Growing like Spain: 1995-2007*

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Abstract

Measured TFP fell at an annual rate of 0.7% in Spain during the boom years of 1995 to 2007. Using administrative data from the quasi-universe of firms 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. Cross-industry variation reveals that the increase in misallocation was more severe in those sectors where connections with public officials are more important for business success, which represents novel evidence on the potential macroeconomic costs of crony capitalism. We write and estimate a simple model of cronyism in which heterogeneous firms invest in political connections. The model is consistent with the facts that (a) there is more dispersion in firm productivity in those sectors more prone to cronyism and (b) a general decline in the quality of institutions generates a larger increase in the dispersion of firm productivities in those sectors more prone to cronyism. Our quantitative exercise concludes that the institutional decline over this period costed 1.9% growth in TFP per year.

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

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1 Introduction

The 1994-2007 expansion was the longest uninterrupted period of growth in Spain since at least 1850, see Berge and Jordá (2013). GDP grew at an average rate 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 misallocation of production factors across firms and that most of this increase in misallocation was due to an intensification of cronyism in Spain.

We start by using a large administrative data set of the quasi-universe of Spanish firms in all sectors to compute standard measures of allocative efficiency. In particular, for every year between 2000 and 2007, we compute the potential TFP Gain due to within-sector factor reallocation across firms as in Hsieh and Klenow (2009). This measure shows a severe deterioration of allocative efficiency over the period, which is present in manufacturing industries —as already highlighted by Gopinath, Kalemli-Ozcan, Karabarbounis, and Villegas-Sanchez (2017)— but also and to a larger extent in construction and in the service and trade industries. In particular, had the within-sector allocative efficiency remained constant at the level observed in 2000, TFP growth between 2000 and 2007 would have been around 2.4% per year.

Next, we exploit the variation in allocative efficiency across industries in order to shed light on the potential sources of the increase in misallocation. We find that industries in which the connections with public officials is more important to success —as measured by the Bribe Payers Index (BPI) of Transparency International— experienced larger productivity losses due to misallocation. In particular, industries in the 95th percentile of the distribution of cronyism ("real estate activities") suffered on average annual productivity losses due to misallocation 1.4 percentage points larger than industries in the 5th percentile ("manufacture of textiles"). This represents novel evidence on the role of crony capitalism in the macroeconomy. Instead, we find that variation in sectoral characteristics such as financial dependence, skill intensity, tradability, or innovative content are unrelated to changes in allocative efficiency.

In order to understand and quantify the impact of cronyism on aggregate productivity, we consider a model of heterogeneous producers with differentiated goods and monopolistic competition where firms spend valuable resources to improve their connections with the political power. These connections allow firms to obtain privileged treatment from the public administrations in potentially different aspects. For instance, the government can promote a given regulation that favours some type of firms, it can grant licenses to operate in some industries, or it can ask public banks to give preferential access to credit to certain firms. In the model firms differ in their ability to connect with the political power as well as in their productivity. The privileged treatment obtained by firms from public officials materializes as idiosyncratic subsidies to capital and labor. Hence, one can see the model as an extension of Hsieh and Klenow (2009) where the wedges are endogenous. Given this framework, sectors differ in the elasticity of capital and labor subsidies to political connections. For instance, in competitive sectors like manufacturing of clothing there is relatively little a public administration can do to promote the success of particular firms. In contrast, local governments can easily generate capital gains to chosen firms in construction by rezoning municipal land.

The model delivers two important theoretical results. First, sectors with higher returns to cronyism exhibit larger dispersion in firm marginal revenue products. The intuition is clear: by lowering the cost of capital and labor, political connections act as a third factor of production that increases the degree of homogeneity of the profit function. A higher elasticity of subsidies to political connections is then akin to a lower curvature in the firm revenue function, which amplifies the dispersion of firm sizes given the existing exogenous differences in firm productivity and firm ability to connect. Because the isoelastic model predicts that the expenditure share in political connections is the same across all firms within the same sector, bigger firms will spend more in political connections in absolute terms than small firms. This dispersion of spending in political connections translates into dispersion of wedges and marginal revenue products. Second, an increase in the returns to cronyism in all sectors —akin to a decline in institutional quality— increases the dispersion in firm marginal revenue products more in sectors more prone to cronyism. The reason for this interaction is as follows. The increase in dispersion of firm marginal revenue products due to an increase in cronyism is proportional to the existing dispersion of marginal revenue products. Because more crony sectors display larger dispersion in firm marginal revenue products, an institutional decline is more severe for them.

We estimate our model to reproduce the second moments of the joint distribution of firm productivity and firm idiosyncratic wedges in 2000 for each of the 500 4-digit industries. The estimation results are interesting on their own. First, firm productivity and firm ability to connect to the public sector are negatively correlated. This result arises because in the data more productive firms display average revenue products of capital and labor that are higher than the average in their sectors, and hence they are inferred to face lower capital and lower labor subsidies. While this correlation is exogenous in our static model, the finding is consistent with the dynamic model by Akcigit, Baslandze, and Lotti (2017) where there is a trade-off between investing in better technology and in better connections. Second, the elasticity of subsidies to political connections is larger for capital than for labor, a result that comes from the observed larger dispersion of capital wedges and larger (negative) correlation between capital wedges and firm productivity. And third, sectors that are more crony according to the BPI are characterized by a larger elasticity of subsidies to political connections as conjectured, but also by more dispersion in both firm productivity and firm ability to connect.

The main hypothesis of the paper is that the increase in misallocation in Spain was due to a process of institutional decline, which intensified the exising problem of cronyism. Challe, López, and Mengus (2016) show a a decline of different indices of institutional quality in Spain between 1996 and 2011. Fernandez-Villaverde, Garicano, and Santos (2013) argue that the deterioration of institutional quality happened because cheap borrowing allowed public administrations to supply large amounts of public goods, which worsened the signal-extraction problem faced by voters in evaluating their politicians. We do not take a stand on the origins of the institutional decline and use the estimated model to quantify its role on the increase of misallocation over the period. To do so we think of the 2007 economy as an economy in which the level of cronyism increased equally in all sectors. We calibrate this increase to match the differential growth of misallocation between more and less crony sectors according to the BPI, and ask the model about the losses in aggregate productivity. Our counterfactual exercise implies that the increase in cronyism generated an overall TFP loss due to misallocation of 14% between 2001 and 2007. This is a 1.9% annual loss and represents more than one half of the 24% overall TFP loss due to increases misallocation measured in the data. Hence, we conclude that the increase in misallocation due to institutional decline accounts for a large part of the productivity slowdown in Spain

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. Second, Díaz and Franjo (2016) show that the large increase in capital accumulation over the period was largely due to capital structures, which they argue was 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.

