Misallocation and aggregate productivity: evidence from the French manufacturing sector*

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PRELIMINARY AND INCOMPLETE

Abstract

This paper provides an assessment of resource misallocation dynamics in the French manufacturing sector between 1990 and 2014. I develop a framework along the lines of Hsieh and Klenow (2009) and apply it to a unique data set covering the universe of French firms with a turnover higher than 750,000 euros. I focus on incumbent firms and show that within-industry misallocation is the main factor driving the fluctuations of allocational efficiency. I find that misallocation increased substantially between 1997 and 2007, generating a loss in annual TFP growth comprised between 0.7 and 2 percentage points. I distinguish between labor and capital misallocation and find that the former increased at a higher pace than the latter during this period. I also quantify the impact of allocational efficiency on the aggregate productivity drop observed during the Great Recession and on the 2010 recovery. I find that it can explain roughly half of the 2007-2009 decline in TFP and between 25% and 40% of the improvement observed in the immediate aftermath of the crisis. Finally, I show that changes in misallocation cannot explain the post-crisis TFP slowdown.

Keywords: Misallocation; Productivity; France; Great Recession.

JEL Classification Numbers: D24, O11, O47.

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1 Introduction

The French manufacturing sector was heavily hit by the 2008 crisis. Between 2007 and 2009 real value added fell by about 6%, while total factor productivity dropped by about 8%\textsuperscript{1}. This huge economic shock was preceded by six years of anemic growth, net output increasing at a rate of roughly 0.5% per year while annual TFP growth rate reached approximately 2%.

Recent empirical papers have shed light on the deterioration of allocational efficiency in various southern European countries during the 2000’s. For example, Dias et al. (2015) use Portuguese firm-level data to show that within-industry misallocation almost doubled between 1996 and 2011. Garcia-Santana et al. (2015) show that resource misallocation gradually increased between 1995 and 2007 in Spain and cost up to 1.5 percentage points of annual TFP growth. Finally, Gopinath et al. (2015) use data for Spanish manufacturing firms and find similar trends in productivity losses from misallocation over time in Spain, Italy and Portugal between 1999 and 2012.

This paper aims at contributing to this growing literature by bringing empirical evidence on the question of how resource misallocation evolves over time, and by assessing to which extent it shaped the fluctuations of aggregate productivity in France. To do so I use a unique French firm-level data set and document a gradual rise in within-industry misallocation in the French manufacturing sector between 1997 and 2007. I also quantify the contribution of misallocation to the sharp decline in TFP observed during the Great Recession and to the post-crisis changes in aggregate productivity. By focusing on incumbent firms I show that the deterioration of allocational efficiency explains roughly half of the 2007-2009 TFP drop, between 25% and 40% of the 2010 recovery, but is unable to account for the post-crisis stagnation in aggregate productivity.

\textsuperscript{1}Source : France’s national statistics office (INSEE) and EU-Klems.
There is a vast literature exploring the link between the allocation of factors of production across firms and measured aggregate productivity\(^2\). Seminal papers focused on misallocation as an important source of measured TFP differences across countries. Banerjee and Duflo (2005) present suggestive evidence that gaps in marginal products of capital in India could play a large role in explaining its low manufacturing TFP. Hsieh and Klenow (2009) develop a methodology to measure misallocation, and find that reallocating labor and capital to equalize marginal products to the extent observed in the United States would lead to manufacturing TFP gains of 30%-50% in China and 40%-60% in India. Restuccia and Rogerson (2008) sketch a version of the growth model with heterogeneous establishments and show that policies creating heterogeneity in the prices faced by individual producers may generate sizeable drops in output and measured TFP. More recently, Bartelsman et al. (2013) take as a measure of resource allocation the within-industry covariance between size and productivity, and document a substantial cross-country variation.

Bellone and Mallen-Pisano (2013) also apply the Hsieh and Klenow (2009) methodology to a French firm-level data set. An important difference between this paper and theirs relies on the fact that I focus on changes in allocational efficiency over time, while they compare the level of misallocation between France and the United States.

Several papers have used theoretical models to identify channels from which resource misallocation could arise. A large part of this literature has focused on the link between financial frictions and aggregate productivity (see e.g., Midrigan and Xu (2014) ; Buera and Moll (2015) ; Moll (2014)). Asker et al. (2015) investigate the role of time-to-build technologies and adjustment costs in shaping the dispersion of static measures of capital misallocation within industries and countries. Peters (2013) argues that cross-sectional productivity disper-

\(^2\)See Restuccia and Rogerson (2013) for a recent survey.
sion reflects the distribution of mark-ups and may be a symptom of fundamental differences in the innovation environment.

