6 Further Testing of theoretical predictions of the HK model

The finding that, according to the HK methodology, misallocation is not larger in France than it is in the U.S. can be interpreted in two ways. First, it may indicate that, despite stronger market regulation in France, market distortions are not larger in French manufacturing industries than they are in U.S. ones. Alternatively, it may indicate that the HK model does not do a good job in picking up the relationship between policy-induced market distortions and misallocation in a country such as France.

One strategy for assessing these two interpretations is looking for further evidence in the case of France supporting the HK model. Indeed, if the HK model is relevant, we should be able to find some evidence that specific policy regulations or market distortions impact the firm TFPR dispersion in France. We intend to perform this investigation through various experiments.

First, we investigate whether industry-year TFPR dispersions are related to different indexes of market distortion. Indeed, the HK model would predict that TFPR dispersion is larger in more distorted industries. We use as a first rough measure of market distortion at the industry-level both the Herfindahl-Hirschman Index (HHI) of the concentration of the industry and the firm turnover rate. A highly distorted industry is expected to be characterized both by high concentration and low firm turnover. In Table 7, we found no evidence that the HHI index is correlated for the TFPR dispersion¹⁵. However, we found that TFPR dispersion is significantly lower

¹⁵This Regression has been replicated for other concentration indexes, such as the C10

in industries in which the firm turnover rate is higher.

Table 7: Regressions of TFPR dispersion on Sectoral Indexes

	Coef.	Std. Err.
HHI	0.002	0.002
Turnover rates	-0.801 ***	0.131
Entrants Growth	0.027 ***	0.010
Exiters Growth	0.048 ***	0.013
Output Growth	0.027	0.055

Notes. The dependent variables are the dispersions of TFPR. The independent variables are the HHI, the Turnover Rate, the Growth of Entrants and Exiters, and the Output Growth. Regressions are weighted least squares, with the weights being industry value-added shares. The results are pooled for all years.

A second prediction of the HK model is that policy-induced market distortions should distort the relationship between Firm Exit and TFPR. Indeed, in distorted markets, firms with low profitability (i.e., low TFPR) but which benefit from policy support should be able to stay in the market, while firms with high TFPR but that face barriers to growth can be forced to exit the market. Consequently, the HK model predicts that, in distorted markets, firm exit should be poorly correlated with TFPR, while in undistorted markets, firm exit should be highly correlated with TFPR. We test for this prediction by regressing the probability of firm exit based on its physical and revenue productivity. In these regressions, the dependent variables are dummies for exiting firms. The independent variables are the deviation of $\log(TFPR)$ and $\log(TFPQ)$ from industry mean and a quartic function of firm age. Regressions are weighted least squares, with the weights being the industry value-added shares.

The results are presented in Table 8, in which entries are the coefficients on $\log(TFPR)$ and $\log(TFPQ)$, with standard errors shown in parentheses. Table 8 shows that lower $TFPR$ is associated with a higher probability of firm exit. A 1-log-point decrease in TFPR is associated with a 1.7% higher exit probability in France. The corresponding figure found by HK for the U.S. economy is 1.1%, which suggests that low-TFPR firms disproportionately exit the French market compared to low-TFPR firms in the U.S. This phenomenon may be interpreted as a further sign that selection in French manufacturing markets works well compared to selection in U.S. manufacturing markets. Finally, note that in both France and the U.S., firm exit is negatively correlated with firm TFPQ, with a weaker relationship in France when compared to the U.S. A 1-log-point decrease in TFPQ is associated with a 2.6% higher exit probability in France, while the corresponding figure

or the C4, including the number of firms.

found by HK for the U.S. economy is 3.9%¹⁶.

Table 8: Regressions of Exit on Productivity in France

	Coef.	Std. Err.
Exit on TFPR	-0,017 ***	0,001
Exit on TFPQ	-0,026 ***	0,001

Notes. The Dependent variables are dummies for exiting firms. The independent variables are the deviation of $\log TFPR$ or $\log TFPQ$ from the industry mean. Regressions are weighted least squares with the weights being industry value added shares. Regressions also include a quartic function of firm age. The results are pooled for all years.