1.1 Related literature

A number of papers have attempted to measure misallocation of production factors across firms by mapping the large observed dispersion in firm productivities into aggregate productivity losses. Hsieh and Klenow (2009) originally did so for China and India and many other have followed. Dias, Robalo, and Richmond (2015) and Calligaris, Del Gatto, Hassan, Ottaviano, and Schivardi (2014) document a sharp decline in allocative efficiency during the stagnant periods of Portugal (between 1996 and 2011) and Italy (since the early 1990's) respectively. Bellone and Mallen-Pisano (2013) find that misallocation remained constant between 1998 and 2005 in France. Bartelsman, Haltiwanger, and Scarpetta (2013) find that the covariance between firm size and productivity, which they interpret as a measure of 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. Before us, Crespo and Segura-Cayuela (2014) and Gopinath, Kalemli-Ozcan, Karabarbounis, and Villegas-Sanchez (2017) provide evidence of increased misallocation within manufacturing also in Spain. The deterioration of factor allocation across firms during the positive part of the cycle is arguably a singular experience of Spain.

Another group of papers has been looking for examples of specific sources of misallocation that could help explain the large heterogeneity in firm productivity measured in the data. For instance, Gourio and Roys (2014) and Garicano, Lelarge, and Van Reenen (2016) looked at the labor regulation in France and García-Santana and Pijoan-Mas (2014) assessed the Small Scale Reservation Laws in India. However, as Hopenhayn (2014) showed, it is hard to create large losses in aggregate productivity through misallocation without large rank reversals in firm sizes between the actual and the efficient economies, something that this type of size-dependent policies do not achieve. Financial frictions have been flagged as a possible mechanism to produce large rank reversals when entrepreneurial talent and net worth are not well correlated, see for instance Erosa and

Allub (2014). Our model of cronyism can also produce these rank reversals because firm productivity and the ability to connect to the public sector are negatively correlated in the cross-section. Specifically, we find that the rank correlation of firm size between our estimated economy and the efficient one is 0.65.

Our paper also connects with a recent empirical literature attempting to measure the economic effects of cronyism, see Olken and Pande (2012) for a survey. Khwaja and Mian (2005) show how politically connected firms in Pakistan receive more credit from public banks, while Goldman, Rocholl, and So (2013) show how politically connected firms in the US obtain better access to public procurement contracts. Akcigit, Baslandze, and Lotti (2017) show that political connected firms in Italy have higher rates of survival, higher growth in employment and revenue, but no better behaviour of productivity. However, macroeconomic estimates are almost inexistent. Alder (2016) measures the aggregate productivity costs of the mismatch between managers and firms, which he attributes to cronyism. Our cross-sector variation in misallocation provides novel evidence of the aggregate costs of cronyism. Furthermore, because the amount of discretion enjoyed by public officials 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).

Finally, our paper is also related to a growing literature trying to understand the productivity slowdown in Spain and other Southern European countries during the boom years prior to the big recession. Reis (2013) and Benigno, Converse, and Fornaro (2015) argue that the large entry of cheap capital resulted in a misallocation of resources towards low-productivity non-tradable sectors (in particular construction) in Portugal and Spain respectively. However, we show that the sectoral data from EU-KLEMS gives a limited role to the increase in misallocation across sectors in Spain. Very much related to our paper, Gopinath, Kalemli-Ozcan, Karabarbounis, and Villegas-Sanchez (2017) show an increase in misallocation within manufacturing, and link this phenomenon to the large capital inflows over the period. They argue that collateral constraints that are more lenient for larger firms resulted in the capital accumulation process happening at different speed by different firms. Our model of cronyism can explain why it makes sense to think about this type of size-dependent financial constraints. Large firms find it more profitable to spend resources in connecting to corrupt public officials, which turns out to be useful in obtaining credit subsidies. Finally, Pellegrino and Zingales (2017) argue that poor management practices in Italy due to lack of meritocracy hindered IT investment. Schivardi and Schmitz (2018) make the point more general and apply it to the whole Southern Europe. Our findings may be related to these papers to the extent that poor management practices are more likely to happen in sectors and countries where political connections and not market forces are more important for business success.

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 documents the increase in the dispersion of firm productivities and its impact on aggregate productivity. Section 4 relates sectoral variation in cronyism (and other variables) to changes in misallocation. Then, Section 5 presents our model and uses it to quantify the productivity losses from the increase in cronyism. Finally, some concluding remarks are provided in Section 6.