Finally this paper is closely related to the literature documenting the evolution of misallocation during crises periods. Oberfield (2013) analyses the Chilean crisis of 1982 and finds that within-industry allocational efficiency remained rather constant, while between-industry misallocation accounts for about one third of the reduction in TFP. Sandleris and Wright (2014) study the Argentine crisis of 2001 and find that half of the decline in measured TFP can be explained by a deterioration in the allocation of resources. Ziebarth (2012) studies changes in within-industry misallocation of various US industries during the Great Depression.

The rest of the article is organized as follows. Section 2 develops a simple theoretical framework following Hsieh and Klenow (2009) and Oberfield (2013). Section 3 describes the data set. Section 4 presents the main empirical results regarding the evolution of misallocation and its contribution to changes in observed TFP. Section 5 provides robustness checks. Section 6 concludes.

2 Theoretical framework

2.1 Production functions and output aggregators

In this section I follow Hsieh and Klenow (2009) and Oberfield (2013) and develop an accounting framework in order to measure the variation of misallocation over time. This framework requires functional-form assumptions on production functions and on output aggregation.

I consider an economy composed of $S$ distinct industries. In industry $s$ firm $i$ produces
a differentiated good using a constant return to scale production function:

\[ y_{is} = z_{is} k_{ia}^{\alpha_s} l_{ia}^{1-\alpha_s} \]

Notice that output elasticities are allowed to differ across industries but not across firms within a given industry.

The output of each industry is the outcome of aggregating those differentiated goods in a CES manner. The elasticity of substitution between goods within a given industry is supposed to be the same for the whole economy. Finally, industry aggregates are combined into a single aggregate good using a Cobb-Douglas production technology:

\[ Y_s = \left( \sum_{i=1}^{N_s} y_{is}^{\frac{\rho}{\rho-1}} \right)^{\frac{\rho-1}{\rho}} \]

\[ Y = \prod_{s=1}^{S} Y_s^{\theta_s} \text{ where } \sum_{s=1}^{S} \theta_s = 1 \]

\( N_s \) denotes the number of firms operating in industry \( s \) at a given period of time. \( \rho \) is the elasticity of substitution between goods within industries. Cost minimization in the final good sector implies that \( \theta_s \) corresponds to the share of industry \( s \) in total nominal value added. These shares are allowed to vary over time.
2.2 Revenue productivity and physical productivity

I follow Foster et al. (2008) and Hsieh and Klenow (2009) by distinguishing between revenue productivity (TFPR) and physical productivity (TFPQ):

\[ TFPR_{is} = p_{is} z_{is} = \frac{p_{is} y_{is}}{k_{is}^{\alpha_s} l_{is}^{1-\alpha_s}} \]
\[ TFPQ_{is} = z_{is} = \frac{y_{is}}{k_{is}^{\alpha_s} l_{is}^{1-\alpha_s}} \]

In most firm-level datasets variables are expressed in nominal terms and firm-specific prices are not available, which makes revenue productivity easier to measure than physical productivity. Optimal spending by the consumer requires that

\[ y_{is} = Y_s \left( \frac{p_{is}}{P_s} \right)^{-\rho} \]

where \( P_s \) denotes the price of industry \( s' \) aggregate good. As a result one can derive physical productivity:

\[ TFPQ_{is} = (Y_s P_s^\rho)^{-\frac{1}{\rho}} \left( \frac{p_{is} y_{is}}{k_{is}^{\alpha_s} l_{is}^{1-\alpha_s}} \right)^{\frac{\rho}{\rho-1}} \]

Interestingly, the previous equation implies that in a given industry and at a given time period one can obtain relative idiosyncratic productivities without using industry deflators (and therefore avoiding a potential source of measurement error, since the use of industry deflators would mean that differences in firm-specific prices would show up in the measure of \( TFPQ_{is} \)).
2.3 Efficient allocation

The allocation of production factors across firms and across industries is efficient if and only if, given the total quantity of labor and capital available, it enables the economy to reach the maximum attainable output $Y^\ast$.

