Growing like Spain: 1995-2007*

Manuel García-Santana
UPF, Barcelona GSE, and CEPR

Enrique Moral-Benito
Banco de España

Josep Pijoan-Mas
CEMFI and CEPR

Roberto Ramos
Banco de España

October 5, 2016

Abstract

Spanish GDP grew at an average rate of 3.5% per year during the expansion of 1995-2007, well above the EU average of 2.2%. However, this growth was based on factor accumulation rather than productivity gains as TFP fell at an annual rate of 0.7%. Using firm-level administrative data for all sectors we show that deterioration in the allocative efficiency of productive factors across firms was at the root of the low TFP growth in Spain, while misallocation across sectors played only a minor role. Cross-industry variation reveals that the increase in misallocation was more severe in sectors where government influence is more important for business success, which represents novel evidence on the potential macroeconomic costs of crony capitalism. In contrast, sectoral differences in financial dependence, skill intensity, innovative content, tradability, or capital structures intensity appear to be unrelated to changes in allocative efficiency. All in all, the observed high output growth together with increasing firm-level misallocation in all sectors is consistent with an expansion driven by a demand boom rather than by structural reforms.

JEL Codes: D24, O11, O47.
Keywords: TFP, Misallocation, Spain.

*The opinions and analyses are the responsibility of the authors and, therefore, do not necessarily coincide with those of the Banco de España or the Eurosystem. We thank John Fernald for sharing the financial intensity data with us, and Eric Bartelsman for helpful discussion. We also thank seminar participants at Banco de España, CEMFI, SAEe in Girona, and Universidad Pablo Olavide for useful comments.

1 Introduction

The 1994-2007 expansion was the longest in Spanish history. GDP grew at an average of 3.5% per year, which compares favourably to the EU average of 2.2% over the same period. However, Spanish growth during this expansion was based on factor accumulation rather than productivity gains. In particular, annual TFP growth was -0.7%, which is low in comparison to other developed economies such as the US (+0.6%) or EU (+0.4%). Such a dismal performance of productivity growth is surprising for a country that is so well integrated in a trade and monetary union with some of the World technology leaders.

We argue that the source of negative TFP growth was the increase in the within-industry misallocation of production factors across firms. We use a large administrative data set of Spanish firms in all sectors to compute several measures of allocative efficiency. In particular, for every year between 1995 and 2007, we compute the potential TFP gains due to factor reallocation as in Hsieh and Klenow (2009) and "model-free" measures of allocative efficiency such as the dynamic decomposition of TFP growth in Foster, Haltiwanger, and Krizan (2006) and the Olley and Pakes (1996) covariances. All types of measures show a severe deterioration of allocative efficiency over the period, which is pervasive across all sectors but larger in construction and services. Instead, we show that the aggregate data from EU-KLEMS is inconsistent with an increase in misallocation across sectors, which casts doubt on the widespread view that specialization in low productivity sectors such as construction was the main force behind Spanish low TFP growth. We thus argue that allocative efficiency of resources across firms is at the root of the low rates of TFP growth observed in Spain. Our results are very stark: had the level of within-sector allocative efficiency remained constant to the level observed in 1995, TFP growth would have been around 0.8% per year. Therefore, our conclusion is that aggregate productivity in Spain stagnated because the economy increasingly allocated capital and labor in the wrong place across firms within each industry.

In order to shed some light on the potential sources of the increase in misallocation, we exploit the variation in allocative efficiency across 2-digit industries and across regions. We find that variation in sectoral characteristics such as financial dependence, capital structures intensity, skill intensity, tradability, or innovative content are unrelated to changes in allocative efficiency. Likewise, we find that the worsening in allocative efficiency was present across all regions and that regional differences in wage growth or house price growth were uncorrelated with the increase in distortions. As we argue in the paper, these results undermine explanations by usual suspects like financial frictions, dual labor markets, or lack of competition. Instead, we find that industries in which the influence of the public sector is more important to success —as measured by the *Bribe Payers Index* of *Transparency International*— experienced productivity losses due to misallocation that are twice as big as in the rest of the economy. On aggregate, had the whole economy behaved as the more competitive sectors, the overall TFP would have increased an extra 0.3% per year. There is a recent literature attempting to measure the economic costs of corruption, but macroeconomic estimates are almost inexistent.[1] Our result provides a novel measurement of the aggregate costs of crony capitalism (or the connection of firms with the political power), which is a very specific form of corruption. Furthermore, because the amount of discretion enjoyed by public officials in the so-called *crony sectors* is likely to depend on the strength of the country's political institutions, this result gives yet another reason for why weak institutions may be detrimental for growth, see Acemoglu, Johnson, and Robinson (2005).

The deterioration of factor allocation across firms during the positive part of the cycle is arguably a singular experience of Spain. Indeed, evidence from other countries shows either no change or improvements in allocative efficiency during expansions.[2] This result connects with the literature on the cleansing effects of recessions. Caballero and Hammour (1994) argued that the allocation of workers to jobs improves during recessions because lower demand diminishes rents and brings inefficient firms out of business.[3] The flip-side of this argument is that higher demand during expansions may allow inefficient firms to thrive. Our findings from firm-level data represent novel evidence of the potential sullying effects of expansions through a very specific channel. Of course, expansions driven by large-scale reforms are associated to increases in allocative efficiency across firms and consequently to improvements in measured TFP.[4] Hence, our results are consistent with the view that the Spanish expansion was driven by a demand boom and not by the improvement of the production possibilities through structural reforms.

Finally, it remains to be discussed why the Spanish economy accumulated capital and labor at such a fast pace despite the negative increase in aggregate productivity. Our view is that this was due to exogenous supply factors in the capital and labor markets. First, interest rates dropped by 8 percentage points between 1994 and 2007 due to the convergence process caused by the Economic and Monetary Union. A standard (open economy) neo-classical growth model predicts fast capital deepening in this situation, even with a slight decline in TFP. Gopinath, Kalemli-Ozcan, Karabarbounis, and Villegas-Sanchez (2015) argue that the fall in interest rates also produced the deterioration of allocative efficiency in Spain because financial frictions resulted in the capital accumulation process

[1] Alder (2016) measures the aggregate productivity costs of the mismatch between managers and firms, which he attributes to cronysm, while Khwaja and Mian (2005) show how politically connected firms in Pakistan receive more credit from public banks. See Olken and Pande (2012) for a recent survey on the topic.

[2] Bartelsman, Haltiwanger, and Scarpetta (2013) find that allocative efficiency remained roughly constant over the 1990s and early 2000s in several developed countries such as US, UK, Germany or the Netherlands, while it clearly increased for the transitional economies of Central and Eastern Europe. There is also evidence of increases in allocative efficiency across firms during economic expansions in Chile and Switzerland (see Chen and Irarrazabal (2015) and Lewrick, Mohler, and Weder (2014), respectively). In contrast, Dias, Robalo, and Richmond (2015) document a sharp decline in allocative efficiency in Portugal during the stagnant period between 1996 and 2011. Finally, Bellone and Mallen-Pisano (2013) find that misallocation remained constant between 1998 and 2005 in France.

[3] The evidence that job destruction is more cyclical than job creation has been taken as supportive of this argument. However, evidence based on job quality is not so conclusive. See Bowlus (1995), Barlevy (2002), or Foster, Grim, and Haltiwanger (2014) for details.

[4] See Buera and Shin (2013) or Midrigan and Xu (2014) for examples of reform-led expansions that improve allocative efficiency.

happening at different speed by different firms. Along these lines, Fernandez-Villaverde, Garicano, and Santos (2013) also argue that the credit boom following the interest rate decline may have been behind the deterioration of allocative efficiency in Spain. In particular, they emphasize that the signal-extraction problem faced by banks to identify good firms becomes more noisy in bubble times, and hence credit may be allocated less efficiently.[5] Second, Díaz and Franjo (Forthcoming) show that the large increase in capital accumulation over the period was largely due to capital structures, which they interpret as the result of government subsidies. And third, there were also labor supply factors at play: the working-age population ratio increased over the period and females of new cohorts participated in the labor market at a much larger rate than females of the older cohorts.

The rest of the article is organized as follows. Section 2 briefly shows the growth accounting results for Spain as well as the evolution of sectoral reallocation. Section 3 describes our firm-level data. Then, Section 4 presents the main results regarding the increase in misallocation. Section 5 discusses the variation of misallocation changes across sectors and Section 6 across regions. Some concluding remarks are provided in Section 7.

2 The 1995-2007 growth experience

The Spanish economy grew at the average rate of 3.5% per year between 1995 and 2007. This expansion, the longest in the twentieth century, helped Spanish income per capita surpass the EU average in the early 2000s. However, a standard growth accounting exercise shows that the boom was driven by factor accumulation (labor and capital) rather than by increases in productivity.

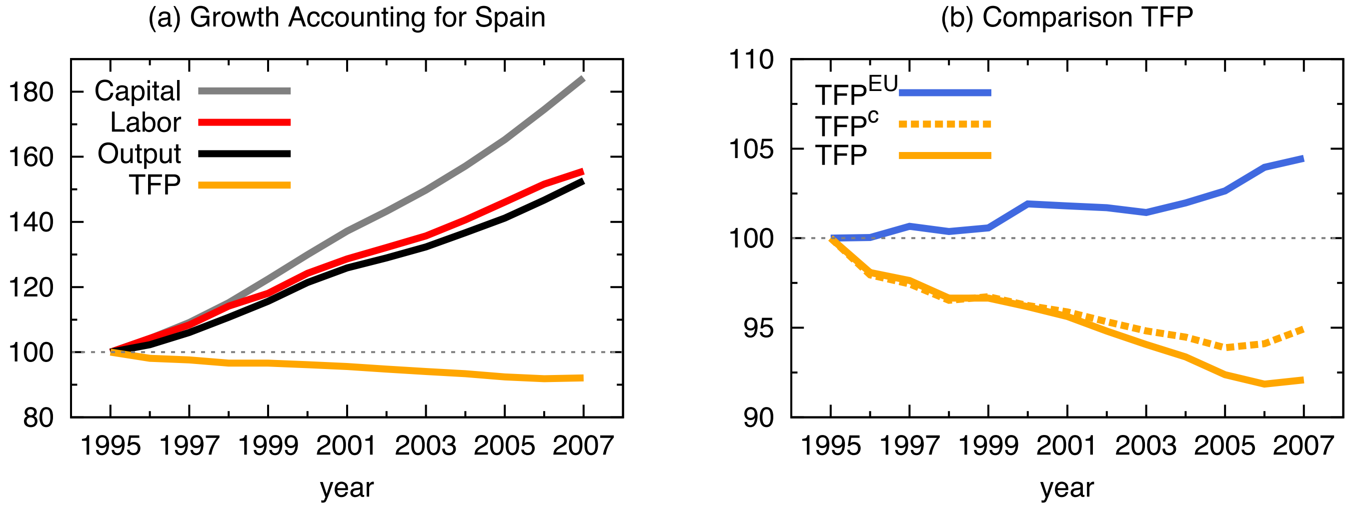
Panel (a) in Figure 1 clearly illustrates this pattern.[6] The labor contribution to output (total hours worked) expanded 3.8 percent a year in 1995-2007. This was the result of three main factors: a fast growing working age population —mainly due to migration flows—, an increasing labor force participation rate —mainly reflecting the incorporation of women into the labor market—, and a decline of the unemployment rate from the high values achieved in 1993.[7] The capital stock also grew at an unprecedented pace of 5.2 percent a year. The rise of the construction sector together with easy borrowing conditions played an important role in the expansion of the capital stock in Spain. Since both labor and capital grew more than final production, total factor productivity (TFP) was

[5] The argument by Fernandez-Villaverde, Garicano, and Santos (2013) is a bit more general as they also talk about a general deterioration of institutions because of the same signal-extraction problem faced by voters when politicians are able to supply large amounts of public goods through cheap borrowing.

[6] We use data from EU-KLEMS. In particular, we plot the volume indices on value added, labor and capital services as well as the value added-based TFP growth.

[7] It has been argued that the arrival of low-skilled immigrants reduced the average quality of the labor force, which would bias downwards the measure of TFP. However, Lacuesta, Puente, and Cuadrado (2011) show that changes in the composition of the labor force are unimportant because the entrance of low-skilled immigrants was offset by the educational transition of natives, with new cohorts of workers being much better educated than their retiring counterparts.

Figure 1: The Spanish growth experience — Macro evidence



Notes. Panel (a) shows the actual evolution of labor, capital, output and TFP during the period 1995-2007. Panel (b) shows the actual evolution of TFP in Spain (solid yellow line) and the EU (solid blue line), and the counterfactual evolution of TFP in Spain if sectoral shares had remained constant to their values in 1995 (dashed yellow line). The source for all the series is EU-KLEMS.

reduced by 0.7% per year.[8]

These Spanish figures are in sharp contrast to other developed economies. In the average EU country, output growth was 2.2% per year with growth rates of 1.1% and 3.3% for labor and capital, respectively.[9] As a result, TFP growth in the EU was on average 0.4% per year, which is in contrast to the Spanish annual rate of -0.7%. This difference is even more pronounced with respect to the US economy, which experienced an average TFP growth rate of 0.6% per year over the 1995-2007 period.