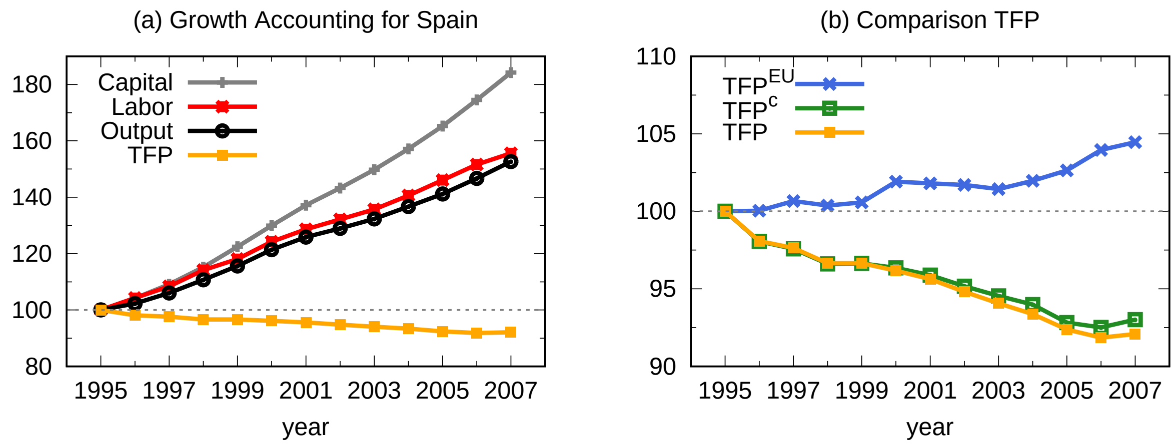
2 The 1995-2007 growth experience

The Spanish economy grew at the average rate of 3.5% per year between 1995 and 2007. This uninterrupted expansion 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. We use data from EU-KLEMS to make this point. In particular, in Panel (a) in Figure 1 we plot the volume indices of value added, labor, and capital services as well as the value added-based TFP growth.[1] Aggregate labor 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.[2] The capital stock also grew at an unprecedented pace of 5.2 percent a year. The decline of interest rates due to the entrance of Spain into the European Monetary Union together with easy borrowing conditions played an important role. Since both labor and capital grew more than final

[1]EU KLEMS provides a decomposition of growth into eight components, namely, energy, materials, services, ICT capital, non-ICT capital, labor composition, total hours worked, and TFP, where the contribution of each element is given by its growth rate times its share in total costs. The capital and labor inputs are measured as capital and labor services, rather than stocks. Therefore, they take into account capital embodied technical change and the educational composition of the labor force. This means that aggregate TFP includes only disembodied technical change and overall efficiency, see O'Mahony and Timmer (2009).

[2]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. This is not the case with the TFP computed by EU KLEMS because it weights the labour input by education. 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.

production, total factor productivity (TFP) declined by 0.7% per year.[3]

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.[4] 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 sectors with bad performance in terms of lower productivity and/or worse productivity growth as conjectured by Benigno, Converse, and Fornaro (2015).[5]

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

[4]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.

[5]Note that as of 1995, the sectoral composition of activity in terms of value added was led by the service sector (58%), followed by manufacturing (20%), construction and real estate (16%), and the

We consider 30 sectors, which is the highest level of granularity provided by the availability of sectoral TPF estimates in EU-KLEMS, and we build on Foster, Haltiwanger, and Krizan (2006) to decompose the productivity growth sources between 1995 and 2007 into three sources. First, the *within-sector* component, which measures the productivity growth within sectors. This is simply an average of the different sectors' productivity growth weighted by initial relative value added shares. Second, the *across-sectors* term, which reflects reallocation of resources across sectors of different productivity. It is measured by the change in value added shares weighted by the initial relative sectoral productivities. And third, the *cross-term*, which captures whether sectors with higher productivity growth were the ones whose size increased the most. It is measured by the covariance between changes in productivity and changes in value added shares.

We find that the *within-industry* component accounts for most of the TFP evolution, explaining 81% of the decline in TFP over the 1995-2007 period. 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 0.6%, 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. In contrast, the *across-sectors* component is almost null and the *cross-term* component explains the remaining 19%, which reflects a negative covariance between TFP growth and value added changes across sectors. Therefore, we conclude that the reallocation of resources towards sectors of low productivity or low productivity growth mattered but did not play a major role.

3 Analysis with firm-level data

We exploit administrative micro-level firm data built from the financial statements that all firms in Spain are legally required to submit to the Commercial Registry (*Registro Mercantil*) every year. In particular, we use the so-called BdE Micro Dataset constructed by Almunia, Lopez-Rodriguez, and Moral-Benito (2018), which combines two different samples taken from the Spanish Commercial Registry. First, the Commercial Registry regularly transfers to the Bank of Spain digitalized raw data on the financial statements submitted by firms, which after processing results in a dataset denominated Central de Balances Integrada (CBI). This dataset, however, does not cover the universe of private-sector firms because it excludes firms that submit information late or on paper. The

primary sector (6%). In 2007, the share of services had increased to 60%, manufacturing had fallen to 15%, construction and real estate had increased to 21%, and the primary sector had fallen to 3%.

second sample is the SABI database (Iberian Balance-Sheet Analysis System), owned by the market research company Informa-Bureau van Dijk (http://www.informa.es/en), which constitutes the Spanish input for the Amadeus and Orbis datasets. The SABI dataset is a sample built using the same financial statements submitted by firms to the Commercial Registry, but it has the advantage of covering firms that are not available in the CBI. The combined dataset is available since the year 2000 and it represents the quasi-universe of Spanish firms as it has data on more than 80% of registered firms every year.[6] Throughout our analysis, we will hence focus on the 2000-2007 period.

Table 1 illustrates the size distribution of firms in our sample (for the year 2004) and compares it to the one 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 from Table 1. First, the coverage of our raw sample is remarkably large in terms of both the number of firms (87% of the operating firms in Spain in 2004) and the level of employment (85% 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 82.30% of the total number of firms and 19.66% of the employment in our sample versus 84.88% and 20.45% in the population. At the other extreme, large firms (more than 200 employees) represent 0.44% of the total number of firms both in our sample and in the population, while they account for 32.23% of the employment in our sample and 33.48% in the population.

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

	Central Business Register				BdE Micro Dataset			
	Firms		Labor		Firms		Labor	
Employees	Total (#)	Share (%)	Total (#)	Share (%)	Total (#)	Share (%)	Total (#)	Share (%)
0-9	882,678	84.88	1,971,401	20.45	743,069	82.30	1,610,635	19.66
10-19	84,464	8.12	1,178,390	12.22	87,346	9.67	1,024,021	12.50
20-49	49,705	4.78	1,557,866	16.16	50,791	5.63	1,411,427	17.23
50-199	18,451	1.77	1,706,499	17.70	17,714	1.96	1,506,839	18.39
+200	4,592	0.44	3,228,252	33.48	3,978	0.44	2,640,710	32.23
All	1,039,890	100.00	9,642,408	100.00	902,898	100.00	8,193,631	100.00

Notes. This figure shows the coverage of the BdE Micro Dataset for the year 2004. It also compares the distributions of firm sizes and employment obtained from this dataset with that from the Central Business Register available from the National Statistics Institute, which contains employment information for the universe of Spanish firms. Self-employed persons are not included.