Formally, the efficient allocation of labor and capital and the optimal level of aggregate production are the solution of the following maximization program:

$$
\max_{\{k_{is}, l_{is}\} \leq N_s, s \leq S} Y
$$

s.t. $\sum_{s=1}^{S} \sum_{i=1}^{N_s} k_{is} \leq K$, $\sum_{s=1}^{S} \sum_{i=1}^{N_s} l_{is} \leq L$

It can be easily shown that at the optimum firm $i$ in industry $s$ would be allocated the following quantity of production factors:

$$
k_{is}^\ast = \frac{z_{is}^{\rho-1}}{N_s \sum_{i=1}^{N_s} z_{is}^{\rho-1}} K_s^\ast, \quad l_{is}^\ast = \frac{z_{is}^{\rho-1}}{N_s \sum_{i=1}^{N_s} z_{is}^{\rho-1}} L_s^\ast
$$

where $L_s^\ast$ and $K_s^\ast$ denote the efficient levels of labour and capital that should be devoted to industry $s$:

$$
K_s^\ast = \frac{\theta_s \alpha_s}{S \sum_{s=1}^{S} \theta_s \alpha_s} K, \quad L_s^\ast = \frac{\theta_s (1 - \alpha_s)}{S \sum_{s=1}^{S} \theta_s (1 - \alpha_s)} L
$$

One can therefore derive the maximum attainable output $Y^\ast$ and the optimal level of production of industry $s$ $Y_s^\ast$:

$$
Y_s^\ast = \left( \sum_{i=1}^{N_s} z_{is}^{\rho-1} \right)^{\frac{1}{\rho-1}} K_s^\ast^{\alpha_s} L_s^\ast^{1-\alpha_s}
$$
Following Oberfield (2013) I also perform a slightly different exercise, which consists in considering the total quantity of production factors $K_s$, $L_s$ in each sector as fixed and in reallocating capital and labour within industries rather than across the whole economy. Given this constraint, the maximum attainable output (denoted $Y^{*,w}$) is the solution of

$$
\text{max}_{\{k_{is}, l_{is}\}_{i \leq N_s, s \leq S}} Y \\
\text{s.t.} \forall s \leq S \sum_{i=1}^{N_s} k_{is} \leq K_s, \sum_{i=1}^{N_s} l_{is} \leq L_s
$$

Perfect allocation of production factors within industry $s$ implies that revenue productivities of all firms operating in this industry are equalized. As a matter of fact, assume that the physical productivity of firm $i$ suddenly increases. To optimize aggregate output labor and capital must be reallocated from firms with lower productivity to firm $i$. Therefore its production increases, which results in a lower price and in a lower TFPR$_{is}$, until revenue productivities are again equalized. As a consequence any dispersion of TFPR$_{is}$ within a given industry indicates that some distortions$^3$ prevent labor and capital to be reallocated from low TFPR firms to high TFPR firms.

Finally I conduct a second thought experiment, which involves keeping the observed distribution of labor $\{l_{is}\}_{i \leq N_s, s \leq S}$ (respectively capital $\{k_{is}\}_{i \leq N_s, s \leq S}$) unchanged and allocating optimally capital (respectively labor) across firms and across industries in order to maximize

$^3$As emphasized by Oberfield (2013) deviations from an efficient optimum may be the consequence of various frictions, and do not necessarily reflect market failures or distortive public interventions. For example physical adjustment costs would prevent a social planner from raising output by reallocating production factors, even if revenue productivities were not equalized.
aggregate output. Under this constraint optimal production is denoted $Y^* \{k_{is}\}$ (respectively $Y^* \{l_{is}\}$), and is the solution of

$$\max_{\{k_{is}\}\leq N_s, s\leq S} \frac{Y}{S} \sum_{s=1}^{S} \sum_{i=1}^{N_s} k_{is} \leq K$$

I perform the same exercise as previously described, computing the maximal output one can achieve by allocating capital (respectively labour) within industries instead of allocating it across the whole economy.