2.1 The evolution of sectoral reallocation

Next, we investigate whether the poor evolution of TFP during the studied period can be explained by resources being systematically allocated to the "wrong" sectors, i.e, sectors with bad performance in terms of productivity growth. To this end, we carry out three different exercises that allows us to quantify the importance of sectoral reallocation of factors in accounting for the aggregate evolution of Spanish TFP.

[8]The fall in aggregate TFP in Spain over this period was first documented by Conesa and Kehoe (2015).

[9]EU average refers to the EU15 group, which includes Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom. We take this reference group of developed countries similar to Spain because we have comparable growth accounting data from EU-KLEMS.

First, we compute an alternative counterfactual TFP series in which we aggregate sector-specific TFP levels with weights given by the sectoral shares in 1995. That is to say, we look at the evolution of TFP in a counterfactual scenario in which the different sectoral TFP's had evolved as in the data but their relative importance in the aggregate economy had remained constant.[10] We plot this counterfactual TFP in the Panel (b) of Figure 1, alongside the evolution of the actual aggregate TFP in Spain and in the EU. While we see that this counterfactual TFP falls at a slightly lower rate than the actual one, it still falls at an annual average rate of 0.4%, much closer to the actual 0.7% fall in Spain than to the positive 0.4% and 0.6% average growth rates of TFP in EU and US respectively.

Second, we build on Foster, Haltiwanger, and Krizan (2006) to perform a TFP growth accounting decomposition that allows us to analyze the connection between the dynamics of across-sectors reallocation and aggregate productivity.[11] For this exercise, we use 34 2-digit industries (ISIC rev. 3) from EU-KLEMS. This decomposition gives us a sense of the quantitative importance of three different types of productivity growth sources between 1995 and 2007: (i) the *within-sector* term, which measures the evolution of within sectors productivity, is simply an average of the different sectors' productivity growth weighted by initial value added shares; (ii) the *across-sectors* term, which reflects changes in productivity coming from reallocation of resources across sectors, is measured by the change in value added shares weighted by the initial relative sectoral productivities; and (iii) the *cross-term*, which captures whether sectors with high productivity growth were the ones that grew the most, is measured by the covariance between changes in productivity and changes in value added shares.[12] We find that the *within-industry* component accounts for almost all of the TFP evolution, explaining 89% of the decline in TFP over the 1995-2007 period. The remaining 11% is explained by the *cross-term* component, which reflects a negative covariance between TFP growth and value added changes across sectors.

Finally, we look at the evolution of the Olley and Pakes (1996) covariance term across the same 34 two-digit industries. This covariance term can be used as a proxy of static allocative efficiency across sectors. A big covariance suggests that sectors with relatively high productivity attract a relatively high amount of resources. By looking at the evolution of this measure, we study whether resources were systematically reallocated towards low productivity sectors during the boom. The covariance between the value added share and TFP was on average -0.01 in the 1995-2000 period, suggesting a low level of allocative efficiency across sectors in Spain. However, it remained basically unchanged, going to -0.02 in 2001-2007. This finding, together with our two previous exercises, confirms the

[10] We use the EU-KLEMS estimates of sectoral TFP (value added based). We consider five broadly-defined sectors: agriculture, fishing, and mining (divisions A, B, and C of ISIC Rev 3); manufacturing (D); construction and real estate (F, and 70); private services (G, H, I; J, K; and 71-74); and public services (E, L, M, N, and O).

[11] Note that this type of dynamic decomposition has extensively been used to study the reallocation dynamics within sector across firms. We will apply and explain this methodology later again in section 4.3 to our firm-level data.

[12] Note that the number of industries is fixed over time, so the contribution of the net entry margin is zero by construction.

minor role of reallocation of resources across industries in shaping the evolution of aggregate TFP in Spain over the period 1995-2007.

3 Firm-level Data

We use a firm-level dataset which contains information of a representative sample of Spanish non-financial companies from 1995 to 2007. The sample contains an average number of 497,782 firms per year. This database is named Central Balance Sheet Data —or *Central de Balances Integrada (CBI)* in Spanish— and is provided by the Banco de España. In contrast to other firm-level datasets that have been used in the misallocation literature, our dataset covers the services and construction sectors.

The database is comprised of two complementary datasets. The first one —*Central de Balances Anual (CBA)*— is based on a standardized voluntary survey handled to companies at the time of requesting compulsory accounting information. Each year, around 9,000 companies fill this survey. The information gathered is very detailed, but the sample size is low and big firms are over-represented. The second dataset —*Registros Mercantiles (CBB)*— contains the balance sheets of a much larger number of companies. It originates from the firms' legal obligation to deposit their balance sheets on the Mercantile Registry. Therefore, coverage is much wider.

The Bank of Spain Central Balance Sheet Office is in charge of collecting and cleaning these datasets. All of the variables contained in the latter database are also included in the former. For each firm, we observe its revenue, total wage bill, employment, book value of the capital stock (both physical and intangible), expenses in intermediate goods, and sector of activity at the 4-digit level (according to the NACE rev. 2 classification). Since most of the variables are recorded in nominal terms, we employ sector-specific deflators for capital and value added to compute real values with 2000 as the base year.[13]

Despite firms have the legal obligation to submit their statements, some observations are missing from our data because firms deposit their balance sheets late or on paper form, in which case they may not have been digitized. Panel A of Table 1 illustrates the size distribution of firms in our raw sample for the year 2001. The table also compares this distribution with that obtained from the Central Business Register available from the National Statistics Institute, which contains employment information for the universe of Spanish firms. There are two important aspects to highlight. First, the coverage of our raw sample is remarkably large in terms of both the number of firms (56% of the operating firms in Spain) and the level of employment (54% of total employment). Second, our sample provides an excellent representation of the firm size distribution in Spain. In particular, small firms (less than 10 employees) account for 83.90% of the total number of firms and 20.47% of the

[13]We take the capital deflators from Mas, Pérez, and Uriel (2013) and the value added deflator from Spanish National Accounts. Both sets of deflators are constructed at the 2-digit NACE classification.

Table 1: Size distribution of firms in our sample and in the census.

	Central Balance Sheet Dataset				Central Business Register			
	Firms		Labor		Firms		Labor	
Employees	Total (#)	Share (%)	Total (#)	Share (%)	Total (#)	Share (%)	Total (#)	Share (%)
				PANEL A: Raw Sample				
0-9	406,924	83.90	941,897	20.47	715,795	83.07	1,718,600	20.23
10-19	41,664	8.59	583,312	12.68	77,372	8.98	1,050,038	12.36
20-49	27,125	5.59	828,714	18.01	46,683	5.42	1,400,422	16.49
50-199	8,064	1.66	707,535	15.38	17,781	2.06	1,596,481	18.79
+200	1,245	0.26	1,540,260	33.47	4,082	0.47	2,728,958	32.13
All	485,022	100.00	4,601,718	100.00	861,713	100.00	8,494,499	100.00
				PANEL B: Final Sample				
1-9	249,770	76.34	907,098	20.00	531,399	78.46	1,718,600	20.23
10-19	41,272	12.62	577,844	12.74	77,372	11.42	1,050,038	12.36
20-49	26,919	8.23	822,699	18.14	46,683	6.89	1,400,422	16.49
50-199	7,984	2.44	700,565	15.44	17,781	2.63	1,596,481	18.79
+200	1,219	0.37	1,528,178	33.69	4,082	0.60	2,728,958	32.13
All	327,164	100.00	4,536,384	100.00	677,317	100.00	8,494,499	100.00

Notes. Figures refer to the year 2001. Self-employed persons are not included.

employment in our sample versus 83.07% and 20.23% in the population. At the other extreme, large firms (more than 200 employees) represent less than 0.5% of the total number of firms both in our sample and in the population, while they account for 33.47% of the employment in our sample and 32.13% in the population.

From this original sample we drop observations with missing or non-positive values for the number of employees, value added, or capital stock. We also eliminate observations at the top and bottom 1% of these variables. Since our misallocation measures are computed within each 4-digit industry, we also drop firms belonging to industries with less than 10 firms per year. We also exclude firms with 0 employees because these firms represent mostly firms with no production, being created merely for tax purposes.[14] We are left with around 350,000 firms per year distributed across 518 4-digit industries. In Panel B of Table 1 we compare this sample to the population of firms in the Central Business Register, from which we have also deleted firms with 0 employees. We see that our screening strategy has minor effects in the distributions of firms and employment, and that the representativeness of our final sample remains noticeably good.[15]

[14]Notice that these firms are not self-employed people, which are not covered in out dataset.

[15]This is true for all years between 2001 and 2007. In 1995 our sample slightly over-represents big firms, a problem that vanishes gradually over the years. see Appendix E for details.

4 Misallocation and productivity in the Spanish boom

In this section we use different methodologies to document the worsening of allocative efficiency across firms over the 1995-2007 period. Our findings support the hypothesis that the increase in misallocation of resources across firms was behind the poor performance of Spanish aggregate TFP.

4.1 The evolution of marginal revenue products of capital and labor

Dispersion of productivities across firms within the same sector is generally taken as a measure of misallocation. We start by showing the evolution of dispersion in the average products of capital and labor. We measure average product of firm i in sector s at time t by dividing value added $P_{sit}Y_{sit}$ by capital K_{sit} and labor L_{sit}, and we compute the standard deviation of the logs within each of our 518 4-digit industries s at time t. We obtain an economy-wide measure of dispersion by taking the value added-weighted average of dispersions within each sector. Figure 2 shows the time evolution of these measures. We uncover three main facts. First, the dispersion in the average products is much larger for capital than for labor: the standard deviation is 1.20 log points for capital and 0.47 for labor in 1995. Second, the dispersion in the average product of capital grew more than the dispersion in the average product of labor. In particular, the dispersion in the average product of capital increased monotonically over the 1995-2007 period, with an overall increase of 0.28 log points, while the dispersion in the average product of labor increased 0.03 log points overall, after an initial decrease until 1999. And third, as shown in panels (b) and (c), there is substantial variation across sectors.

Under the theoretical framework of Hsieh and Klenow (2009) (HK hereafter) the average products of capital and labor can be mapped into marginal revenue products, and subsequently into firm-level idiosyncratic wedges in capital (τ_{Ksit}) and labor (τ_{Ksit}).[16] In particular, the marginal revenue products of capital and labor (MRPK and MRPL) are as follow:

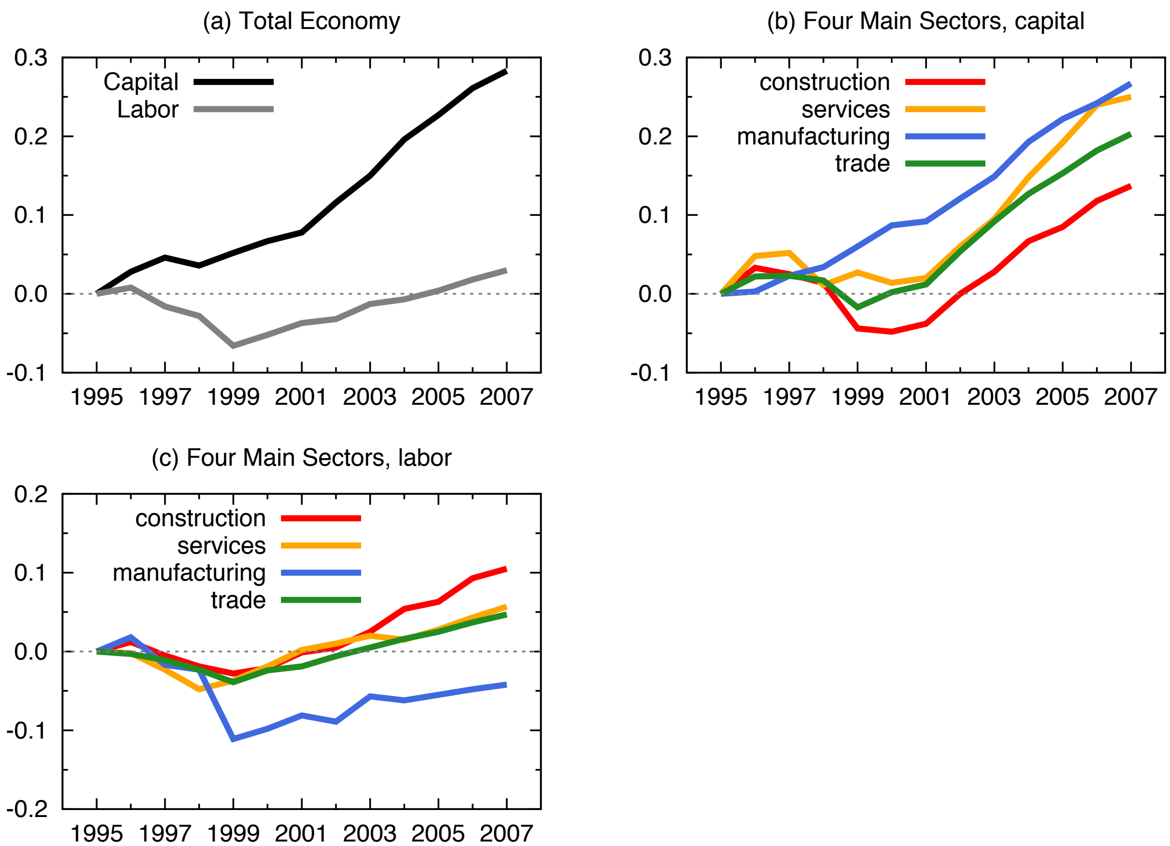
$$\mathrm{MRPK}_{sit} = \alpha_s \left(\frac{\sigma-1}{\sigma}\right)\left(\frac{P_{sit}Y_{sit}}{K_{sit}}\right) = (1+\tau_{Ksit})\, r_t \tag{1}$$

$$\mathrm{MRPL}_{sit} = (1-\alpha_s) \left(\frac{\sigma-1}{\sigma}\right)\left(\frac{P_{sit}Y_{sit}}{L_{sit}}\right) = (1+\tau_{Lsit})\, w_t \tag{2}$$

where α_s is a sector specific capital share, σ is the elasticity of substitution, and r_t and w_t are economy-wide factor prices. In an undistorted economy ($\tau_{Ksit}=0$ and $\tau_{Lsit}=0\ \forall sit$) all firms within a sector s in period t would equalize their marginal revenue products to the factor prices r_t and

[16] See appendix A for a detailed presentation of the HK model. Note that we depart slightly from HK in the characterization of the distortions by focusing on distortions in the level of capital (τ_{Ksi}) and labor (τ_{Lsi}) instead of output (τ^*_{Ysi}) and capital to labor ratio (τ^*_{Ksi}). Firms' first order conditions and sectoral TFP's are identical under these two specifications when $(1+\tau_{Lsi}) = 1/(1-\tau^*_{Ysi})$ and $(1+\tau_{Ksi})/(1+\tau_{Lsi}) = (1+\tau^*_{Ksi})$.