[6]The BdE Micro Dataset starts in 2000 because the coverage and quality of firms' information is significantly inferior before that as firms were not required to report their information electronically. See Almunia, Lopez-Rodriguez, and Moral-Benito (2018) for details.

The dataset includes information on the firm's name, fiscal identifier, sector of activity (4-digit NACE Rev. 2 code), 5-digit zip code location, net operating revenue, material expenditures (cost of all raw materials and services purchased by the firm in the production process), number of employees, labor expenditures (total wage bill, including social security contributions) and total fixed assets.[7]

3.1 The evolution of 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 revenue products of capital and labor. We measure the average revenue products 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}.[8] Then, we compute the variance of the logs within each of our 500 4-digit industries s at time t and we obtain the economy-wide measures 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 revenue products is larger for capital than for labor: the variance is 1.61 log points for capital and 0.21 for labor in 2000. Second, Panel (a) shows that the dispersion in the average revenue product of capital grew more than the dispersion in the average revenue product of labor. In particular, the dispersion in the average revenue product of capital increased roughly monotonically over the 2000-2007 period, with an overall increase of 0.6 log points, while the dispersion in the average revenue product of labor increased 0.1 log points. And third, we aggregate the dispersion of the average revenue products within the 4-digit industries into 4 main sectors: manufacturing, construction, trade, and services. In Panels (b) and (c) of Figure 2 we see that there is substantial variation across sectors but that dispersion increased in all of them. The increase in both capital and labor revenue produts was lowest in manufacturing and largest in construction and services.

Under the theoretical framework of Hsieh and Klenow (2009) (HK hereafter), the firm-level average revenue products of capital and labor can be mapped into firm-level marginal revenue products through a Cobb-Douglas production function, and subsequently into firm-level idiosyncratic wedges in capital and labor. In particular, the optimality condi-

[7]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. 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.

[8]In practice, we follow Hsieh and Klenow (2009) and compute the average revenue product of labor by dividing firm's value added by wage bill wL_{sit}. This is done to control for differences in labor quality across firms.

tions imply that the marginal revenue products of capital (MRPK) and labor (MRPL) are equalized to each firm's effective factor cost of capital and labor as follows:

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

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

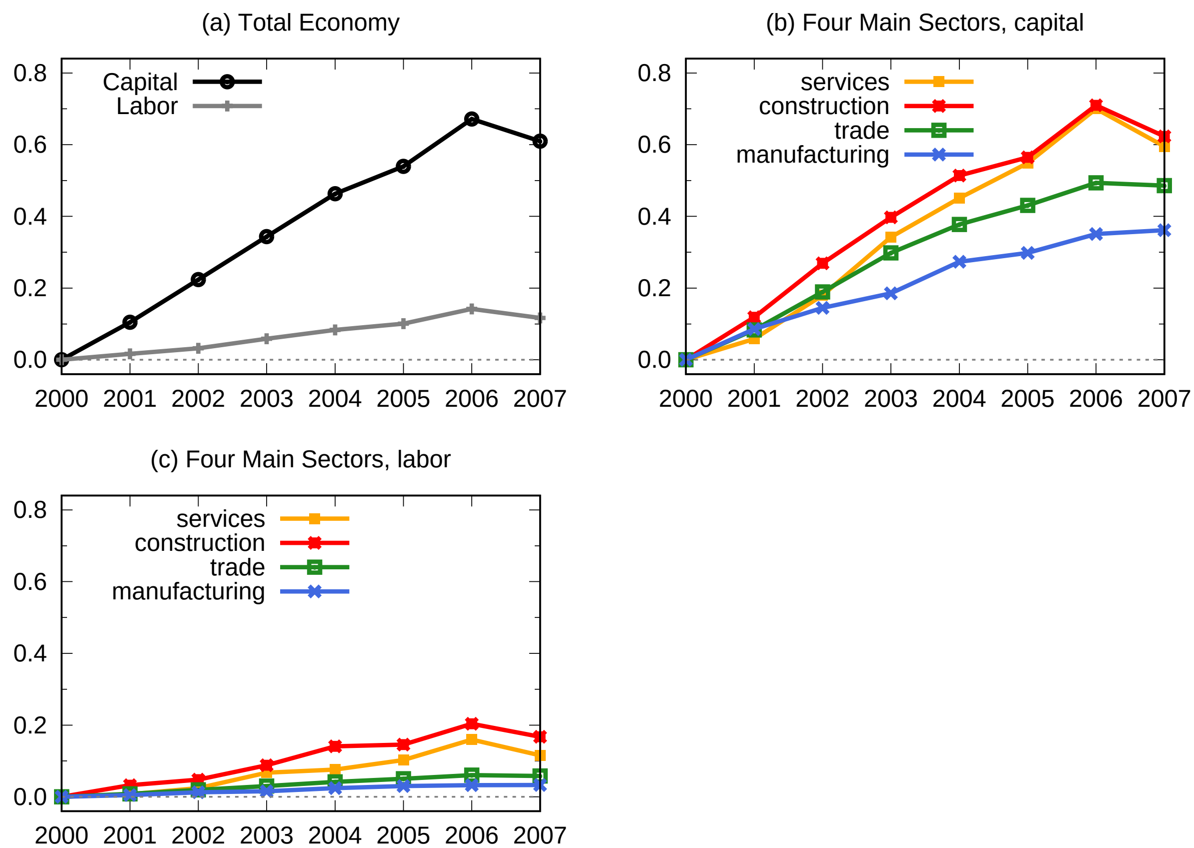
where α_s is a sector specific capital share, σ is the elasticity of substitution, r_t and w_t are economy-wide factor prices, and τ_{Ksit} and τ_{Lsit} are the idiosyncratic distortions in form of subsidy. In an undistorted economy ($\tau_{Ksit} = 0$ and $\tau_{Lsit} = 0\ \forall sit$) all firms within a sector s in period t would equalize their marginal revenue products to the factor prices r_t and w_t. Hence, within sector variation in marginal revenue products necessarily arises from variation in firms' idiosyncratic distortions. Equations (1) and (2) show that the dispersions in the log of average revenue products documented in Figure 2 correspond to the dispersions in the log of marginal revenue products and to the dispersion in the log of wedges.