Our finding of a negative relationship between firm productivity and its probability of exit is consistent with the idea that market selection operates rather efficiently in French manufacturing markets.¹⁷

A last testable prediction of the HK model is that, in the presence of distortions, particularly in input markets, a firm TFPR should be positively related to firm TFPQ growth. Indeed, if capital or labor market distortions restrict the ability of firms to acquire inputs when their efficiency rises, then we would expect firms with rising TFPQ to have higher TFPR. We test for this prediction on our sample of manufacturing firms and plot the result of this simple regression exercise in Figure 2.

Figure 2 exhibits a clear positive correlation between a firm's TFPR in year t and its subsequent TFPQ growth, i.e., between t and $t+1$, supporting the idea that market distortion does indeed prevail in France.

All in all, our investigations in this section support the idea that the HK model has the ability to detect some of the relationship between market distortion and misallocation in a country such as France. Consequently, we must seriously consider our main result that, *according to this model*, the extent of misallocation is not larger in France than it is in the U.S. Below, we compare this result to other evidence on France and the U.S. recently added to the literature.

¹⁶Note that if the true relationship between TFPQ and firm exit is the same in both countries, it suggests that measurement errors are higher in France than they are in the U.S. (Hsieh and Klenow (2009))

¹⁷This result is partly in line with previous work by Bellone et al. (2008). In this previous work, French firms were also found to be selected in and out of the market depending on their productivity records, which is a sign of market efficiency. However, the previous research also found that firm productivity is becoming more critical to firm survival over time. Thus, firm productivity is a good predictor of the probability of exit of old firms, but not of the probability of exit of young firms. Conversely, the selection effect of industry characteristics, both in terms of industry concentration and turbulence, is much larger on young firms than it is on old firms. In light of the HK theoretical framework, these previous results may suggest that young firms in France face higher market distortions than do mature firms. It may be worthwhile to investigate this assumption in future research.

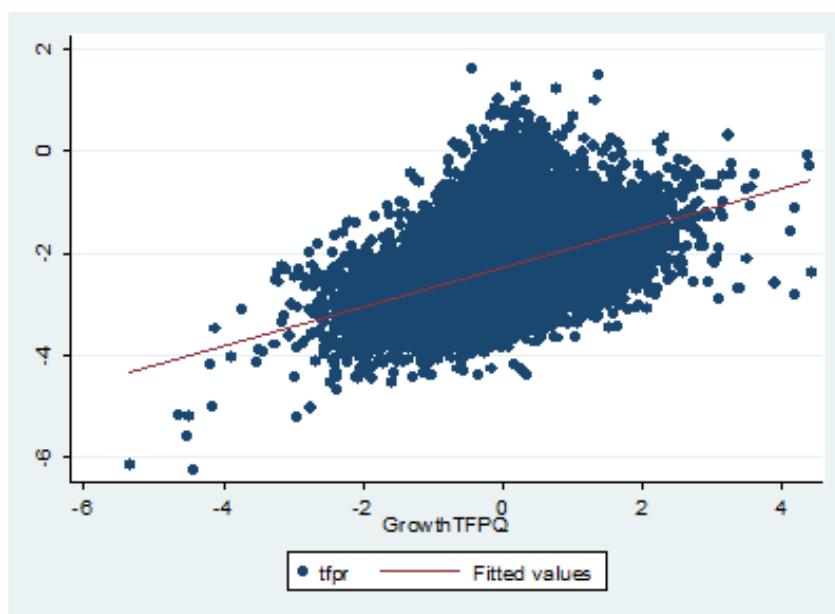


Figure 2: TFPR on TFPQ Growth

7 Related new findings in the International productivity gaps literature

In this paper, our basic finding is that, according to the HK methodology, France is similar to the U.S. in terms of allocative efficiency in manufacturing. This finding challenges established beliefs that continental European economies have higher input and output distortions than does the U.S. economy. Nonetheless, this finding is not at odds with some new evidence recently provided by the literature on productivity and misallocation.