Figure 2: Within-industry dispersion of average products of capital and labour



Notes. Panel (a) reports the within-sector standard deviations of average products of capital and labor measured at the 4-digit industry level and then aggregated to the whole economy using value added weights. We report the difference with respect to the 1995 values, which were 1.20 and 0.47 log points for capital and labor. Panels (b) and (c) report the aggregation for the four main sectors of activity.

w_t. Hence, within sector variation in MRPK and MRPL necessarily arises from variation in firms' idiosyncratic distortions. Taking logs we see that the dispersions in average products documented in Figure 2 correspond to the dispersions of MRPK and MRPL.

4.2 Aggregate TFP losses

Next, we exploit the whole structure of the HK framework to study how the increase in dispersion of marginal revenue products translated into aggregate TFP losses. Following the standard approach, the TFP in sector s at time t can be computed as

$$\mathrm{TFP}_{st} = \left[\sum_{i=1}^{M_{st}} \left(A_{sit} \left(\frac{\overline{\mathrm{MRPK}}_{st}}{\mathrm{MRPK}_{sit}}\right)^{\alpha_s} \left(\frac{\overline{\mathrm{MRPL}}_{st}}{\mathrm{MRPL}_{sit}}\right)^{1-\alpha_s} \right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \tag{3}$$

where A_{sit} is firm i TFP and $\overline{\mathrm{MRPK}}_{st}$ and $\overline{\mathrm{MRPL}}_{st}$ are harmonic means of firm-level marginal revenue products in sector s weighted by the value added shares. Absent the idiosyncratic distortions the marginal revenue products equalize across firms and TFP under the efficient allocation would be given by

$$\mathrm{TFP}^{*}_{st} = \left[\sum_{i=1}^{M_{st}} A_{sit}^{\sigma-1}\right]^{\frac{1}{\sigma-1}}$$

Hence, we can measure the potential TFP gains of reallocation in sector s at time t as the ratio of efficient to observed TFP, i.e., $\mathrm{TFP}^{*}_{st}/\mathrm{TFP}_{st}$, and we can obtain the economy-wide gains by taking the value added-weighted average over all 4-digit industries. We parametrize the model following HK, see Appendix A.3, but we also perform some robustness exercises in Appendix B.

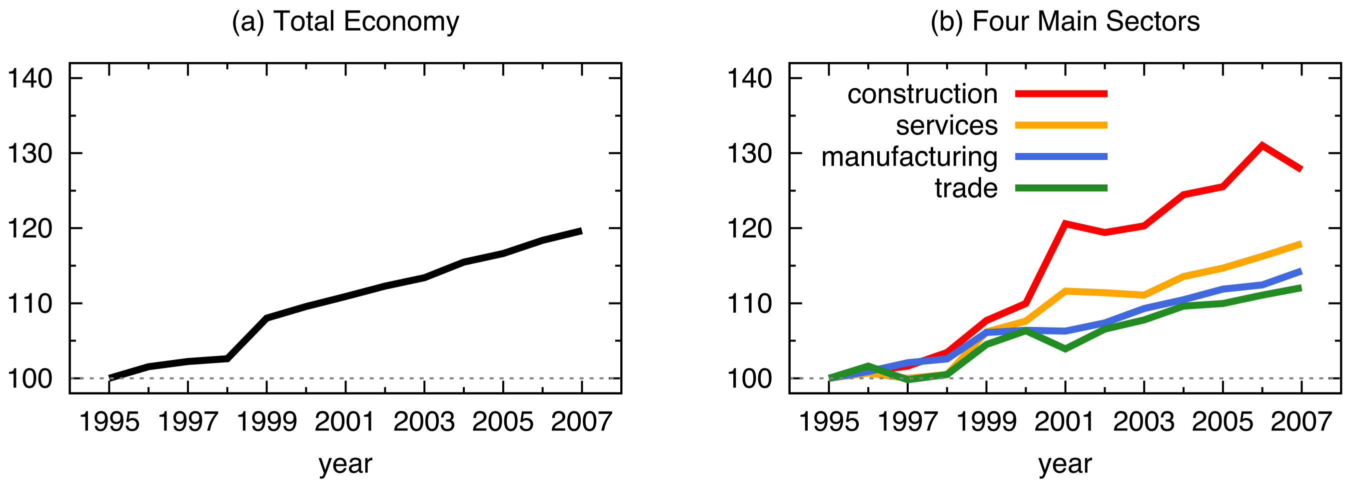
We report the yearly evolution of potential TFP gains of removing misallocation for the overall economy in Panel (a) of Figure 3.[17] We find that allocative efficiency decreased substantially over the period, eroding a potential increase in TFP of 20 percent between 1995 and 2007, an average of 1.5 percent per year. Importantly, in Panel (b) of Figure 3 we also see that this increase in misallocation is a general phenomenon across the major sectors of the economy. More precisely, we find that the potential TFP gains in construction are the largest, around 30%, followed by services, around 20%, and then trade and manufacturing with potential TFP gains between 10% and 15%.[18]

We argue that the stark increase in within-sector misallocation is at the root of the bad performance of aggregate TFP in Spain as compared to the EU. To show this more clearly, we compute a counterfactual TFP growth under the assumption that misallocation remains constant at its 1995 level by multiplying every year the observed aggregate TFP by the potential TFP gains reported in Panel (a) of Figure 3. We plot the resulting counterfactual TFP growth rates together with the observed ones in Figure 4, after applying a moving average filter to the series. We find that annual growth rates of potential TFP would have been between 0.6% and 1.1% with an average of 0.8% under the assumption of constant within-sector misallocation (dashed blue line). In contrast, observed

[17]The counterfactual TFP gain (ratio of efficient to observed TFP) does not allow for measurement error or model misspecification, which may cast doubt on the usefulness of these numbers without a reference point to compare. However, we do not focus on the level but on the change of potential TFP gains relative to the year 1995. Our implicit assumption is that neither measurement error nor model misspecification have changed over time.

[18]The decline in allocative efficiency in manufacturing within the second half of our sample period is consistent with the findings by Crespo and Segura-Cayuela (2014) and Gopinath, Kalemli-Ozcan, Karabarbounis, and Villegas-Sanchez (2015) using the AMADEUS data set.

Figure 3: Potential TFP gains from reallocation



Notes. Panel (a) describes the evolution of potential TFP gains of removing distortions for the overall economy, normalized by the level in 1995. Panel (b) plots the evolution of potential TFP gains for different sectors. Potential TFP gains have been computed using the Hsieh and Klenow (2009) methodology, i.e, $\frac{\text{TFP}^*}{\text{TFP}}$. See Appendix A for details.

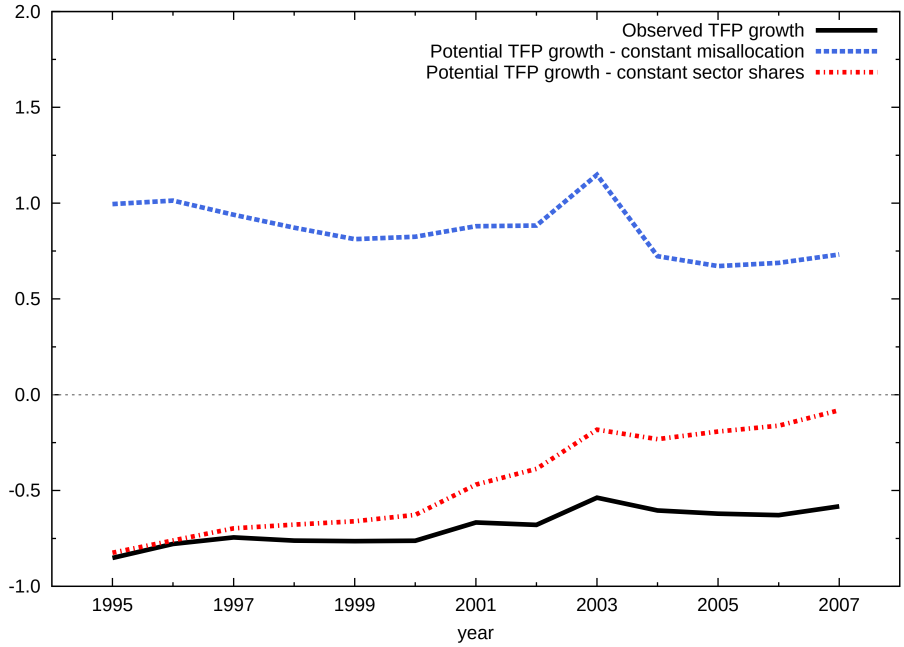
TFP growth was -0.7% on average, ranging from -0.8% to -0.5% (solid black line). For comparison, we also plot in the same Figure 4 the counterfactual series of TFP growth in which we keep the relative size of sectors constant at the 1995 level (see footnote 10 in Section 2). We observe that the TFP growth would have been slightly larger than observed in the data, ranging from -0.8% to -0.1%, with an average of -0.5% (dotted red line). This suggests that there was a shift of resources towards less productive sectors. However, the difference between this counterfactual TFP growth and the actual one is rather small.

4.3 Sources of misallocation

Finally, we investigate the relative importance of distortions in capital, τ_{Ksit}, and labor, τ_{Lsit}, in accounting for the overall increase in misallocation. Note that assuming joint log-normality for the distribution of $(1+\tau_{Ksit})$, $(1+\tau_{Lsit})$, and A_{sit}, the potential TFP gains of removing distortions in sector s at time t can be expressed as:

$$\begin{aligned}\log\left(\frac{\text{TFP}^*_{st}}{\text{TFP}_{st}}\right) &= \frac{\sigma\alpha_s^2+\alpha_s(1-\alpha_s)}{2}\text{Var}\Big[\log(1+\tau_{Ksit})\Big] + \frac{\sigma(1-\alpha_s)^2+\alpha_s(1-\alpha_s)}{2}\text{Var}\Big[\log(1+\tau_{Lsit})\Big] \\ &+ (\sigma-1)\,\alpha_s(1-\alpha_s)\,\text{Cov}\Big[\log(1+\tau_{Ksit}),\log(1+\tau_{Lsit})\Big]\end{aligned}$$

Figure 4: Potential TFP growth under 1995 misallocation level



Notes. This Figure shows the time series of (i) the observed TFP growth; (ii) the counterfactual TFP growth if misallocation had remained constant to its 1995 level; and (iii) the counterfactual TFP growth if sectoral shares had remained constant to their 1995 values. A moving average filter is applied to smooth the series.

Losses to misallocation increase with the dispersion of the idiosyncratic wedges, which correspond to the dispersion of revenue marginal and average products in Figure 2, and with their covariances.