3.2 The evolution of productivity losses

Following the standard HK approach, we can measure the aggregate productivity losses associated to the observed dispersion of firm productivities. In particular, we compute the potential TFP Gain of between-firm reallocation in sector s at time t as the log difference between the efficient (TFP^*_{st}) and the observed (TFP_{st}) sectoral productivity, a difference that increases with the dispersion of MRPK_{sit} and MRPL_{sit}. To be precise, we define $\text{TFP Gain}_{st} \equiv \log \mathrm{TFP}^*_{st} - \log \mathrm{TFP}_{st}$. We can measure the economy-wide gains by taking the value added-weighted average over all 4-digit industries.[9] In Panel (a) of Figure 3 we report the yearly evolution of $\Delta\text{TFP Gain}_{st} = \text{TFP Gain}_{st} - \text{TFP Gain}_{s2000}$, which captures the increase in the potential TFP Gain of removing misallocation for the overall economy every in year t as compared to year 2000. We find that allocative efficiency decreased substantially over the period. In particular, we find that the potential TFP Gain increased by around 0.24 log points between 2000 and 2007. Importantly, in Panel (b) of Figure 3 we also see that this increase in misallocation is a general phenomenon across the four major sectors of the economy. More precisely, we find that the increase in the potential TFP Gain is largest in construction and services, with 0.29 and 0.25 log points respectively, while the increase in the TFP Gain in trade and manufacturing is 0.17

[9] See Appendix A for details, including Section A.5 for the standard strategies for the calibration and for the measurement of firm level distortions and productivity.

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



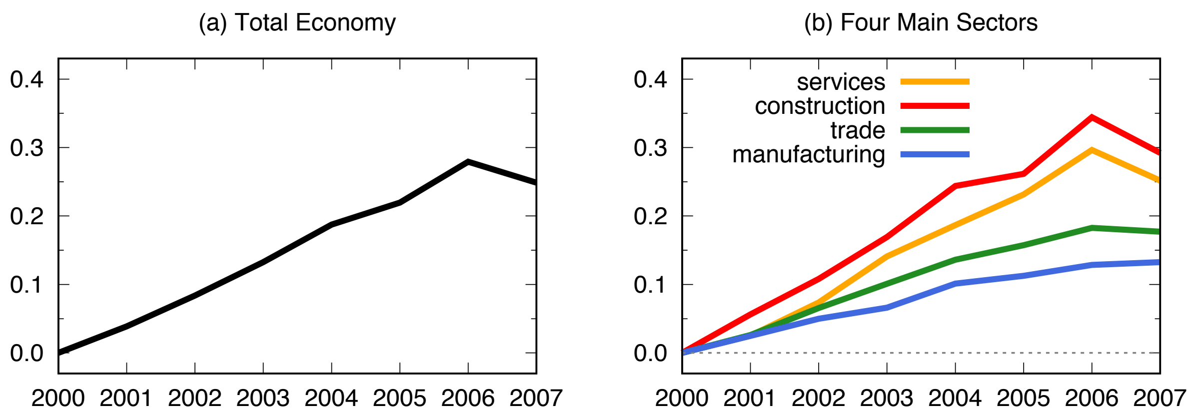
Notes. Panel (a) reports the within-sector variance of the average products of capital and labor, measured at the 4-digit industry level and then aggregated to the whole economy using value added weights. We report the difference with respect to the 2000 values, which were 1.61 and 0.21 log points for capital and labor. Panels (b) and (c) report the aggregation for the four main sectors of activity.

and 0.13 respectively. The decline in allocative efficiency in manufacturing is consistent with the findings by Crespo and Segura-Cayuela (2014) and Gopinath, Kalemli-Ozcan, Karabarbounis, and Villegas-Sanchez (2017) using the AMADEUS data set. We confirm their finding with a wider data set and show that this phenomenon has been more severe for the overall economy than for manufacturing.

4 Cronyism and variation across sectors

While the decline in allocative efficiency between firms was widespread over the whole economy, it is also true that there was substantial variation across industries. In this

FIGURE 3: Potential ΔTFP Gain from reallocation



Notes. Panel (a) describes the evolution of potential ΔTFP Gain of removing distortions for the overall economy in each year t with respect to the initial year 2000. Panel (b) plots the evolution of potential ΔTFP Gain for different sectors. Potential TFP Gain have been computed using the Hsieh and Klenow (2009) methodology, i.e, TFP Gain $= \log \mathrm{TFP}^* - \log \mathrm{TFP}$. See Appendix A for details.

Section we exploit the rich variation of misallocation experiences across industries to learn about the potential reasons of the phenomenon. To do so, and because we have information on several sectoral characteristics at the 2-digit NACE rev. 2 classification only, we aggregate the HK measure of misallocation —the TFP Gain— computed at the 4-digit level into 2-digit level industries. Looking at the 2-digit industries, we find that the unweighed average of the ΔTFP Gain between 2000 and 2007 across sectors is 0.19 log points, the median is 0.18, the standard deviation is 0.12, and allocative efficiency worsened in all but 3 of the 61 sectors.

4.1 Cronyism

Crony capitalism (or cronyism) is a term describing an economic system in which success in business depends on a close relationship with government officials. The main hypothesis of the paper is that the increase in misallocation in Spain was partly driven by a decline in the quality of institutions, which led to an increasing problem of cronyism. There has been an increasing number of cases of corruption of public officials brought to court for offences during the boom years. Furthermore, the World Bank's World Governance Indicators show a clear decline of institutional quality in Spain between 1996 and 2011, which is common with other Southern European countries but not with the rest of the EU, see Challe, López, and Mengus (2016) for details. In particular, the indices for

“Regulatory Quality” and “Control of Corruption”, which are very much related to crony capitalism, show a sharp decline. The reasons for this institutional decline are not clear. Fernandez-Villaverde, Garicano, and Santos (2013) argue that this was because voters face a more severe signal-extraction problem in evaluating their politicians when these are able to supply large amounts of public goods through cheap borrowing.