2.4 Misallocation and TFP

Following Hsieh and Klenow (2009) I measure total misallocation as the ratio between the level of output one would observe if production factors were efficiently allocated and the actual aggregate production:

$$M = \frac{Y^*}{Y} = \prod_{s=1}^{S} \left( \frac{Y^*_s}{Y_s} \right)^{\theta_s}$$

This measure can be separated into two parts. The first one measures within-industry misallocation, and is defined as the ratio between maximal output reachable by allocating production factors across firms within each industry, $Y^* \{w\}$, and actual production. The second one measures between-industry misallocation, and is defined as the ratio between efficient output $Y^*$ and $Y^* \{w\}$.

$$M_w = \frac{Y^*}{Y}$$
$$M_b = \frac{Y^*}{Y^* \{w\}}$$
$$M = M_w M_b$$

I now distinguish between labor misallocation and capital misallocation. I measure labor
(respectively capital) misallocation as the ratio between efficient output and the maximum output that can be reached keeping unchanged the distribution of labor (respectively capital) and reallocating capital (respectively labor) across firms. In other words it measures how costly it is in terms of output to produce with the observed allocation rather than with the efficient one.

\[ M_L = \frac{Y^*}{Y^*\{l_i\}} \]
\[ M_K = \frac{Y^*}{Y^*\{k_{is}\}} \]

Following the same reasoning than previously I differentiate between within-industry labor (respectively capital) misallocation and between-industry labor (respectively capital) misallocation.

From the efficient aggregate production function obtained in equation 4 one can naturally define the efficient aggregate total factor productivity and the observed aggregate TFP as:

\[ TFP^* = \frac{Y^*}{K \sum_{s=1}^{S} \alpha_s \theta_s L^{1-\sum_{s=1}^{S} \alpha_s \theta_s}} \]  
(5)

\[ TFP = \frac{Y}{K \sum_{s=1}^{S} \alpha_s \theta_s L^{1-\sum_{s=1}^{S} \alpha_s \theta_s}} \]  
(6)

Therefore variations in observed TFP can be decomposed into variations in efficient TFP, which is a function of the framework’s parameters and of firms’ indiosyncratic productivities reflecting the contribution of technology to production\(^4\), and variations in misallocation:

\[ \Delta \ln TFP = \Delta \ln TFP^* - \Delta \ln M_w - \Delta \ln M_b \]  
(7)

\(^4\)Actually firm level productivity may reflect the influence of various factors beside pure technology, as managerial practices, organizational structures, or learning-by-doing processes. See Syverson (2011) for a survey on the micro-data productivity literature.
3 Data

3.1 Data description

In this section I describe the firm-level dataset I use to perform my analysis, the FIBEN database. This unique database was initially set up by the Banque de France to facilitate the implementation of monetary policy. All the companies recorded in the database are awarded a rating that provides information on their ability to meet their financial commitments. Only claims on the most highly-rated companies are eligible for bank refinancing.

The database gathers information on all companies with a turnover of at least 750,000 euros, covering the years 1990 to the present day. A broad range of information is gathered, including accounting and financial data from the balance sheet, but also descriptive details, such as the firm’s name, legal status and business code. The information is gathered from a variety of sources, including journals of legal notices, registrars of commercial courts, France’s national statistics office (INSEE) and credit institutions, as well as the companies themselves.

Restricting the database to the manufacturing sector the dataset is an unbalanced panel of approximately 1,000,000 observations covering a total of about 110,000 firms. For my analysis I particularly focus on gross output, intermediate consumption, payments to labor, tangible and intangible fixed assets, and average number of employees. The first challenge in the dataset is to harmonize accounting periods; as a matter of fact, even if most of the firms follow the regular calendar year, a non-negligible share of the data collected corresponds to other accounting periods. In order to deal with this issue I assume that the gross output, the intermediate consumption, the payments to labor and the number of employees of a given firm over a given accounting period are the same each month. Then for each firm I
reconstruct yearly data by summing monthly data (or averaging, in the case of the number of employees). In the dataset the stock of fixed assets is recorded at the end of the accounting period; I proceed with linear interpolation to estimate the quantity of assets at the end of the calendar year, and I assume that fixed assets used by a firm in order to produce during year t correspond to the mean of the fixed assets stocks at the end of year t-1 and year t.

Throughout my analysis I assume that industries in my framework correspond to three-digit industries in the dataset\(^5\). I measure labor input as the average number of employees multiplied by the average number of hours worked by employee over the year in the corresponding sector\(^6\). I measure the capital stock with the book value of tangible and intangible fixed assets, net of depreciation, deflated by the industry price deflator for investment goods. Finally, I measure production with nominal value added (gross output minus intermediate consumption) deflated by the corresponding value-added deflator\(^7\). Firm-level observations are dropped if the capital stock, the labor input or the value-added variable are either non-positive or missing. At this point the dataset is composed of 901,240 firm-year observations.