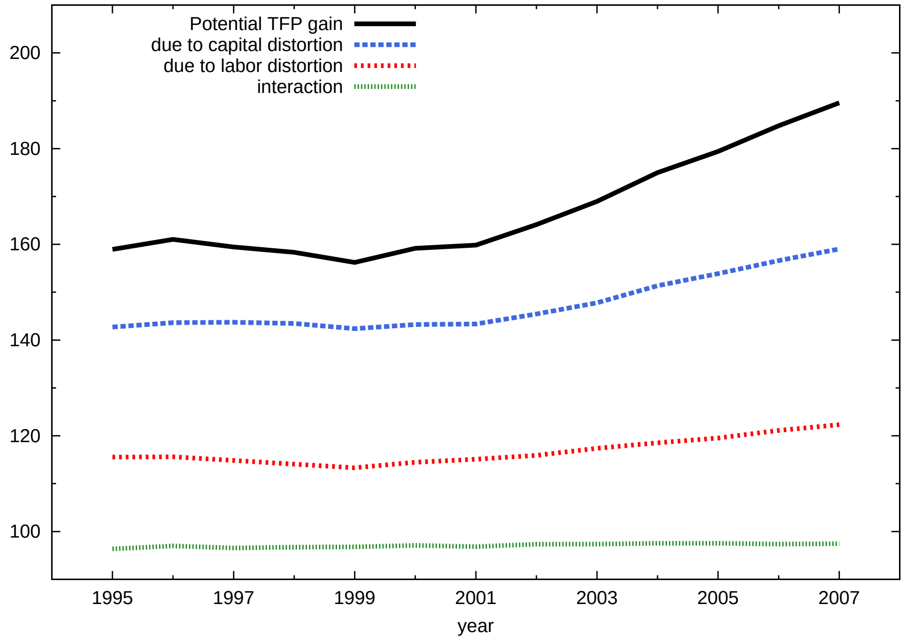
We report the results of this decomposition by plotting in Figure 5 the resulting potential TFP gains from each of the three components when aggregating across all 4-digit industries with corresponding value-added weights.[19] We find that both distortions are important. The labor distortion accounts for around 1/3 of the total losses to misallocation in 1995, the capital distortion accounts for around 2/3, and the covariance between them is almost negligible. In terms of the increase in misallocation between 1995 and 2007, the relative contributions are of the same order of magnitude.

4.4 Model-free measures of allocative efficiency

In order to further explore the role of of the various sources of productivity growth during the studied period, we apply the decomposition considered by Foster, Haltiwanger, and Krizan (2006) to our

[19]Note that the overall TFP gains under log-normality do not coincide with our benchmark numbers without log-normality presented in Figure 3. In contrast to our benchmark, potential TFP gains start increasing in 2001 in the case of log-normality.

Figure 5: Potential TFP gains from reallocation by type of distortion



Notes. This Figure reports potential TFP gains of eliminating all distortions (solid black line) and the decomposition on TFP gains due to each distortion and their covariance.

firm-level data for the period 2001-2007.[20] This allows us to decompose sectoral productivity growth into four different sources: *within-firm*, *between-firm*, *cross-term*, and *entry/exit*. In particular, total productivity growth between $t-1$ and t in industry s can be decomposed as

$$\begin{aligned}\Delta\Omega_{st} &= \sum_{i\in C}\theta_{sit-1}\Delta\omega_{sit} + \sum_{i\in C}\Delta\theta_{sit}(\omega_{sit-1}-\Omega_{st-1}) + \sum_{i\in C}\Delta\theta_{sit}\Delta\omega_{sit} \\ &+ \sum_{i\in N}\theta_{sit}(\omega_{sit}-\Omega_{st-1}) - \sum_{i\in X}\theta_{sit-1}(\omega_{sit-1}-\Omega_{st-1})\end{aligned}$$

where Ω_{st} refers to the productivity (log-TFP) of a given 4-digit industry s at time t, ω_{sit} is a measure of productivity of firm i in year t operating in industry s, θ_{sit} represents the firm-specific share, and Δ represents the first-differences operator. Moreover, C denotes continuing firms, N denotes entering firms, and X denotes exiting firms. The first term represents a within-firm component based on firm-specific TFP growth, weighted by initial value added shares in the industry. The second term represents a between-firm component that reflects changing shares, weighted by the deviation of initial firm-specific TFP from the industry-level TFP. The third term represents a cross

[20]We restrict our sample to the 2001-2007 period because census data from the Central Business Register with detailed information on firm entry and exit is not available before the year 2001.

Table 2: Evolution of model-free measures of allocative efficiency

	Economy	Manuf.	Const.	Trade	Services
(A) TFP growth (%)	-3.7	-1.3	-8.1	-3.6	-4.1
(B) Contributions to TFP growth					
Within	0.3	0.1	-0.4	0.3	0.7
Between	-4.5	-1.4	-8.4	-4.0	-6.4
Cross term	0.3	0.1	0.6	0.4	0.3
Net entry	0.3	0.0	0.1	-0.3	1.3
(C) OP Covariance term (TFP)					
Period 1995-2000	1.59	1.43	1.61	1.73	1.72
Period 2001-2007	1.35	1.13	1.28	1.39	1.58
(D) OP Covariance term (LPR)					
Period 1995-2000	0.30	0.32	0.15	0.31	0.37
Period 2001-2007	0.21	0.27	0.10	0.25	0.19

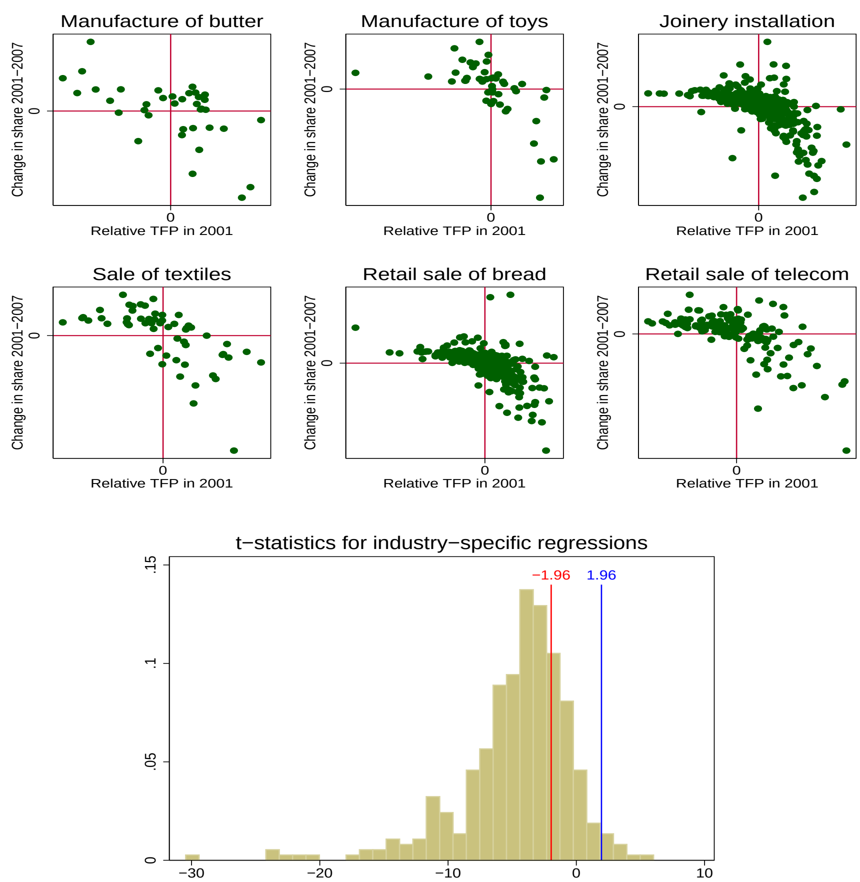
Notes: Panel (A) shows the TFP growth rate for the period 2001-2007, and Panel (B) its decomposition into four different components, which comes from applying Foster, Haltiwanger, and Krizan (2006) to our firm level data. Panels (C) and (D) show the TFP and labor productivity OP covariance terms for the periods 1995-2000 and 2001-2007, respectively. The different columns show the value of these measures for the aggregate and for the main four sectors separately.

term capturing whether businesses with large positive productivity changes are more likely to have decreased their shares and viceversa. The last two terms represent the contribution of entering and exiting firms, respectively.

Panel (B) in Table 2 shows the results for the total economy as well as for the four main sectors. These aggregate figures are computed as weighted averages of 4-digit industry-level data using value added as weights. The first column shows that the *within-firm* component, the *cross-term* component, and the *net entry* component contribute positively to total TFP growth for the overall economy. In contrast, the *between-firm* component, which reflects reallocation of resources across firms, was at the root of the decline in overall TFP growth over the period 2001-2007. While overall TFP fell -3.7% over the six-year period, the *between* component fell even more (-4.5%). This finding confirms the crucial role of increasing within-industry misallocation as a source of low productivity growth in Spain. The remaining columns of Panel (B) in Table 2 show that, while this pattern was present in all main four sectors of activity, losses to misallocation between firms were substantially more severe in construction and services.

The negative *between-firm* component implies a negative covariance between changes in firm-specific sectoral shares and initial TFP within each 4-digit industry. We illustrate this pattern in the upper panel of Figure 6, where we plot the change in firm market shares over the 2001-2007 period against the level of firm TFP in 2001 for six selected 4-digit industries. We focus on firms that are in our panel during this 6-year period. In all the six cases the relationship is negative, which means that firms with initial TFP below the industry average gained market share at the expense of firms with larger TFP. This relationship is negative and statistically significant for 80 per cent of the 356 industries considered, as shown in the bottom panel of Figure 6, which plots the distribution of the t-statistics resulting from the 356 sector-specific regressions. A very similar result arises if we measure relative share by employment.

FIGURE 6: The Spanish growth experience — Micro evidence



Notes. Relative TFP refers to the logarithm of firm-specific TFP relative to the industry average, $\log(\text{TFP}_{sit}/\overline{\text{TFP}}_{sit})$. Change in share refers to the difference in firm-specific market share measured in terms of value added. The bottom panel plots the distribution of the t-statistics resulting from the 356 sector-specific regressions.

Finally, as an alternative measure of misallocation, we also compute the Olley and Pakes (1996) within-industry covariance between size and productivity, recently used by Bartelsman, Haltiwanger, and Scarpetta (2013). The idea is that in a frictionless economy more productive firms should attract more labor and capital. So, let ω_{sit} be a measure of productivity of firm i in sector s at time t and θ_{sit} a measure of relative size of firm i. We can define an index Ω_{st} of aggregate productivity in sector s as follows

$$\Omega_{st} = \bar{\omega}_{st} + \sum_{i}^{N} \left(\theta_{sit} - \bar{\theta}_{st}\right)\left(\omega_{sit} - \bar{\omega}_{st}\right)$$

where $\bar{\omega}_{st} = \frac{1}{N}\sum_i^N \omega_{sit}$ and $\bar{\theta}_{st} = \frac{1}{N}\sum_i^N \theta_{sit}$. Hence, aggregate productivity can be decomposed between a term summarizing the productivity of firms (the unweighted average of productivities) and a term summarizing the allocation of inputs across firms (the covariance term between size and productivity).

For each industry-year pair, we compute the within-sector cross-sectional covariance between firm-specific value added shares and total factor productivity. Then, we aggregate for each year the industry-specific covariances using value added weights and analyze the evolution over time of the resulting covariances. Under an efficient allocation of resources, more productive firms should produce more and employ more capital and workers. Panel (C) in Table 2 shows that the covariance between TFP and firms sizes fell from 1.59 to 1.35, which clearly points to an increase in the degree of misallocation. Panel (D) in Table 2 shows that the results are similar if instead of TFP we use labor productivity as a measure of firm productivity.

5 Sector-level analysis

The decline in allocative efficiency between firms was widespread over the whole economy, but it is also true that there was substantial variation across industries. In this section we exploit the rich variation of misallocation experiences across industries to learn about the potential reasons of the phenomenon.

We start by aggregating our HK measures of misallocation at the 4-digit level into 2-digit level industries because we have information on several sectoral characteristics at the 2-digit NACE rev. 2 classification only (see Table D.1 in the Appendix). We find that 51 out of 58 two-digit level industries experienced increases in the HK potential TFP gains.[21]

Next, we consider six different dimensions that might be related to the evolution of allocative efficiency. First, we explore the role of skill intensity differences across sectors as an indirect way to look into the duality of the Spanish labor market in terms of contracts. Firing costs have been long

[21] Allocative efficiency worsens the most in "*Warehousing and support activities for transportation*", "*Electricity, gas, steam and air conditioning supply*", and "*Activities of head offices; management consultancy activities*", while "*Manufacture of furniture*", "*Manufacture of beverages*", and "*Motion picture, video and television show production, sound recording*" experienced slight improvements in allocative efficiency.

blamed as a possible source of misallocation of workers across firms (see Hopenhayn and Rogerson (1993)). Firing costs on open ended contracts are high in Spain, but at the same time the use of flexible fixed-term contracts is widespread.[22] Fixed-term contracts are less prevalent among high skilled occupations, probably because employee turnover precludes on-the-job human capital accumulation.[23] Hence, if firing costs are an important source of misallocation, we may expect a larger increase in misallocation in high-skill industries in a period of factor accumulation. We take skill intensity in US sectors as our baseline proxy because it is expected to be exogenous to the evolution of allocative efficiency in Spanish sectors of activity.