First, Bartelsman et al. (2013) (BHS afterwards) exploit a rich source of data with harmonized statistics on firm-level variation in manufacturing industries on a number of countries (5 industrialized economies, including the U.S. and France, and 3 emerging economies in Eastern Europe) between 1993 and 2001¹⁸. Consistent with our findings, the data show that within-industry labor productivity dispersion in France is slightly lower than it is in the U.S. Specifically, the BHS data show that the standard deviation in revenue labor productivity (firm value added over employment) is 0.53 for the French economy and 0.58 for the U.S. economy. Additionally, the BHS revealed an even larger gap in the within-industry dispersions of TFP in France and the U.S. in favor of France (0.22 standard deviation for France against 0.38 for the U.S.)¹⁹.

However, BHS did not conclude that France faces less misallocation than the U.S., but rather that the within-industry dispersion of productivity may be too sensitive to measurement error. BHS proposes instead using, as a preferred measure of misallocation, the within-industry covariance between productivity and size following the industry-level index of productivity developed by Olley and Pakes (1996). According to the OP methodology, a high covariance term means that firms with higher than average productivity have a higher than average market share. Accordingly, a low covariance term should signal misallocation. Following this alternative approach to misallocation, BHS compared the OP covariance term for labor productivity across countries and found, in particular, that France is much less efficient than the U.S., with an OP covariance term (in labor productivity) of 0.24 against an OP covariance term of 0.51 for the U.S. Replicating the BHS methodology on our own sample, we found a consistent estimate of the OP covariance terms (in labor productivity) of an average of 0.27 between 1998 and 2005. However, the observed productivity dispersion and productivity covariance of the BHS methodology do not move in the same direction contrary to what

¹⁸For more details on the BHS database, visit the website [http : //econweb.umd.edu/ haltiwanger/BHS_jobflows_productivity/](http://econweb.umd.edu/haltiwanger/BHS_jobflows_productivity/)

¹⁹However, the BHS measure of TFP is not directly comparable to the HK measure of TFP, as the BHS measure relied on gross output (sales deflated with the industry price index).

its theoretical model predicts.

A second piece of recent research relevant to our discussion is Van Ark et al. (2008) the rich and newly available international productivity database, called the EU KLEMS Growth and Productivity accounts²⁰. These sources will provide an assessment of the trends and causes of the productivity gap between Europe and the U.S. over the last decades. The data show that over the most recent period, from 1995 to 2004, the major source of the increasing labor productivity gap between the U.S. and Europe was a large difference in TFP growth. However, looking at detailed industries, the data show that the diverging labor productivity pattern emanates from market services, while the manufacturing industries, particularly the machinery and car manufacturing industries, are still an important source of productivity growth for some European countries, including France²¹. In a companion paper, Inklaar and Timmer (2008) use the GGDC productivity levels database, which extends the EU KLEMS database to productivity *levels* comparisons²². This research documents TFP gaps in specific industries across 29 OECD countries for the benchmark year 2005. It shows that the French TFP level was only 0.81% of the U.S. level for the overall economy. However, once this gap is decomposed across industries, the French TFP level becomes 0.97% of the U.S. level in manufacturing (excluding electrical machinery; 0.93% in electrical machinery and post and communication services, and only 0.80% in market services). Interestingly, the lowest performance of France in terms of relative 2005 TFP levels is found in "other production" industries, which include mining, energy supply, construction and agriculture. For those industries, the French TFP level is only 0.75% of the U.S. level.

Finally, we would like to highlight the recent paper by Rodrik (2013), which documents a new, stylized fact about international productivity convergence in manufacturing using a rich and detailed industry database that encompassed comparable data on 127 different manufacturing industries across 72 developed and developing countries²³. In his paper, Rodrik shows that unconditional convergence has been occurring in manufacturing industries since the early 1990s. Moreover, he shows that this convergence pattern had failed to create equal prosperity in all economies in terms of aggregated

²⁰For more details on the EU KLEMS Growth and Productivity accounts see O'Mahony and Timmer (2009) or visit the website at <http://www.euklems.net/>

²¹Basically, the data show that labor productivity growth in French manufacturing (including agriculture but excluding ICT) was 1.0% over the period 1995-2004, while it was only 0.7% in the U.S. over the same period. However, labor productivity in the French market services was 0.6% against 1.8% in the U.S.