Importantly, entry and exit from the dataset do not correspond to actual entry and exit; firms may disappear from the dataset when their turnover falls below the 750,000 euros threshold, and exit may also reflect restructurations and takeovers rather than firms shutting down their businesses. Finally, I emphasize that I work only with unconsolidated accounts.

\(^5\)The FIBEN database use the NACE classification (European standard classification of productive economic activities).

\(^6\)In some studies labor input is measured by the wage bill. The main assumption is that wages per worker enable to adjust the measure of idiosyncratic productivities to firm differences in hours worked per worker and in workers skills. However differences in wages may also be explained by rent sharing and by wage bargaining between the firms and the workers. I will use this alternative specification as a robustness check.

\(^7\)The average number of hours worked by employee for a given year, the investment deflators and the value-added deflators are taken from the INSEE database (available online), although the data are given for a broader level of aggregation than the three-digit level.
3.2 Estimation of the parameters

I now describe how I infer the parameters used in the theoretical framework from the dataset. In a perfect economy with no frictions one would naturally approximate the elasticity of output with respect to labor by the share of nominal value-added devoted to nominal expenditure on labor. But as the whole analysis relies on the existence of distortions driving the economy away from an efficient optimum one cannot separately identify differences in technology and differences in distortions from differences in factor expenditure shares. I assume that on average firms within a given industry are undistorted (even if a particular firm still may face a distortion in a particular year). More precisely, I compute for each year and for each firm operating in industry $s$ its labor expenditure share and I assume that the median of this variable over the years and over the firms reflects the true value of the elasticity of output with respect to labor. Then under the assumption of constant return to scale it is straightforward to deduce for each industry the elasticity of output with respect to capital. As stressed by Hsieh and Klenow (2009) another issue that arises when deducing production elasticities from factor shares is that we have to take into account the markups associated with the market power of the firms in these differentiated good industries. I assume that rents coming from these markups are divided between workers and capital owners proportionally to the factor expenditure shares, and directly appear in the payments to labor used to deduce output elasticities.

In order to measure industries’ shares $\theta_s$ I compute for each year and for each industry the ratio of the industry’s nominal value added to total nominal value added in the economy. Notice that these parameters are time-varying.

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8Payments to labor used to compute labor expenditure shares include the wage bills, fringe benefits and employer social security contributions.
Finally in line with numerous other studies I set $\rho = 3$ in my baseline computations. As the value of the elasticity of substitution between goods probably impacts the magnitude of the results I will consider alternative values as a robustness check. I am well aware that the elasticity of substitution is likely to differ between industries and that it also may vary over time, so considering a constant elasticity of substitution is of course a simplifying assumption.

4 Empirical results

In this section I apply the theoretical framework developed in section 2 to the FIBEN dataset in order to quantify the evolution of misallocation over time and its contribution to the variations in observed TFP.

To guard against the effect of mismeasurement I trim the top and bottom 1\% outliers of both physical and revenue productivity for each year and within each industry. After trimming the data set includes 871,324 firm-year observations. I then remove from the sample industries with less than ten observations per year. I also remove from my data set the manufacture of refined petroleum products (industry 192). As a matter of fact, this industry represents on average 7\% of the aggregate nominal value added in my data set, while its average share in the French manufacturing sector between 1990 and 2014 is less than 1\%\textsuperscript{9}. The overestimation of this industry’s size would have biased the observed fluctuations in allocational efficiency. At this point the data set includes 866,840 firm-year observations and accounts on average for roughly two-thirds of total employment and of total nominal value-added of the French manufacturing sector.

\textsuperscript{9}Source : INSEE.
4.1 Preliminary measures of misallocation

I first focus on several commonly used measures of misallocation. As emphasized by Hsieh and Klenow (2009) the efficient allocation of resources within a given industry requires revenue productivities to be equalized. Therefore the dispersion of TFPR may be considered as an indicator of the extent of within-sector misallocation.\(^\text{10}\)

Figure 1 shows the evolution of the standard deviation of log-revenue productivity (industries are weighted by their value-added shares). The dispersion of TFPR follows clearly an upward trend until 2005-2006, increasing at a rate of roughly 1% per year. This first observation suggests a gradual increase in within-industry misallocation over this period of time. Moreover, figure 1 shows that the standard deviation of revenue productivity sharply increases during the Great Recession with a peak in 2009, falls down in 2010 and then remains stable. It suggests that within-sector allocational efficiency may play a substantial role in the 2007-2009 decline of observed TFP and in the 2010 recovery.