Second, differences in external financial dependence across sectors may affect the resource allocation process. The sharp expansion in bank lending during the period 1995-2007 originated an increase in the stock of loans from credit institutions to non-financial corporations from 38% of GDP in 1995 to 90% in 2007. The increasing abundance of new credit to firms together with a loose screening process by banks can generate a deterioration in allocative efficiency if bad firms are able to survive hampering the reallocation process towards better firms. In order to check this potential channel, we consider a sector-specific finance intensity variable constructed by Fernald (2014) for the US. Exploiting Input-Output tables, this finance intensity variable is given by nominal purchases of intermediate financial services as a share of industry gross output. Again, using US sector characteristics ensures exogeneity with respect to the evolution of allocative efficiency in Spanish industries.

Third, more dynamic industries can be expected to produce better allocations of resources. For instance, more innovative sectors have usually larger shares of innovative and young firms that can easily adapt to shifts in demand or actions taken by competitors. Cecchetti and Kharroubi (2012) argue that credit booms (such as the one witnessed in Spain over 1995-2007) undermine R&D intensive sectors, which might be related to the deterioration in TFP growth. Along these lines, we consider Fernald (2014) IT intensity variable at the sector level in the US, which consists on the payments for IT as a share of income (taken from the Bureau of Labor Statistics).

Fourth, industries more exposed to international trade are likely to exhibit a better allocation of resources because foreign competition exerts additional market pressures on firms to operate efficiently (see for instance Pavcnik (2002)). We proxy the tradability of each industry with the ratio of industry exports over final industry demand (consumption, investment and exports). These data comes from the Input-Output Tables of the Spanish National Statistical Institute.

Fifth, Díaz and Franjo (Forthcoming) argue that subsidies to investment in structures can generate an inefficient level of capital structures with respect to capital equipment. We thus investigate

[22] The share of fixed-term contracts in Spain was stable around 35% of employment between 1995 and 2007. There was however a sharp increase in its use before 1995.

[23] For instance, in 1991 the share of fixed-term contracts among *ingenieros y licenciados* —the top occupational group according to the classification of the Social Security Administration— with 5 years of labor market experience was 30%. In contrast, the share for *peones* —the bottom occupational group— was 70%, see Estrada, Izquierdo, and Lacuesta (2009).

to what extent sectors more intensive in structures presented higher misallocation because this type of subsidies may also generate excessive investment in structures at the firm level. We consider the ratio of capital compensation in structures over total value added at the 2-digit industry level. Structures comprise residential structures and non-residential structures. These data are taken from EU-KLEMS, which computes capital compensation as gross value added minus labor compensation.

Finally, some sectors may be less competitive because business success is related to state licensing or regulation. If this is the case, we could expect some firms in such sectors to operate with size or input mix far from optimal and still survive. To explore this hypothesis, we follow the classification of *crony sectors* used by *The Economist*, which is based on the *Bribe Payers Index*, conducted by *Transparency Internacional*. This index is based on a survey to business executives in many countries, who are asked: "How often do firms in each sector (i) engage of bribery of low level public officials, for example to speed-up administrative processes and/or to facilitate the granting licenses?; (ii) use improper contributions to high-ranking politicians or political parties to achieve influence?; and (iii) pay or receive bribes from other private firms?".[24] We define a dummy variable taking value 1 for those sectors considered to be *crony sectors*.[25]

Table 3 shows some correlations between the sector characteristics just described and the changes in allocative efficiency. In particular, we regress the change in sector-specific potential TFP gains on the different characteristics measured as the average over the 1995-2007 period. Columns (1)-(7) are based on linear regressions with different covariates. Column (8) is based on weighted-average least squares (WALS), a model averaging approach that provides standard errors incorporating not only parameter uncertainty but also model uncertainty.[26]

We fail to find any statistically significant relationship between skill intensity, innovative content, financial dependence, tradability or capital structures intensity with the change in allocative efficiency (see Columns (1)-(5) in Table 3). Furthermore, the R-squared indicates that variation in these characteristics can only account for less than 0.5% of the variation in misallocation changes. In contrast, Column (6) in Table 3 indicates that the deterioration in allocative efficiency was 22.6 points larger in crony sectors, an increase that is more than twice the increase in the non-crony sectors. This statistically significant difference implies that the eleven industries in which success in business depends more on relationships between firm managers and public sector officials were the industries

[24]See http://goo.gl/w4mgxd for details.

[25]These sectors are, casinos, coal, palm oil and timber, defense, deposit-taking banking and investment banking, infrastructure and pipelines, ports, airports, real estate and construction, steel, other metals, mining and commodities, utilities and telecoms services. In our dataset, we label as crony the following 2-digit sectors: 24, 35, 37, 38, 39, 41, 42, 50, 51, 61, and 68 (see Table D.1 in the Appendix).

[26]Model uncertainty results from the lack of theoretical guidance on the particular regressors to include in the empirical model. When model uncertainty is present, traditional standard errors would under-estimate the real uncertainty associated to the estimate of interest because variation across models is ignored. In order to account for both levels of uncertainty, model averaging techniques (e.g. WALS) estimate all possible combinations of regressors and constructs a single estimate by averaging all model-specific estimates (see Moral-Benito (2015) for an in-depth analysis of model averaging).

Table 3: Misallocation and sector-specific characteristics.

	Dependent variable: ΔTFP Gain							
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) WALS
High-skill intensity	0.064						-0.007	-0.018
	(0.219)						(0.282)	(0.244)
Innovative content		0.284					0.091	0.077
		(0.445)					(0.529)	(0.435)
Financial dependence			0.044				0.026	0.019
			(0.029)				(0.034)	(0.028)
Tradability				-0.199			-0.155	-0.106
				(0.121)			(0.137)	(0.112)
Capital structures					0.187		-0.408	-0.273
					(0.236)		(0.316)	(0.282)
Public sector						0.226***	0.277**	0.182**
						(0.081)	(0.105)	(0.089)
Constant	0.219***	0.216***	0.148**	0.303***	0.207***	0.199***	0.248**	0.244**
	(0.069)	(0.046)	(0.066)	(0.051)	(0.049)	(0.069)	(0.121)	(0.104)
Observations	58	58	58	58	58	58	58	58
R-squared	0.00	0.01	0.04	0.05	0.01	0.12	0.19	-

Notes. This Table shows the results of regressing changes in allocative efficiency against 2-digit sector characteristics. ΔTFP Gain refers to the change over the 1995-2007 period in the ratio of optimal TFP in the absence of misallocation to observed TFP, according to the HK methodology.

experiencing the largest increases in misallocation over the 1995-2007 period. In addition, the crony dummy is able to account for 12% of this variation. When all the variables are jointly included in the regression in column (7), the magnitude and significance of the crony dummy remains virtually unaltered; however, partial correlations of skill intensity, innovative content, financial dependence, tradability, and capital structures intensity remain statistically indistinguishable from zero. Column (8) reports WALS estimates confirming the conclusion from column (7) even when we also account for model uncertainty.

In Appendix C we provide several robustness checks. First, we consider alternative definitions for all our six sectoral variables, and results are unchanged.[27] Second, because the increase in misallocation in construction was large (see Panel (b) in Figure 3), we explore whether the construction

[27]In particular, we consider directly the share of temporary workers computed with our firm-level data; the ratio of sectors total liabilities as a percentage of its total assets computed using firm-level data from the Central Balance Sheet Data; as an alternative measure of sector-specific IT content, we exploit the Spanish PITEC survey to construct shares of R&D investment over total investment; the share of industry exports over total exports; we expand the capital structures intensity definition by including not only residential and non-residential structures but also other fixed capital assets taken from EU-KLEMS; and we also consider the Bribe Payers Index as a continuous variable.

sector itself may be driving the results of cronyism. We find that when we exclude the industries *construction of buildings*, *civil engineering*, and *specialised construction activities* the coefficient associated to the crony dummy remains significant at 1 percent and is similar in magnitude (0.252). And third, the recent paper by Gopinath, Kalemli-Ozcan, Karabarbounis, and Villegas-Sanchez (2015) argues that financial frictions were important in Spain to understand the increase of misallocation in manufacturing. To look into this in more detail, we repeat our regressions for financial dependence only for industries within the manufacturing sector, and we also explore the alternative measure of Rajan and Zingales (1998) for financial dependence, which is only available for manufactures. In both cases we fail to find a relationship between the increase in misallocation and the strength of financial dependence.

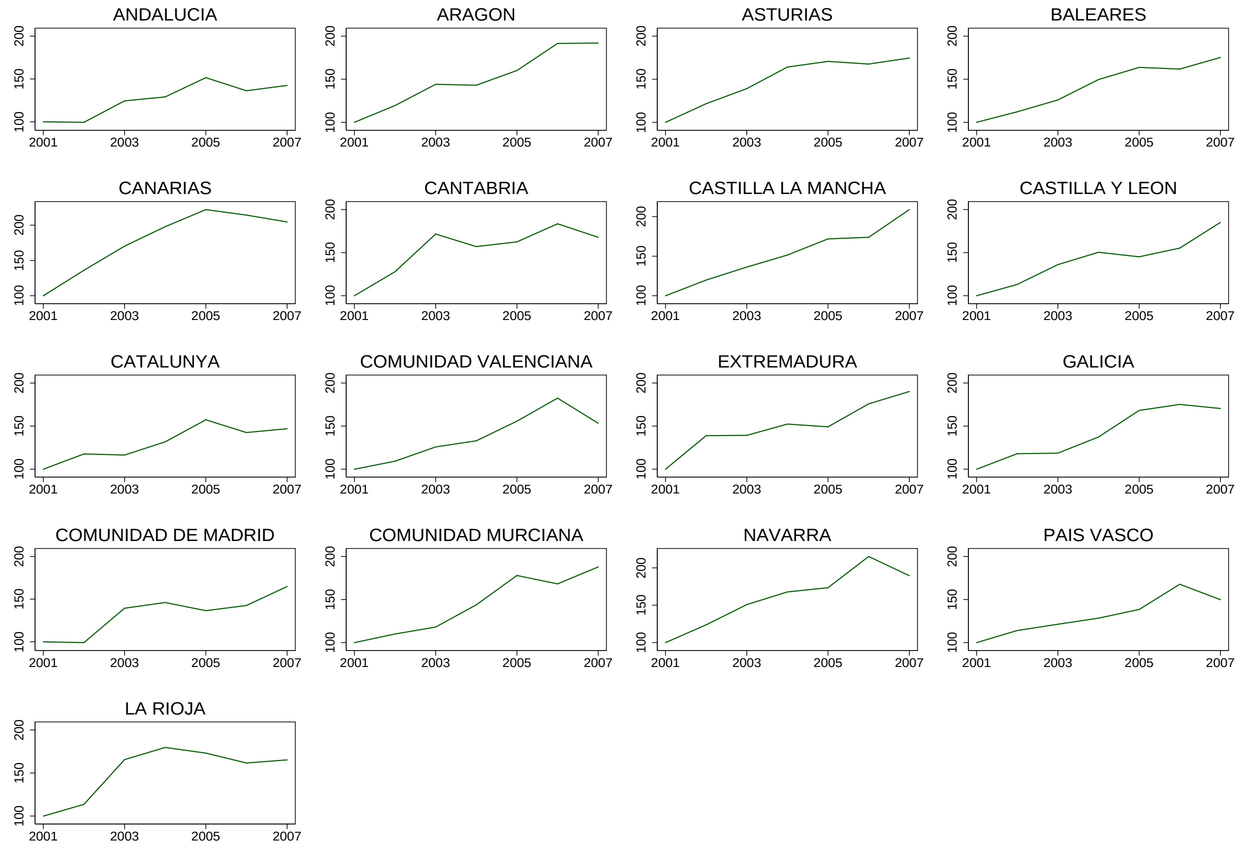
To sum up, financial frictions, dual labor markets, or lack of competition do not seem to have had large effects on the decline of allocative efficiency between firms. Instead, the results for cronyism are noteworthy: misallocation increased about twice as much in the sectors where the licensing and regulation by the government is relatively more important, which points towards important aggregate productivity costs of cronyism. However, the (value-added) share of crony sectors in our sample is around 28% of the total, so the overall effect of cronyism is partly offset by the small importance of these sectors. In order to account for the macroeconomic impact of cronyism in Spain, we aggregate the misallocation increases in our 4-digit industries for the crony and non-crony sectors separately for every year. We find that the increase in misallocation was around 2% per year in the crony sectors while it was 1.2% per year in the non-crony sectors. Hence, had the whole economy behaved as the non-crony sectors, the overall loss of TFP due the decline of allocative efficiency would have been 1.2% instead of 1.5%. We think this may be a lower bound on the costs of cronyism because our measure only captures variation between two types of sectors (crony and no crony). Yet, the influence of personal contacts or bribes to obtain favorable regulations, subsidies, privileged access to credit, or public procurement contracts may also be widespread in sectors not labelled as crony, and we do not have a way to measure this.

6 Regional misallocation

Spanish regions (*Comunidades Autónomas*) have the political power to enact laws and establish regulations. Indeed, Marcos, Santaló, and Sánchez-Graells (2010) document the existence of substantial heterogeneity in region-specific regulations. In addition, the Spanish labor market is characterized by large regional differences in employment and wages, see Bentolila and Jimeno (1998). Under these circumstances, a natural concern is whether the overall deterioration in allocative efficiency across firms might be just reflecting heterogeneity in the change of the relative cost of capital and labor in different regions.