²²For more details on the GGDC productivity levels database, visit <http://www.ggdc.net/databases/levels.htm>

²³The dataset is drawn from the INDSTAT4 database of the United Nations Industrial Development Organization (UNIDO). More information can be found on UNIDO's website at <http://www.unido.org/index.php?id=1000309>

labor productivity (in the sense that some economies have performed badly in terms of aggregate labor productivity while converging in terms of manufacturing labor productivity). Rodrik (2013) also shows that the countries that have experienced deteriorating aggregate performance (despite achieving productivity gains in the manufacturing industries) are the ones that have failed to reallocate their labor force towards their highest productive sectors. Consequently, Rodrik argues that the source of poor performance in some countries (both developed and developing) is not so much a function of economy-wide misgovernance or endogenous technological change, but of specific circumstances that influence the speed of structural reallocation from low productivity to high productivity activities. As France and the U.S. may differ according to these specific circumstances, Rodrik’s argument may explain why the aggregate productivity gap between France and the U.S. is still large despite close performance within each single manufacturing industry.

8 Conclusion

In this paper, we applied the Hsieh and Klenow (2009) methodology on French microdata on manufacturing firms to quantify the potential extent of intra-industry misallocation in France versus the U.S. In contrast to what has been found for developing countries, such as China, India and certain countries in Latin America, we do not find any sizeable “efficiency gap” between France and the U.S. in the manufacturing industries. Specifically, the estimated absolute TFP gains for France due to misallocation are approximately 30 percent, which is very close to the figure found for the U.S. and much lower than the corresponding figures found for developing countries (which usually range between 50 and 100 percent).

Our results may indicate that the HK methodology can detect large efficiency gaps between developing and developed countries, but it does not do a good job discriminating across developed countries. Alternatively, our results may indicate that allocative efficiency in manufacturing industries is indeed close in France and the U.S. This latter interpretation challenges established beliefs that Continental European economies have higher input and output distortions than does the U.S. economy. Nonetheless, our results echo some supportive evidence in the recent literature on international productivity gaps and misallocation.

We see three main avenues for further research. First, it may be worthwhile to extend the HK comparison to non-manufacturing industries when looking at efficiency gaps across developed countries. The working assumption would be that market distortions have a stronger impact in terms of misallocation within service industries than within manufacturing industries. This could be due either to the fact that the most binding constraints

on TFP reallocation gains are specific product market regulations (PMR) in non-manufacturing French industries²⁴ or to the fact that service industries respond differently to labor and capital markets distortions.

Second, it may be worthwhile to extend the comparison to other developed countries. Japan would be an interesting case study. Nishimura et al. (2005) show how misallocation lowered aggregate TFP in Japanese manufacturing industries during the recession of the 1990s. The current research Bellone et al. (2013) shows that TFP gaps between France and Japan are still large in some manufacturing industries. Thus, despite the general trend of productivity convergence documented by Rodrik, intra-industry misallocation could still explain part of the productivity gaps in manufacturing industries across specific economies. Extending misallocation comparisons across countries of similar income levels could also help reveal the determinants of economic inefficiency. For instance, Ziebarth (2013) shows that the level of productivity dispersion in China and India documented by HK (2009) is actually very similar to the level of productivity in 19th century America. For this author, Ziebarth's result suggests that the institutional basis of misallocation may go beyond the distortionary policies typically emphasized in the literature, as those policies did not exist in the U.S. during the 19th century.

Finally, it may be worthwhile to investigate the interplay between intra-industry and inter-industry misallocation in aggregate TFP gaps across countries. In the HK model, market distortions impact TFP only through intra-industry misallocation because of the simplifying assumption created by a Cobb-Douglas aggregator in the homogenous final goods industry. Augmenting the HK framework to allow for both intra- and inter-industry misallocation could bring new insights in to the role of market distortions and policy regulations in shaping international productivity gaps.

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