Table 1 shows that other measures of dispersion tends to corroborate this pattern. I find no significant increase of the 75-25 ratio between 2000 and 2005 and a small increase in the 90-10 ratio over the same period; however the upward trend is clear between 1995 and 2000. Both ratios exhibit a sharp increase during the Great Recession and a sharp decrease in 2010.

Bartelsman et al. (2013) propose using as a preferred measure of misallocation the within-sector covariance between productivity and size following the decomposition of Olley and Pakes (1996). This decomposition splits an index of industry-level productivity, defined in

\(^{10}\)Hsieh and Klenow (2009) show that when TFPQ and TFPR are jointly lognormally distributed observed TFP writes

\[
\log TFP_s = \log TFP'_s - \frac{\rho}{2} \text{var}(\log TFPR_{si})
\]
Figure 1: Evolution of the standard deviation of TFPR over time

Note: Industries are weighted by their value-added shares. The statistic is for log deviation of TFPR from industry means

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<td>33,478</td>
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Note: Statistics are for deviations of log(TFPR) from industry means. Std. = standard deviation, 75-25 = difference between the 75th and the 25th percentiles, 90-10 = difference between the 90th and the 10th percentiles, nobs = number of observations. Industries are weighted by their value-added shares.

Table 1: Various measures of TFPR dispersion

this paper as the weighted average of firm-level log-productivity, into an unweighted average and the covariance term used by Bartelsman et al. (2013)\(^\text{11}\). If the allocation of factors of production within an industry is efficient firms with relatively high productivity should be allocated more resources, and should therefore have a relatively high share of activity.

\(^{11}\)Formally, Olley and Pakes (1996) note that this index can be decomposed as follows:

\[
\sum_{i=1}^{N_t} \theta_{it} \omega_{it} = \bar{\omega}_t + \sum_{i=1}^{N_t} (\theta_{it} - \bar{\theta}_t)(\omega_{it} - \bar{\omega}_t)
\]

where \(\omega_{it}\) is idiosyncratic productivity and \(\theta_{it}\) is the share of activity of the firm.
Therefore low covariance between size and productivity should signal within-industry misallocation.

Figure 2: Evolution of the covariance between TFPR and activity share over time

*Note: Industries are weighted by their value-added shares.*

Figure 2 shows the evolution over time of this covariance term, where size is measured as the relative share of the firm in the industry-level nominal value-added, and where we focus on revenue productivity. The covariance measure follows an increasing trend between 1990 and 1997, which suggests an improvement in allocational efficiency and contradicts what could be inferred from the observed increase in TFPR dispersion during the same period. It then decreases until 2009 before bouncing back in 2010, and slightly increases between 2010 and 2014. All in all, these findings tend to suggest that within-industry misallocation gradually rose in the lead-up to the Great Recession, reached a peak in 2009 and sharply decreased in 2010 before stabilizing.

Finally, Gopinath et al. (2015) document a significant increase in the dispersion of the log marginal revenue product of capital (MRPK) in the Spanish manufacturing sector between 1999 and 2012, while the dispersion of the log marginal revenue product of labor (MRPL)
remains stable over the same period of time. Allocating efficiently capital across firms within a given industry requires equalizing the marginal revenue products of capital; therefore an increase in MRPK dispersion implies that one could rise output by reallocating capital from low MRPK firms to high MRPK firms. The same reasoning applies to labor input. Gopinath et al. (2015) also document a smaller increase in the dispersion of log-MRPK and no particular trend in the dispersion of log-MRPL in France during the same period. These findings are partly corroborated by figure 3: as a matter of fact, the dispersion of the log MRPK follows an upward trend close to the one documented by Gopinath et al. (2015). It shows no particularly sharp increase during the Great Recession, and stabilizes from 2011 onwards. On the other hand I find evidence of a slightly upward trend in the dispersion of the log MRPL, with a peak in 2009 and a sharp decrease in the aftermath of the crisis followed by a relative stabilization, therefore reproducing the pattern already identified in the previous measures of misallocation.