We argue that this does not seem to be the case. First, Figure 7 shows that the increase in

Figure 7: Evolution of TFP gains in Spanish regions



Notes. Each panel represents the evolution of potential TFP gains as measured in Figure 3, but aggregating over Spanish NUTS 2 regions (or *Comunidades Autónomas*).

misallocation was present in all and each of the seventeen Spanish regions.[28] Second, using data from the *Encuesta de Estructura Salarial* for the years 2002 and 2006, we regress the region-specific average wage growth on the change in misallocation.[29] The estimated coefficient renders this relationship statistically insignificant, and has a point estimate of 0.047 (t-statistic = 0.79). Finally, by using data on housing prices across regions collected by the Spanish Ministry of Planning, we regress the change in housing prices between 2001 and 2007 on changes in allocative efficiency over the same period. We find an estimated coefficient of -0.19 with an associated t-statistic of -0.74. We thus conclude that the deterioration in allocative efficiency uncovered in this paper is caused by nationwide forces.

[28]We compute potential TFP gains from within-industry reallocation for each region-year pair over the 2001-2007 period. The number of firms steadily increased over the sample period in Spain so that for certain small regions there are not enough firms in each 4-digit sector in the first years to estimate meaningful TFP gains. Focusing on 2-digit sectors we can compute those measures and the increases are also generalized for these initial years.

[29]Available at http://goo.gl/tbYiOp.

7 Concluding Remarks

Spanish growth during the 1994-2007 expansion was based on factor accumulation rather than productivity gains. In particular, annual TFP growth was -0.7%, which is low in comparison to other developed economies such as the US or the EU. In this paper, we argue that the source of negative TFP growth has been the increase in the within-sector misallocation of production factors across firms.

In order to shed some light on the potential sources of this phenomenon in Spain, we find that industries in which the influence of the public sector is larger (e.g. through licensing or regulations) experienced significantly larger increases in misallocation. In contrast, other characteristics such as skill intensity, innovative content, and financial dependence are unrelated to changes in allocative efficiency.

The specific channels through which a higher influence of the public sector might deteriorate the allocation of resources across firms remain to be explored. The arbitrary assignment of public procurements to firms that have better connections with politicians might be a potential explanation, since these firms would end up being too big and attracting too much credit. The relationship between the prevalence of public procurement in a sector and its poor productivity performance could be explained by theories that relate productivity to mismatches between the characteristics of projects and the people who run them. For instance, Alder (2016) finds that matching frictions that make the economy allocate high quality projects to the "wrong hands" might generate aggregate productivity losses of up to 40%.

References

Acemoglu, D., S. Johnson, and J. Robinson (2005): “Institutions as the Fundamental Cause of Long-Run Growth,” in *Handbook of Economic Growth*, ed. by P. Aghion, and S. Durlauf, vol. 1, chap. 6. Elsevier Science Publishers.

Alder, S. D. (2016): “In the Wrong Hands: Complementarities, Resource Allocation, and TFP,” *AEJ: Macroeconomics*, 8(1), 199–241.

Barlevy, G. (2002): “The Sullying Effect of Recessions,” *The Review of Economic Studies*, 69(1), 65–96.

Bartelsman, E., J. Haltiwanger, and S. Scarpetta (2013): “Cross-Country Differences in Productivity,” *American Economic Review*, 103(1), 305–334.

Bellone, F., and J. Mallen-Pisano (2013): “Is misallocation higher in France than in the United States?,” *GREDEG Working Paper*, 38.

Bentolila, S., and J. F. Jimeno (1998): “Regional Unemployment Persistence: Spain 1976-1994,” *Labour Economics*, 5(1), 25–42.

Bowlus, A. J. (1995): “Matching Workers and Jobs: Cyclical Fluctuations in Match Quality,” *Journal of Labor Economics*, 13(2), 335–350.

Buera, F., and Y. Shin (2013): “Financial Frictions and the Persistence of History: A Quantitative Exploration,” *Journal of Political Economy*, 121(2), 221–272.

Caballero, R., and M. Hammour (1994): “The Cleansing Effect of Recessions,” *American Economic Review*, 84(5), 1350–1368.

Cecchetti, S., and E. Kharroubi (2012): “Reassessing the impact of finance on growth,” *BIS Working Paper*, 381.

Chen, K., and A. Irarrazabal (2015): “The role of allocative efficiency in a decade of recovery,” *Review of Economic Dynamics*, 18(3), 523–550.

Christopoulou, R., and P. Vermeulen (2012): “Markups in the Euro area and the US over the period 1981-2004: a comparison of 50 sectors,” *Empirical Economics*, 42(1), 53–77.

Conesa, J. C., and T. Kehoe (2015): “Productivity, Taxes, and Hours Worked in Spain: 1970-2013,” *Mimeo.*

Crespo, A., and R. Segura-Cayuela (2014): "Understanding Competitiveness," *EUI Working Papers*, 20.

Dias, D., C. Robalo, and C. Richmond (2015): "Misallocation and productivity in the lead up to the Eurozone crisis," *International Finance Discussion Papers 1146*.

Díaz, A., and L. Franjo (Forthcoming): "Capital goods, measured TFP and Growth: The case of Spain," *European Economic Review*.

Estrada, A., M. Izquierdo, and A. Lacuesta (2009): "The Functioning of the Labour Market and Unemployment Growth in Spain," *Economic Bulletin, Bank of Spain*, pp. 103–122.

Fernald, J. (2014): "Productivity and Potential Output before, during, and after the Great Recession," in *NBER Macroeconomics Annual*, ed. by J. Parker, and M. Woodford, vol. 29. MIT Press, Boston.

Fernandez-Villaverde, J., L. Garicano, and T. Santos (2013): "Political Credit Cycles: the Case of the Euro Zone," *Journal of Economic Perspectives*, 27(3), 145–66.

Foster, L., C. Grim, and J. Haltiwanger (2014): "Reallocation in the Great Recession: Cleansing or Not?," *NBER Working Paper 20427*.

Foster, L., J. Haltiwanger, and C. Krizan (2006): "Market selection, reallocation, and restructuring in the US retail trade sector in the 1990s," *The Review of Economics and Statistics*, 88(4), 748–758.

Gopinath, G., S. Kalemli-Ozcan, L. Karabarbounis, and C. Villegas-Sanchez (2015): "Capital Allocation and Productivity in South Europe," *NBER Working Paper No. 21453*.

Hopenhayn, H., and R. Rogerson (1993): "Job Turnover and Policy Evaluation: a General Equilibrium Analysis," *Journal of Political Economy*, 101(5), 915–938.

Hsieh, C. T., and P. J. Klenow (2009): "Misallocation and manufacturing TFP in China and India," *The Quaterly Journal of Economics*, 124(4), 1403–1448.

Khwaja, A. I., and A. Mian (2005): "Do Lenders Favor Politically Connected Firms? Rent Provision in an Emerging Financial Market," *Quarterly Journal of Economics*, 120(4), 1371–1411.

Lacuesta, A., S. Puente, and P. Cuadrado (2011): "Omitted Variables in the Measurement of a Labor Quality Index: the Case of Spain," *Review of Income and Wealth*, 57(1), 84–110.

Lewrick, U., L. Mohler, and R. Weder (2014): "When firms and industries matter: understanding the sources of productivity growth," *BIS Working Paper*, 469.

Marcos, F., J. Santaló, and A. Sánchez-Graells (2010): "Measuring Regulatory Intensity by the Spanish Regions (1978-2009)," IE Working Paper 10-07.

Mas, M., F. Pérez, and E. Uriel (2013): "Inversión y stock de capital en España (1964-2011). Evolución y perspectivas del patrón de acumulación," *Bilbao: Fundación BBVA*.

Midrigan, V., and D. Xu (2014): "Finance and Misallocation: Evidence from Plant Level Data," *American Economic Review*, 2(104), 422–58.

Moral-Benito, E. (2015): "Model Averaging in Economics: an Overview," *Journal of Economic Surveys*, 29(1), 46–75.

Olken, B. A., and R. Pande (2012): "Corruption in Developing Countries," *Annual Review of Economics*, 4, 479–505.

Olley, S., and A. Pakes (1996): "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 64(6), 1263–1297.

Pavcnik, N. (2002): "Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants," *Review of Economic Studies*, 69(1), 245–276.

Rajan, R. G., and L. Zingales (1998): "Financial Dependence and Growth," *American Economic Review*, 88(3), 559–586.

A Hsieh and Klenow measure of misallocation

The HK model is characterized by a closed economy with two primary inputs (capital and labor) and S industries producing differentiated intermediate goods that are combined by a pure assembly sector to produce an homogeneous final good. Firms producing the intermediate differentiated goods operate under monopolistic competition and sell their products to the final good producers. In the absence of distortions, the allocation of resources across firms producing the intermediate goods depends only on physical levels of firm-specific TFP, which yields to the optimal level of aggregate TFP. However, the model features firm-specific distortions that preclude firms from optimally choosing their levels of output and capital-labor mix. This implies within industry misallocation, which deviates aggregate measured TFP from its optimal level.

HK assume that there are S different industries in the economy. The output of each of the industries $s \in S$ is the outcome of aggregating M_s differentiated intermediate goods:

$$Y_s = \left(\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{4}$$

where σ is the elasticity of substitution between goods. Each of these goods is produced by a firm i that operates in a monopolistic competitive market and has access to a Cobb-Douglas production function that combines labor and capital:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s} \tag{5}$$

Firm i in sector s choose labor and capital to maximize profits:

$$\pi_{si} = \max_{L_{si}, K_{si}} \{ P_{si} Y_{si} - (1 + \tau_{L_{si}}) w L_{si} - (1 + \tau_{K_{si}}) r K_{si} \} \tag{6}$$

where $\tau_{L_{si}}$ and $\tau_{K_{si}}$ are firm-specific distortions. Notice that $\tau_{L_{si}}$ distorts the cost of labor, whereas $\tau_{K_{si}}$ distorts the cost of capital. This problem yields the first order conditions (1) and (2) (see section 4.1), which together imply that the price of firm's output equals a mark-up over the marginal cost:

$$P_{si} = \frac{\sigma}{\sigma - 1} \left(\frac{r}{\alpha_s} \right)^{\alpha_s} \left(\frac{W}{1 - \alpha_s} \right)^{1-\alpha_s} \frac{(1 + \tau_{K_{si}})^{\alpha_s} (1 + \tau_{L_{si}})^{1-\alpha_s}}{A_{si}} \tag{7}$$

where $\frac{\sigma}{\sigma-1}$ is the mark-up charged by the firm and $\left(\frac{r}{\alpha_s} \right)^{\alpha_s} \left(\frac{W}{1-\alpha_s} \right)^{1-\alpha_s} \frac{(1+\tau_{K_{si}})^{\alpha_s} (1+\tau_{L_{si}})^{1-\alpha_s}}{A_{si}}$ is its marginal cost. This optimal pricing rule yields labor demand and capital that are proportional to the firms physical TFP and the idiosyncratic distortions:

$$
\begin{aligned}
L_{si} &\propto A_{si}^{\sigma-1}(1+\tau_{K_{si}})^{\alpha_s(1-\sigma)}(1+\tau_{L_{si}})^{\alpha_s(\sigma-1)-\alpha_s} \\
K_{si} &\propto A_{si}^{\sigma}(1+\tau_{K_{si}})^{\alpha_s(1-\sigma)-1}(1+\tau_{L_{si}})^{\sigma(\alpha_s-1)-\alpha_s+1}
\end{aligned}
$$

and a capital-labor ratio that depends only on the firm's idiosyncratic distortions and relative prices:

$$
\frac{K_{si}}{L_{si}} = \frac{\alpha_s}{1-\alpha_s}\frac{w}{r}\frac{1+\tau_{L_{si}}}{1+\tau_{K_{si}}} \tag{8}
$$

In the absence of distortions, the allocation of resources across firms depends only on physical levels of firms' TFP, yielding to a equalization of capital-labor ratios and marginal revenue products of labor and capital. In the presence of distortions, both capital-labor ratios and total outputs become distorted, generating variation on the marginal revenue products and hence misallocation.

A.1 Within-industry Misallocation

Total factor productivity revenue of firm i is defined as:

$$
\mathrm{TFPR}_{si} \equiv P_{si}A_{si} \tag{9}
$$

Therefore, substituting equation (7) into equation (9):

$$
\mathrm{TFPR}_{si} = \frac{\sigma}{\sigma-1}\left(\frac{r}{\alpha_s}\right)^{\alpha_s}\left(\frac{W}{1-\alpha_s}\right)^{1-\alpha_s}(1+\tau_{K_{si}})^{\alpha_s}(1+\tau_{L_{si}})^{1-\alpha_s} \tag{10}
$$

and using the FOC (1) and (2) from section 4.1:

$$
\mathrm{TFPR}_{si} = \frac{\sigma}{\sigma-1}\left(\frac{\mathrm{MRPK}_{si}}{\alpha_s}\right)^{\alpha_s}\left(\frac{\mathrm{MRPL}_{si}}{1-\alpha_s}\right)^{1-\alpha_s}
$$

Note that, in the absence of idiosyncratic distortions the TFPR_{si} would equalize across firms operating in the same industry. Suppose, for example, that there is a firm with a relatively high level of physical TFP (A_{si}). This firm would want to attract labor and capital until reaching the point where its lower price makes its TFPR_{si} the same as the one of less productive firms. In this situation, revenue marginal products of labor and capital are equalized across firms and the first best allocation is achieved.