The challenge in testing this hypothesis is that crony capitalism is notoriously hard to measure. We proceed as follows. We conjecture that some sectors are more prone to cronyism than others because there is sectoral variation in the importance of state licensing or regulation for business success. We exploit this sectoral variation to test whether sectors more prone to cronyism experienced a larger increase in misallocation.

In order to measure differential cronyism across sectors we use the Bribe Payer Index (BPI) of Transparency International.[10] Transparency International is an NGO that runs the survey Bribe Payer Survey with entrepreneurs all over the World. In 2011 the survey asked 3,016 senior business executives in 30 different countries about the perceptions of the likelihood of companies to engage in bribery. In particular, after giving a list of 19 possible sectors in which the business executives deal with, the survey asks “In your experience, how often do firms in each sector (i) engage of bribery of <u>low-level public officials</u>, for example to speed-up administrative processes and/or to facilitate the granting licenses?; (ii) use improper contributions to <u>high-ranking politicians or political parties</u> to achieve influence?; and (iii) pay or receive bribes from <u>other private firms</u>?”.[11] The answers are qualitative and Transparency International builds the BPI, an index of cronyism across sectors that ranges from 5 to 10 and is constructed such that a higher value means a smaller role of cronyism in the sector. We multiply the Index by -1 such that higher values mean higher prevalence of cronyism.[12]

To test whether misallocation was larger in sectors more prone to cronyism we assign a BPI value to each of our 2-digit sectors and regress the HK measure of misallocation in 2000, the TFP Gain, against the BPI. We find a strong, positive and significant correlation with a regression coefficient of 0.238, indicating that more crony sectors display more

[10]The magazine The Economist also uses the BPI to classify sectors into crony vs non-crony and it combines it with Forbes' World's Billionaires to create its Crony Capitalism Index, see https://goo.gl/oLpQ1Z.

[11]The underlying is ours. For more details on the BPI see http://goo.gl/w4mgxd.

[12]The survey was run in 1999, 2002, 2006, 2008, 2011. We use the 2011 version in our empirical analysis for several reasons. First, the surveys of 1999 and 2006 cannot be used because the BPI index is not reported at the sector level for these years. Second, we discard 2002 because the BPI index is not reported for “Consumer Services” nor “Utilities”, which implies losing information about 10 sectors at the CNAE 2-digit level. Finally, between 2008 and 2011, we pick the latter because its larger sample size (2,742 vs 3,016).

Table 2: Misallocation and cronyism.

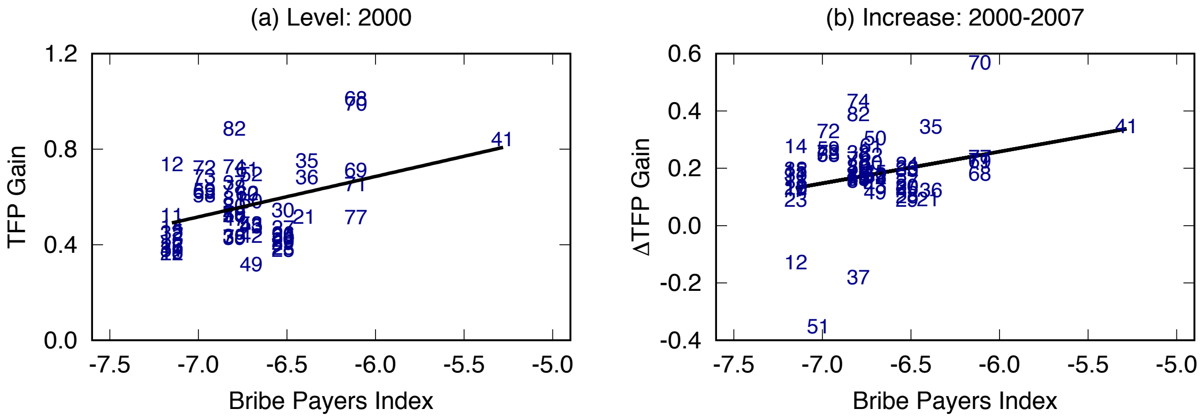
	TFP Gain	Var [log MRPK_{si}]	Var [log MRPL_{si}]
Level in 2000	0.238***	0.623***	0.183***
	(0.022)	(0.059)	(0.039)
Change 2000 to 2007	0.101***	0.134***	0.087***
	(0.015)	(0.045)	(0.012)

Notes. This Table shows the results of regressing the 2000 level and the change between 2000 and 2007 of the TFP Gain, Var [log MRPK_{si}] and Var [log MRPL_{si}] against the BPI index. The dependent variables have been computed at the 4-digit level and then aggregated to 2-digit level using a weighted average. Standard errors in parenthesis. *** indicates statistical significance at the 1% level.

severe misallocation (see first row in Table 2 and Panel A of Figure 4). The difference in the BPI between the sectors in the 95th of the distribution of cronyism ("real estate activities") the sectors in the 5th percentiles ("manufacture of textiles") is 1.04. Hence, we can interpret the estimated regression coefficient as the average difference in the TFP Gain between a sector in the 95th percentile of the distribution of cronyism and a sector in the 5th percentile. Hence, the most crony sectors have a potential TFP Gain 24% higher than the least crony sectors (which is a large number given the aggregate value for 2000 is 54%). We also regress the variance in the log of MRPK and MRPL against our measure of cronyism, and find that more crony sectors display statistically significant more dispersion in firm productivities, see the second and third columns in Table 2. In particular, the estimated coefficients imply that the most crony sectors display 0.62 more log points in the variance of MRPK and 0.18 more log points in the variance of MRPL than the least crony sectors. Note that the aggregate values for 2000 were 1.61, and 0.21 respectively.