Figure 3: Evolution of the dispersion of log-MRPL and log-MRPK

*Note: Industries are weighted by their value-added shares.*
4.2 Changes in misallocation and contribution to the variations in TFP

In this section I use the theoretical framework developed in section 2 in order to measure changes in misallocation and to quantify its contribution to the variations in observed TFP. Importantly, to evaluate the fluctuations of misallocation between year $t$ and year $t+1$ I only keep in my sample firms for which I have an observation at year $t$ and at year $t+1$. I then recompute industry shares and aggregate stocks of factors of production. This means that the changes in misallocation I observe in the remainder of this article should be interpreted as changes in misallocation within incumbent firms. The reason for focusing on incumbent firms is that as stressed previously entry and exit from the data set do not correspond to actual entry and exit. As a result the observed variation in allocational efficiency may be biased by these artificial entry and exit, and its volatility may be exacerbated. An immediate caveat is that my analysis does not assess the role of entry and exit in the evolution of misallocation. As stressed by Oberfield (2013), a reason to think that net entry is not the main factor driving misallocation is that aggregate TFP and allocational efficiency tend to be dominated by large firms, while most exiting and entering firms are small. Osotimehin (2013) uses a firm-level data set of French manufacturing and service firms over the period 1991-2006 to show that the efficiency of resource allocation between incumbent firms is more important to understand the dynamics of aggregate productivity, while entry and exit play a limited role. In order to check if restricting the data set to incumbent firms introduces a bias in the fluctuations of observed productivity I compare in figure 4 TFP as measured using my data set\textsuperscript{12} and aggregate TFP of the French manufacturing sector (data available

\textsuperscript{12}I measure observed TFP using equation 6 ; changes in aggregate value-added are computed using a Tornqvist approximation. Aggregate capital share used to deduce changes in TFP between two consecutive years $t$ and $t + 1$ is the mean of the capital shares of equation 6 in year $t$ and year $t + 1$.}
until 2009): while productivity growth between 2002 and 2007 tends to be overestimated, the drop in observed TFP during the Great Recession matches the drop in aggregate TFP (approximately -8% between 2007 and 2009 in both cases). I find no significant difference in the upward trend of productivity for both times series before 2002 (although observed TFP slightly decreases between 1990 and 1993, while aggregate TFP remains constant). Observed TFP sharply increases between 2009 and 2010, before stagnating.

![Figure 4: variation in TFP over time](image)

*Note: This figure compares the evolution of TFP measured with the FIBEN dataset and TFP as reported by EU-klems. Data from EU-klems are only available until 2009.*

Figure 5 shows the evolution of $M$, $M_L$, $M_K$ and their within-industry and between-industry components over time. First of all I find that the between-industry component seems to be rather stable over the period. Between-industry capital misallocation shows a peak in 2009, as between-industry misallocation, but all in all no significant trend clearly appears. On the other hand within-industry misallocation remains stable until 1997 and then progressively rises during the decade preceding the Great Recession: $M_w$ is found to

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13Source : EU-Klems.
rise by 6.5 log-points between 1997 and 2007. Within-sector labor misallocation increases at a higher pace than its capital counterpart, both rising respectively by 5.7 log-points and 3.5 log-points. In the three cases within-industry misallocation sharply increases between 2007 and 2009 (+4 log-points for $M_w$, +3 log-points and +2.3 log-points for its labor and capital counterparts) and decreases in 2010 (respectively -1.9, -1.6 and -0.9 log-points), before stabilizing. Eventually total misallocation appears to be overwhelmingly driven by its within-industry component, and displays the same evolution over time: a sustained rise between 1997 and 2007, a sharp increase during the Great Recession and a sharp decrease between 2009 and 2010, before stagnating. Deterioration of allocational efficiency is found to have shaved approximately 0.65 percentage points (pp) off the annual TFP growth during the 1997-2007 period. These findings resemble the results of Dias et al. (2015), who find that misallocation may have cost 1.3 pp of annual GDP growth in the Portuguese economy between 1996 and 2011, and the results of Garcia-Santana et al. (2015) who find the decline in allocation efficiency to have shaved around 1.5 pp of average annual TFP growth in Spain during the expansion of 1995-2007.