Then, observed TFP_s in a given industry s is given by equation (3), where sectoral-wide marginal revenue products of capital and labor are the weighted harmonic means of each firm marginal revenue product:

$$\overline{\text{MRPK}}_s \equiv \left[\sum_i^{M_s} \left(\frac{P_{si}Y_{si}}{P_sY_s}\right) \frac{1}{\text{MRPK}_{si}}\right]^{-1} = r \left[\sum_i^{M_s} \left(\frac{P_{si}Y_{si}}{P_sY_s}\right) \frac{1-\tau_{Ysi}}{1+\tau_{Ksi}}\right]^{-1}$$

$$\overline{\text{MRPL}}_s \equiv \left[\sum_i^{M_s} \left(\frac{P_{si}Y_{si}}{P_sY_s}\right) \frac{1}{\text{MRPL}_{si}}\right]^{-1} = w \left[\sum_i^{M_s} \left(\frac{P_{si}Y_{si}}{P_sY_s}\right) \frac{1-\tau_{Ysi}}{1+\tau_{Lsi}}\right]^{-1}$$

Equation (3) (see section 4.2) clearly shows that, conditional on the distribution of firms' physical productivity A_{si}, the industry TFP_s is maximized when there is no variation in TFPR_{si} across firms. Then, the higher the variation in the firms' idiosyncratic distortions, the higher the variation in the within-industry TFPR_{si}, and hence the higher the amount of misallocation.

A.2 Aggregate TFP

In the model, there is a single final consumption good produced by a representative firm in a perfectly competitive final good market. This firm combines intermediate goods Y_s produced in a finite number of different industries $s \in S$. These intermediates are aggregated to produce the final good using a Cobb-Douglas technology:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s} \tag{11}$$

where $\sum_{s=1}^{S} \theta_s = 1$. The optimization problem of the representative firm implies:

$$P_sY_s = \theta_s Y \tag{12}$$

where P_s refers to the price of industry output Y_s. The price index $P \equiv \prod_{s=1}^{S} \left(\frac{P_s}{\theta_s}\right)^{\theta_s}$ is set equal to 1. It is important to emphasize that, due to the Cobb-Douglas assumption, the only source of inefficiency in this model is the within-industry misallocation: the increase in an industry's productivity is fully compensated by the decrease in its price index, so firms' idiosyncratic distortions do not affect the sectoral composition of the economy. GDP can be expressed as a function of industries' amounts of labor, capital, and TFP_s:

$$Y = \prod_{s=1}^{S} (TFP_s K_s^{\alpha_s} L_s^{\alpha_s})^{\theta_s} \tag{13}$$

Then, by using equations (3) and (13) the aggregate observed TFP becomes:

$$\text{TFP} = \prod_{s=1}^{S} \text{TFP}_s^{\theta_s} = \prod_{s=1}^{S} \left[\left(\sum_{i=1}^{M_s} \left(A_{si} \frac{\overline{\text{TFPR}}_s}{\text{TFPR}_{si}} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \right]^{\theta_s} \tag{14}$$

This expression clearly shows how within-industry misallocation of labor and capital yields a lower measured aggregate TFP. To understand how costly are the idiosyncratic distortions one can define the optimal level of TFP (i.e. the TFP level in the absence of firm-specific distortions):

$$\text{TFP}^* = \prod_{s=1}^{S} \text{TFP}_s^{*\theta_s} = \prod_{s=1}^{S} \left[\left(\sum_{i=1}^{M_s} (A_{si})^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \right]^{\theta_s} \tag{15}$$

The ratio of optimal TFP to observed TFP (i.e. $\frac{\text{TFP}^*}{\text{TFP}} - 1$) is the potential TFP gain from reallocation that we use in the paper. In particular, we analyze its evolution over time as an indication of the relevance of changes in within sector misallocation to explain the evolution of aggregate TFP growth in Spain.

A.3 Baseline parametrization

Using the firms' optimality conditions we can infer the level of idiosyncratic distortions by picking the values of $\tau_{K_{si}}$ and $\tau_{Y_{si}}$ that, through the lens of the model, rationalize the combinations of labor, capital, and production that we observe in the data.

Aggregate parameters: we follow Hsieh and Klenow (2009) by setting r to 10% (5% interest rate and 5% depreciation rate) and the elasticity of substitution σ to 3.[30] The industry-specific capital shares α_s are set to 1 minus the labor share in industry s in the US.

Pinning-down firms' physical TFP: For every firm in the data we infer its physical TFP using the expression:

$$A_{si} = \kappa_s \frac{(P_{si} Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \tag{16}$$

where $\kappa_s = \frac{w^{1-\alpha_s}(P_s Y_s)^{-\frac{1}{\sigma-1}}}{P_s}$ is an industry-specific constant. Since it does not affect relative productivities within industry, we set $\kappa_s = 1$ for all industries. Note that we do not observe firms' real output Y_{si} but rather its total revenue $P_{si} Y_{si}$. We hence use revenue data and the elasticity of substitution σ to infer real output.

[30]Note that the gains from reallocation increase in σ, and this is a conservative value given that industries are defined at the 4-digit level. Moreover, we later conduct some robustness checks evaluating the importance of this assumption.

Pinning-down capital and labor distortions: Equations 1 and 2 (see section 4.1) pin-down the distortions associated to capital and labor accumulation respectively:

$$(1+\tau_{Lsi}) = \left(\frac{P_{si}Y_{si}}{wL_{si}}\right)(1-\alpha)\left(\frac{\sigma-1}{\sigma}\right) \tag{17}$$

$$(1+\tau_{Ksi}) = \left(\frac{P_{si}Y_{si}}{rK_{si}}\right)\alpha\left(\frac{\sigma-1}{\sigma}\right) \tag{18}$$

These equations imply that distortions on capital and labor accumulation are high when their compensations are low compared to what one would expect given the industry elasticity of output with respect to each of them (adjusted for mark-ups). In the presence of distortions, the before-taxes marginal revenue products are not equalized across firms, and hence misallocation arises. Any policy that penalizes firms' capital (labor) accumulation would appear in the form of a high inferred τ_{Ksi} (τ_{Lsi}).

B Robustness analysis for the HK exercise

In this Appendix we perform five robustness exercises within the HK methodology. In particular, these robustness checks are related to the level of industry disaggregation, to the distinction between intensive and extensive margin, to the elasticity of substitution, to the treatment of extreme observations, and to the size of firms used for our sample.

B.1 Industry classification

Our baseline results are based on misallocation within 4-digit industries because the HK theoretical framework relies on the assumption that each industry represents a monopolistic competitive market in which firms produce different varieties of the same intermediate good. Therefore, the greater the level of disaggregation the more plausible this assumption is when taken to the data. However, since the 4-digit level of disaggregation requires a very large sample of firms, we investigate if the deterioration in allocative efficiency documented for Spain at the 4-digit level is also present when considering 2- and 3-digit classifications.

Table B.1 shows the evolution of allocative efficiency in Spain in terms of potential TFP gains from reallocation to an efficient allocation of resources across firms within each 4-, 3-, and 2-digit sectors in columns (1), (2) and (3). The increase in TFP gains, or the deterioration in allocative efficiency, is prevalent among all the three industry classifications. Moreover, the increases over the whole period are of the same magnitude, around 20% or 1.7% per year, in all the cases. In particular, the average increases are 1.7, 1.6, and 1.8 percent per year for the exercises at 4-, 3-, and 2-digit industries, respectively.

B.2 Balanced versus unbalanced panel

Our baseline sample is an unbalanced panel including firms that might enter or exit at any time. The extensive margin may also play a role in shaping the evolution of allocative efficiency depicted above. However, the potential sources of misallocation might be different depending on the importance of this extensive margin relative to the intensive margin of misallocation of resources within established firms. In order to quantify the importance of the extensive margin in terms of efficient TFP and the evolution of allocative efficiency over time, we consider a balanced panel restricted to firms that were in the sample for the whole period (1995-2007). In the balanced version of the panel we have only 5,419 firms per year,[31] which precludes us from considering misallocation within 4-digit industries. Column (4) in Table B.1 shows the resulting TFP gains from the balanced panel under the 2-digit disaggregation. We find that the deterioration in allocative efficiency over time still holds, although

[31] The number of firms in our sample is 126,848 in the year 1995. Only 5,419 of them remain active all the 13 years from 1995 to 2007.

Table B.1: Misallocation in Spain over the period 1995-2007 — Robustness analysis

Year	TFP gain from reallocation						
	Baseline (1)	3-digit (2)	2-digit (3)	Balanced (4)	$\sigma = 5$ (5)	M. error (6)	Large firms (7)
1995	0.24	0.27	0.33	0.20	0.39	0.25	0.14
1996	0.26	0.28	0.37	0.20	0.45	0.26	0.14
1997	0.27	0.31	0.38	0.22	0.42	0.27	0.16
1998	0.28	0.32	0.41	0.20	0.45	0.29	0.16
1999	0.34	0.39	0.45	0.23	0.52	0.32	0.18
2000	0.36	0.39	0.46	0.23	0.52	0.32	0.17
2001	0.38	0.40	0.46	0.23	0.53	0.33	0.21
2002	0.40	0.42	0.48	0.23	0.53	0.35	0.23
2003	0.41	0.44	0.51	0.24	0.54	0.36	0.20
2004	0.44	0.46	0.54	0.25	0.61	0.38	0.20
2005	0.45	0.48	0.58	0.27	0.61	0.39	0.23
2006	0.47	0.51	0.62	0.29	0.72	0.40	0.21
2007	0.49	0.52	0.62	0.28	0.69	0.42	0.22

Notes. Baseline in column (1) refers to our benchmark results based on misallocation within 4-digit industries, σ=3, and the unbalanced panel. Columns (2) and (3) report the results when considering indutries at 3- and 2-digit classifications (NACE 2 rev. 2). Column (4) is based on the balanced version of our panel. Column (5) reports the TFP gains when considering σ=5 instead of σ=3. Column (6) refers to the trimming of the 2% tails of TFPR and TFPQ in order to alleviate the influence of measurement error. Finally, column (7) is based on a sample of large firms (more than 50 employees).

smaller in size: while the increase in misallocation is around 20% (1.49/1.24 - 1) or 1.7% per year when considering the unbalanced panel, the corresponding figures are 7% (1.28/1.20 - 1) and 0.6% under the balanced panel. These numbers suggest that about two thirds of the deterioration in allocative efficiency is due to the extensive margin.

B.3 Elasticity of substitution

As as final robustness test we repeat the exercise with a higher elasticity of substitution: σ=5. This figure is also used by Dias, Robalo, and Richmond (2015) for Portugal and comes from the estimates for the Eurozone in Christopoulou and Vermeulen (2012). In column (5) of Table B.1 we report the results. Potential TFP gains also increase for all years when σ=5. Moreover, the magnitude of the increase in misallocation over the 1995-2007 period is similar to that of the case σ=3, a decrease of 21% (1.69/1.39 - 1) or 1.8 percent per year.

B.4 Measurement error

Our estimated increases in TFP gains from reallocation might be driven by an increase in measurement error in our data as a result of the year-to-year increases in our sample size. While this concern is partially addressed in the balanced panel exercise, we also consider an alternative robustness check based on recording errors created by extreme outliers. In particular, following Hsieh and Klenow (2009) we trim the 2% tails of TFPR and TFPQ in order to avoid the potentially increasing influence of outliers in our sample. Column (6) of Table B.1 shows the resulting TFP gains, which clearly point to a large deterioration in allocative efficiency of around 14% (1.42/1.25 - 1) or 1.1 percent per year.

B.5 Sample of large firms

We now check the sensitivity of our findings to the size distribution of firms in our sample. In particular, we compute the TFP gains resulting from removing idiosyncratic distortions in a subsample of large firms (more than 50 employees). We report the results in Column (7) of Table B.1. While the deterioration in allocative efficiency still arises, its magnitude is substantially smaller, 0.6% percent per year against the baseline of 1.7% per year. Moreover, the levels of potential TFP gains are substantially smaller than those of the full sample in the baseline case. This finding shows that the datasets with only large firms typically used in the literature might under-estimate the magnitude of within-industry misallocation.

C Robustness Analysis for the Sector-Level Regressions

In this section we present a series of robustness checks to confirm our conclusions based on the sector-level analysis in Section 5.