Next, to test whether misallocation increased more in sectors more prone to cronyism we regress the change in the HK measure of misallocation, the ΔTFP Gain between 2000 and 2007, against the BPI, see the second row in Table 2. We find that the deterioration in allocative efficiency is positively and significantly correlated to the BPI index. This relationship is also plotted in Panel B of Figure 4. The estimated coefficient implies that a sector in the 95th percentile of the distribution of cronyism experienced a productivity loss 10% higher than a sector in the 5th percentile. This number is large, compared to the aggregate productivity loss of 24% over the period. We also regress the increase in the variance of log MRPK and MRPL against the BPI index and also find that firm level dispersion increased more in more crony sector, see the second row in Table 2. The estimated coefficients imply that the variance in the log of MRPK and MRPL increased

Figure 4: Misallocation and crony capitalism



Notes. Panel (a) of this graph plots the level of TFP gains in 2000 against the BPI index. Panel (b) shows the change in TFP gains between 2000 and 2007 and the BPI index. TFP gains have been computed at the 4-digit level and then aggregated to the 2-digit level using a weighted average. See Table D.1 in Appendix D for the list of the 2-digit sectors.

by 0.13, and 0.09 log points more in the more crony sectors, which again are large numbers compared to the aggregate increases of 0.60 and 0.10.

4.2 Other explanations

Next, we consider four other 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 blamed as a possible source of misallocation of workers across firms (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.[13] Fixed-term contracts are less prevalent among high skilled occupations, probably because employee turnover precludes on-the-job human capital accumulation.[14] 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

[13]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.

[14]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).

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).

And 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.

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 Gain on the different characteristics measured as the average over the 2000-2007 period. Columns (1)-(4) are based on linear regressions with different covariates introduced once at a time. We fail to find any statistically significant relationship between skill intensity, innovative content, financial dependence or tradability with the change in allocative efficiency. Furthermore, the R^2 indicates that variation in these characteristics can only account for less than 11% of the variation in misallocation changes.[15]

[15] The lack of correlation between financial dependence and the increase in misallocation is puzzling.

Table 3: Misallocation and sector-specific characteristics.

	Dependent variable: ΔTFP Gain					
	(1)	(2)	(3)	(4)	(5)	(6)
High-skill intensity	0.001					0.001
	(0.001)					(0.001)
Innovative content		0.001				0.005***
		(0.004)				(0.001)
Financial dependence			0.012			0.002
			(0.012)			(0.010)
Tradability				-0.096		-0.039
				(0.065)		(0.030)
Bribe Payers Index					0.101***	0.105***
					(0.015)	(0.019)
Observations	60	61	61	61	61	60
R-squared	0.012	0.003	0.025	0.101	0.420	0.505

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 2000-2007 period in the ratio of optimal TFP in the absence of misallocation to observed TFP, according to the HK methodology.

In contrast, Column (5) in Table 3 indicates that the deterioration in allocative efficiency is significantly correlated to the BPI index (as we saw in the previous Section) and that the BPI index is able to account for 42% of the variation in the increase of misallocation across sectors as measured by the R^2 of the regression. When all the variables are jointly included in the regression in column (6), we see that the sign and significance of the coefficient on BPI is preserved as well as the irrelevance of the other co-variates, with the exception of innovative content that becomes positive and significant.

5 Model

We consider a closed economy with heterogenous producers, which differ in their productivity and in their ability to connect to public officials. These producers choose how much to spend in pursuing political connections as well as how much capital and labor

Gopinath, Kalemli-Ozcan, Karabarbounis, and Villegas-Sanchez (2017) provide firm-level evidence showing the importance of financial frictions in explaining misallocation within sectors over the same period. Similarly, Cette, Fernald, and Mojon (2016) provide aggregate time series evidence showing that the decline in real interest rates that took place in Italy and Spain were able to reduce the level of TFP. We see our sectoral-level evidence as complementary.

to hire. There are many sectors in the economy, differing in the value of political connections to obtain favorable conditions to operate. The model is an extension of Hsieh and Klenow (2009) with endogenous wedges, and for this reason many details can be found in Appendix A.

Aggregate output Y is the combination of the output Y_s in S industries indexed by s:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s}, \qquad \text{with } \ \theta_s > 0 \ \text{ and } \ \sum_{s=1}^{S} \theta_s = 1 \tag{3}$$

while industry s output is the aggregation of output of N_s different varieties:

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

where $\sigma > 1$ is the elasticity of substitution between varieties.

Each variety si is produced by only one firm with technology given by,

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s} \qquad \text{with } \ 0 < \alpha_s < 1 \tag{5}$$

Every firm si is characterized by its productivity A_{si} and its ability to connect to the public sector Z_{si}. It hires capital K_{si} and labor L_{si} in competitive markets (takes factor prices r and w as given) and sells output Y_{si} at price P_{si}, which depends on its own production through the demand curve from the sectoral aggregator:

$$P_{si} = \left(\frac{\theta_s Y}{P_s^{1-\sigma}} \right)^{1/\sigma} Y_{si}^{-1/\sigma} \tag{6}$$

In addition, every firm decides the amount M_{si} of spending in political connections. As a result of this spending, it obtains capital and labor subsidies τ_{Ksi} and τ_{Lsi} as follows:

$$(1 + \tau_{Ksi}) = (Z_{si} \, M_{si})^{\beta_{Ks}} \tag{7}$$

$$(1 + \tau_{Lsi}) = (Z_{si} \, M_{si})^{\beta_{Ls}} \tag{8}$$

where β_{Ks} and β_{Ls} are sector specific elasticities of capital and labor wedges to political connections. Then, the optimization problem is given by:

$$\max_{L_{si}, K_{si}, M_{si}} \left\{ P_{si} Y_{si} - (1 + \tau_{Lsi})^{-1} \, w \, L_{si} - (1 + \tau_{Ksi})^{-1} \, r \, K_{si} - P_M M_{si} \right\} \tag{9}$$