Figure 6 shows the evolution of observed TFP if misallocation would have remained at its 1990 level. Removing the variations of between-industry misallocation would have let rather unchanged aggregate productivity. Removing both components I find that misallocation explains half of the decline of TFP during the Great Recession (44% for the sole within-industry misallocation) and 25% of the 2010 recovery (22% for the within-industry component). These results contradict the conclusions of Gopinath et al. (2015), who find allocational efficiency in the French manufacturing sector to remain rather unchanged between 2000 and 2012. Finally, from 2011 onwards misallocation tends to be stable and therefore is found unable to explain the post-crisis slowdown in aggregate TFP.
5 Robustness checks

In this section I perform some robustness checks related to the measure of physical productivities and to the value of the elasticity of substitution.
5.1 Using wage bill in order to measure TFPQ

Numerous studies use the wage bill rather than the number of employees in order to control for differences in the quality of the workforce and in the quantity of hours by employee. Figure 7 shows the evolution of $M$, $M_L$, and $M_K$ under the same methodology. Conclusions regarding the extent of between-industry misallocation remain the same. Within-industry misallocation is still the main factor driving changes in allocational efficiency. Labor misallocation is also found to have increased at a higher pace than its capital counterpart between 1997 and 2007. The same trends appear: total misallocation shaves around 0.94 percentage points off annual TFP growth during this period, slightly more than what was found in the previous section.

Total misallocation explains 42.3% of the decrease in observed TFP between 2007 and 2009 (37% for within-industry misallocation), and 27% of the 2010 recovery (22.8% for the within component), which is a bit lower than the previous results (see figure 8).
Figure 7: Variation of misallocation over time

Note: We perform the same exercise as in the previous section, using the wage bill to measure firm-level physical productivity.

5.2 Considering other values for the elasticity of substitution

As stressed at the beginning of this article the elasticity of substitution between goods may impact the magnitude of the results. I therefore perform my empirical analysis by
setting successively $\rho$ equal to 5 and $\rho$ equal to 7. $\rho=5$ is a value used by Dias et al. (2015) and by Garcia-Santana et al. (2015), while $\rho=7$ is close to the elasticity of substitution found by Christopolou and Vermeulen (2012) for the manufacturing sector in the Eurozone.

In both specifications the between-industry component of allocational efficiency remains negligible compared to the within-industry component, and labor misallocation rises relatively more than capital misallocation during the decade preceding the Great Recession (see figures 9 and 11). The increase of misallocation during this period is stronger than what was found previously (the deterioration of allocational efficiency shaves around 1.4 pp off annual TFP growth when $\rho$ is set to 5, 2 pp when $\rho$ is set to 7).

In both cases total misallocation explains 55% of the drop in aggregate TFP between 2007 and 2009 (50% for within-industry misallocation), which is rather close to the 50% found in the previous section (see figures 10 and 12).

Setting $\rho$ equal to 5 changes little the results regarding the contribution of misallocation to
the 2010 recovery: 28.3% of the increase in TFP comes from an improvement of allocational efficiency (25% for the within-sector component). Setting $\rho$ to 7 tends to increase this result, as misallocation explains 41% of the rise in aggregate productivity (37% for the within sector).
component) under this specification.

Finally, notice that in the three cases (using the wage bill, setting $\rho$ equal to 5, setting $\rho$ equal to 7) misallocation seems stable after 2010 and therefore cannot explain the post-crisis slowdown in aggregate TFP.
6 Conclusion

In this paper I use a unique French firm-level data set to measure the contribution of resource misallocation and its within-industry and between-industry components to the
Figure 12: Contributions of within and between-industry misallocations to TFP

Note: Results obtained for $\rho=7$


I focus on incumbent firms and show that within-industry misallocation is the main factor driving the fluctuations of allocational efficiency, while changes in between-sector misallocation are found to be rather negligible. Allocational efficiency gradually deteriorates during the decade preceding the Great Recession, shaving approximately 0.7 percentage points off the annual TFP growth in the most conservative specification. Robustness checks using the wage bill to measure firm-level productivity or choosing alternative values for the elasticity of substitution show that actual efficiency gains may well be higher, up to 2 percentage points of annual productivity growth. These findings resemble the results of various studies which shed light on a similar pattern of allocational efficiency deterioration in southern Europe economies during the 2000’s. I measure separately labor misallocation and capital misallocation and find that the latter increases at a lower pace than its labor
counterpart.

I also quantify the impact of misallocation on the decline of aggregate productivity observed during the Great Recession and on the 2010 recovery. I find that it can explain roughly half of the 2007-2009 TFP drop and between 25% and 40% of the improvement observed in the immediate aftermath of the crisis. Finally I find that changes in the efficiency of resource allocation are unable to explain the post-crisis productivity slowdown.

I believe that further research should be done in order to assess the role of firms entry and exit in shaping resource misallocation, especially during the Great Recession. Moreover I believe that more work is needed to identify the specific channels through which misallocation occurs and the underlying sources determining allocational efficiency.
Appendix

To be completed
References