C.1 Alternative variable definitions

First, we consider alternative proxies for each of the six sector-specific characteristics considered in Table 3. First, as alternative proxies to high-skill intensity, we consider the share of temporary workers computed from our firm-level data as well as the share of skilled workers taken from PITEC (Panel de Innovación Tecnológica), which is based on a survey of innovative firms conducted by the National Statistics Institute.[32] Second, as an alternative measure of sector-specific "financial dependence", we consider the ratio of sector's total liabilities as a percentage of its total assets computed using firm-level data from the Central Balance Sheet Data. Third, as an alternative measure of sector-specific IT content, we exploit the Spanish PITEC to construct shares of R&D investment over total investment. Fourth, we consider the share of industry exports over total export as a substitute of our baseline sector-specific tradability proxy. Fifth, we exploit an alternative measure of capital structures intesitiy based on a definition of structures that includes not only residential structures and non-residential structures but also other fixed capital assets taken fro EU-KLEMS. Finally, as an alternative measure to public sector influence, we also consider the Bribe Payers Index as a continuous variable.[33]

Table C.1 shows the results. Public sector influence is significantly related to changes in misallocation, see column (8); in particular, sectors in which the incidence of bribery is larger experienced large increases in misallocation over the 1995-2007 period (note that the lower the BPI index the higher the bribery incidence). Turning to the other characteristics in columns (1)-(6), we again fail to find statistically significant correlations in all the three cases. Using these alternative proxies, columns (9) and (10) of Table C.1 also confirm the results in columns (7) and (8) of Table 3.

[32] See www.icono.fecyt.es/PITEC for more details.

[33] The survey asked how often three different types of bribery were perceived to occur in each sector: firstly, bribery of low-ranking public officials; secondly, improper contributions to high-ranking politicians to achieve influence; and thirdly, bribery between private companies. Answers were given on a 5-point scale. This was then converted to a 10-point scale where 0 indicates that companies in that sector are perceived to always pay bribes and 10 to never pay bribes.

Table C.1: Misallocation and sector-specific characteristics — Robustness.

	Dep. Variable: ΔTFP Gain									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	OLS	OLS		OLS	OLS	WALS
High-skill intensity (Spain share)	0.163								0.086	0.045
	(0.155)								(0.164)	(0.143)
Share of temporary workers		-0.117							-0.368	-0.262
		(0.227)							(0.233)	(0.207)
Innovative content (Spain R&D share)			-0.303						-0.594**	-0.402*
			(0.249)						(0.269)	(0.235)
Financial dependence (Spain debt burden)				0.021					-0.086	-0.066
				(0.097)					(0.097)	(0.087)
Tradability (Over total exports)					-0.593				-0.968	-0.731
					(0.876)				(0.940)	(0.834)
Capital structures intensity (no other assets)						0.186			-0.236	-0.169
						(0.237)			(0.267)	(0.242)
Public sector (excluding construction)							0.252***			
							(0.086)			
Public sector influence (BPI index)								-0.264***	-0.325***	-0.226**
								(0.086)	(0.099)	(0.091)
Constant	0.187***	0.262***	0.257***	0.228***	0.255***	0.207***	0.198***	2.015***	2.647***	1.917***
	(0.054)	(0.069)	(0.040)	(0.051)	(0.043)	(0.050)	(0.138)	(0.584)	(0.736)	(0.684)
Observations	58	58	58	58	58	58	55	58	58	58
R-squared	0.02	0.01	0.03	0.00	0.01	0.01	0.14	0.26	-	

Notes: This table shows the results of regressing changes in allocative efficiency against 2-digit sector characteristics. ΔTFP Gain refers to the change over the 1995-2007 period in the ratio of optimal TFP in the absence of misallocation to observed TFP, according to the HK methodology.

C.2 Crony sectors and construction

The increase in misallocation in construction was substantially larger than in manufacturing, services or trade (see Panel (b) in Figure 3). To see whether the construction sector itself may be driving the results of cronyism, we exclude industries linked to this sector (*construction of buildings*, *civil engineering*, and *specialised construction activities*). We provide the results in column (7) of Table C.1. We find that the coefficient associated to the crony dummy remains significant at 1 percent and similar in magnitude (0.252).

C.3 Robustness analysis on the measurement of financial dependence

In this section we show that the insignificant relationship between financial dependence of a sector and the increase in misallocation that we documented in section 5 is robust to using alternative measures of sectors' external financial dependence.

As we mentioned earlier, our benchmark measure of external financial dependence across sectors is based on the sector-specific finance intensity variable constructed by Fernald (2014). The reason is that he reports these measures for all sectors in the economy. We next focus only on industries falling into the manufacturing sector, for which more standard measures of external financial dependence are available. In particular, we use measures of external financial dependence as measured by Rajan and Zingales (1998) and run similar regressions as in section 5. For comparison, we also run regressions using Fernald (2014) measures but only for industries within the manufacturing sector.

Table C.2: Misallocation and external finance dependence – Robustness

	Dependent variable: ΔTFP Gain			
	(1)	(2)	(3)	(4)
Rajan-Zingales	0.175			
	(0.134)			
Rajan-Zingales (dummy)		0.016		
		(0.067)		
Fernald			-0.046	
			(0.050)	
Fernald (dummy)				-0.130
				(0.154)
Observations	21	21	21	21
R-squared	0.082	0.001	0.034	0.034

Notes. Table 3 shows the results of regressing changes in allocative efficiency against 2-digit measures of external financial dependence within the manufacturing sector. ΔTFP Gain refers to the change over the 1995-2007 period in the ratio of optimal TFP in the absence of misallocation to observed TFP, according to the HK methodology. The variable *Rajan-Zingales* measures the sectoral external financial dependence as reported in Rajan and Zingales (1998). For each industry, external dependence is computed as the median fraction of capital expenditures not financed with cash flow from operations across firms producing in that particular industry. The variable *Rajan-Zingales (dummy)* is a binary version of the same variable that takes value 1 if the industry is above the median of the distribution of external dependence and 0 otherwise. The variable *Fernald* measures nominal purchases of intermediate financial services as a share of industry gross output, constructed by Fernald (2014). The variable *Fernald (dummy)* is a binary version of *Fernald* that takes value 1 if the industry is above the median of the distribution of external dependence and 0 otherwise.

Table C.2 shows the results of these regressions. We find that the measures of external financial dependence as computed by Rajan and Zingales (1998) are positively correlated to the increase in misallocation over the studied period. However, these relationships are not statistically significant.

D Two Digit NACE rev.2 Classification

Table D.1: Description of sectors

Code	Main sector	Description
10	Manufacturing	Manufacture of food products
11	Manufacturing	Manufacture of beverages
12	Manufacturing	Manufacture of tobacco products
13	Manufacturing	Manufacture of textiles
14	Manufacturing	Manufacture of wearing apparel
15	Manufacturing	Manufacture of leather and related products
16	Manufacturing	Manufacture of wood and of products of wood and cork, except furniture
17	Manufacturing	Manufacture of paper and paper products
18	Manufacturing	Printing and reproduction of recorded media
20	Manufacturing	Manufacture of chemicals and chemical products
21	Manufacturing	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacturing	Manufacture of rubber and plastic products
23	Manufacturing	Manufacture of other non-metallic mineral products
24	Manufacturing	Manufacture of basic metals
25	Manufacturing	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacturing	Manufacture of computer, electronic and optical products
27	Manufacturing	Manufacture of electrical equipment
28	Manufacturing	Manufacture of machinery and equipment n.e.c.
29	Manufacturing	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacturing	Manufacture of other transport equipment
31	Manufacturing	Manufacture of furniture
32	Manufacturing	Other manufacturing
33	Manufacturing	Repair and installation of machinery and equipment
35	Manufacturing	Electricity, gas, steam and air conditioning supply
37	Manufacturing	Sewerage
38	Manufacturing	Waste collection, treatment and disposal activities; materials recovery
39	Manufacturing	Remediation activities and other waste management services
41	Construction	Construction of buildings
42	Construction	Civil engineering
43	Construction	Specialised construction activities

Table D.2: Description of sectors (cont.)

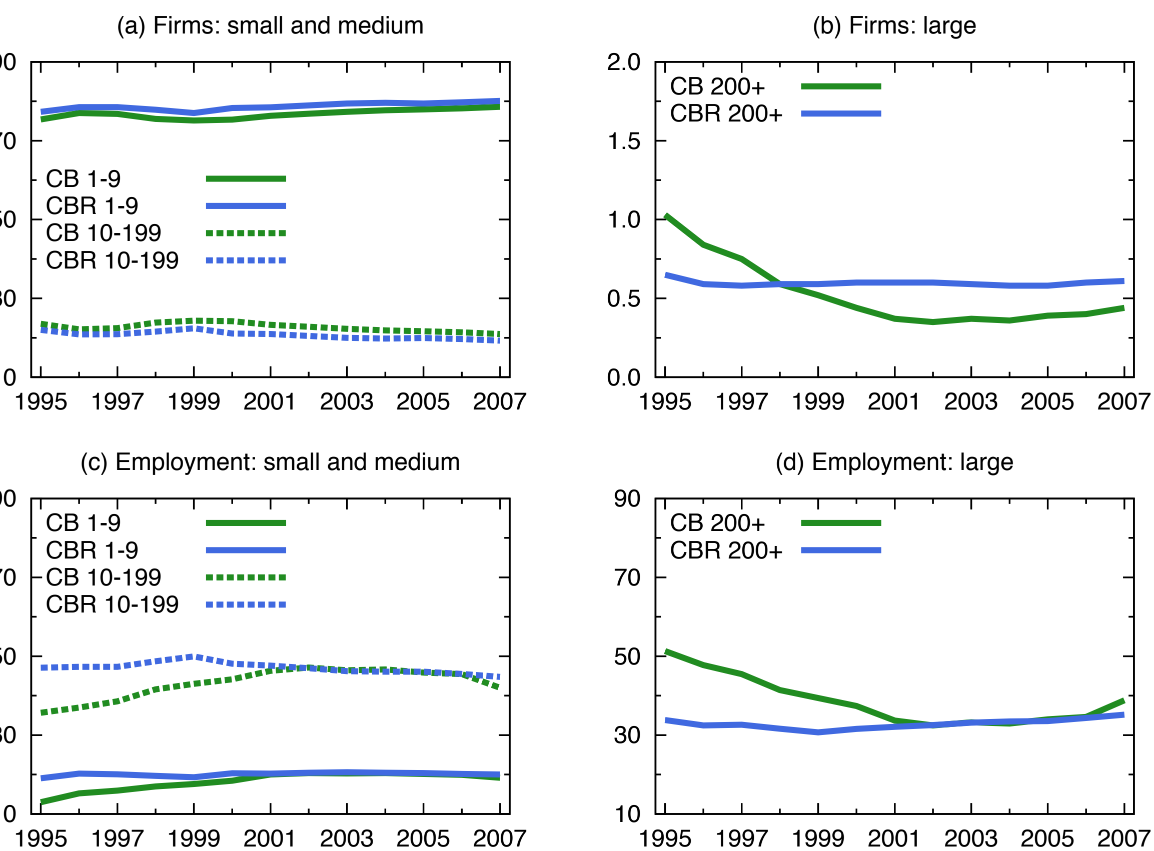
Code	Big sector	Description
45	Trade	Wholesale and retail trade and repair of motor vehicles and motorcycles
46	Trade	Wholesale trade, except of motor vehicles and motorcycles
47	Trade	Retail trade, except of motor vehicles and motorcycles
49	Services	Land transport and transport via pipelines
50	Services	Water transport
51	Services	Air transport
52	Services	Warehousing and support activities for transportation
53	Services	Postal and courier activities
55	Services	Accommodation
56	Services	Food and beverage service activities
58	Services	Publishing activities
59	Services	Motion picture, video and television programme production, sound recording
60	Services	Programming and broadcasting activities
61	Services	Telecommunications
62	Services	Computer programming, consultancy and related activities
63	Services	Information service activities
68	Services	Real estate activities
69	Services	Legal and accounting activities
70	Services	Activities of head offices; management consultancy activities
71	Services	Architectural and engineering activities; technical testing and analysis
72	Services	Scientific research and development
73	Services	Advertising and market research
74	Services	Other professional, scientific and technical activities
75	Services	Veterinary activities
77	Services	Rental and leasing activities
78	Services	Employment activities
79	Services	Travel agency, tour operator reservation service and related activities
80	Services	Security and investigation activities
81	Services	Services to buildings and landscape activities
82	Services	Office administrative, office support and other business support activities

E Comparison of our firm-level data with the census of firms

Table 1 in Section 3 shows that our sample from *Central de Balances* (CB) provides a firm and employment distributions very close to the ones in the census of firms from the Central Business Register (CBR) for 2011. In this Appendix we document the representativeness of our sample for the whole period.

Figure E.1 plots the share of firms —panels (a) and (b)— and the share of employment —panels (c) and (d)— in firms of different sizes, both for our CB sample and for the census of firms from the CBR. What we see is that both the firm and employment distribution in our sample are extremely close to the one in the census between 2001 and 2007. Before 2001, however, our CB sample slightly over-represents big firms: in 1995 our sample has 1% of firms with 200+ employees, while the census of firms shows a share of 0.65%. This gap disappears gradually over the years.

FIGURE E.1: Size distribution of firms, 1995-2007



Notes. Panel (a) plots the percentage number of firms with 1-9 workers and 10-199 workers both for our sample from the *Central de Balances* (CB) and for the census from the Central Business Register (CBR). Panel (b) does the same for firms with 200+ employees. Panels (c) and (d) report the employment shares in the same size categories.