subject to firm demand (6), firm production technology (5), and the expressions for wedges (7) and (8). P_M is the price of political connections that can be normalized to one. Let's define $\gamma_s \equiv (\alpha_s \beta_{Ks} + (1-\alpha_s)\beta_{Ls})$ as the average of the elasticities of political connections on each input subsidy weighted by the factor shares. Under the parametric assumption that $1 > \alpha_s > 0$, $\sigma > 1$, $\gamma_s > 0$, and $(\sigma - 1)\gamma_s < 1$ the first order conditions (FOC) determine the solution of this optimization problem. In particular, we have the standard FOC for capital and labor as given by equations (1) and (2). In addition, there is the FOC that characterizes the optimal spending on political connections:

$$\beta_{Ks}\frac{1}{M_{si}}(1+\tau_{Ksi})^{-1} r\, K_{si} + \beta_{Ls}\frac{1}{M_{si}}(1+\tau_{Lsi})^{-1} w\, L_{si} = P_M \tag{10}$$

which after substituting the FOC for capital and labor can be written as:

$$\left(\frac{\sigma-1}{\sigma}\right)\gamma_s \frac{P_{si}Y_{si}}{M_{si}} = P_M \tag{11}$$

This condition implies that the optimal expenditure share in political connections is identical across firms and that larger firms invest more in political connections and get higher subsidies in return. This is because at the same cost per unit of subsidy, larger firms enjoy a larger *subsidy base*. It can be shown that firm size in terms of total revenues is given by

$$P_{si}Y_{si} = \left(\frac{\theta_s Y}{P_s^{1-\sigma}}\right)^{\frac{1}{1-(\sigma-1)\gamma_s}} \left[\left(\frac{\sigma-1}{\sigma}\right)^{1-\gamma_s} \frac{1}{\tilde{c}_s(w,r,P_M)} A_{si} Z_{si}^{\gamma_s}\right]^{\frac{\sigma-1}{1-(\sigma-1)\gamma_s}} \tag{12}$$

where $\tilde{c}_s(w,r,P_M)$ is a properly defined marginal cost function. This expression is important. It says that there are two ways for firms to become big. The standard one is that more productive firms choose larger size because their larger productivity (higher A_{si}) compensates the decline in price when selling larger quantities. The new one is that better connected firms (higher Z_{si}) also choose to be big because they obtain cost reductions that compensate the decline in price when selling larger quantities. Combining equations (11) and (12) shows that spending in political connections M_{si} and hence idiosyncratic subsidies τ_{Ksi} and τ_{Lsi} increase with both firm productivity A_{si} and firm ability to connect to the public sector Z_{si}.

Finally, note that absent variation in Z_{si} across firms, this model of cronyism generates national champions: more productive firms invest more in political connections, obtain favorable regulation, and become larger than in an efficient economy detracting capital and labor from the rest. This type of misallocation would preserve the rank of firm sizes, and it would be in contrast to size distortions that limit optimal firm size as in Guner, Ventura, and Yi (2008) or Restuccia and Rogerson (2008). Whether firms are too large in the presence of cronyism, however, depends on the correlation between A_{si} and Z_{si}. If this correlation is positive the problem of national champions is magnified. Instead, when A_{si} and Z_{si} are negatively correlated aggregate productivity losses may be less.

5.1 Cronyism and the dispersion of wedges

The model has important implications for the dispersion of wedges. Let σ^2_{As}, σ^2_{Zs}, and σ_{AZs} be the second moments of the joint distribution of $\log A_{si}$ and $\log Z_{si}$ in sector s, which are three sector-specific model parameters. Using the definition of the capital wedge τ_{Ksi} we obtain,

$$\mathrm{Var}\left[\log\left(1+\tau_{Ksi}\right)\right] = \beta^2_{Ks}\big(\sigma^2_{Zs} + \mathrm{Var}\left[\log M_{si}\right] + 2\,\mathrm{Cov}\left[\log M_{si}, \log Z_{si}\right]\big) \tag{13}$$

and a similar expression obtains for $\mathrm{Var}\left[\log\left(1+\tau_{Lsi}\right)\right]$. Note that $\log M_{si}$ is endogenous in equation (13), but we can write it as a function of $\log A_{si}$ and $\log Z_{si}$ by combining equations (11) and (12):

$$\log M_{si} = \frac{\sigma-1}{1-\tilde{\gamma}_s}\log A_{si} + \frac{\tilde{\gamma}_s}{1-\tilde{\gamma}_s}\log Z_{si} + \text{constants} \tag{14}$$

where we define $\tilde{\gamma}_s \equiv (\sigma-1)\,\gamma_s$. Then, we can write the variance of $\log M_{si}$ and its covariance with $\log Z_{si}$ and $\log A_{si}$ as follows:

$$\mathrm{Var}\left[\log M_{si}\right] = \left(\frac{\sigma-1}{1-\tilde{\gamma}_s}\right)^2\left[\sigma^2_{As} + \gamma_s^2\sigma^2_{Zs} + 2\gamma_s\,\sigma_{AZ_s}\right] \tag{15}$$

$$\mathrm{Cov}\left[\log M_{si}, \log Z_{si}\right] = \left(\frac{\sigma-1}{1-\tilde{\gamma}_s}\right)\left[\sigma_{AZs} + \gamma_s\,\sigma^2_{Zs}\right] \tag{16}$$

$$\mathrm{Cov}\left[\log M_{si}, \log A_{si}\right] = \left(\frac{\sigma-1}{1-\tilde{\gamma}_s}\right)\left[\sigma^2_{As} + \gamma_s\,\sigma_{AZs}\right] \tag{17}$$

Hence, plugging equations (15) and (16) into (13) one can describe the dispersion of capital wedges as function of model parameters only. An increase in β_{Ks} (or β_{Ls}) affects the dispersion of wedges τ_{Ksi} and τ_{Lsi} —and hence misallocation— through a direct and an indirect effect. The direct effect is the amplification in the dispersion of wedges due to the higher elasticity given the existing dispersion in political connections (that is, given the existing dispersion of $\log Z_{si}M_{si}$), and it only affects the wedges of the own factor (β_{Ks} affects the dispersion of τ_{Ksi} but not of τ_{Lsi} and *vice versa*). The indirect effect is the endogenous increase in the dispersion of political connections (that is, the increase in the dispersion of $\log Z_{si} M_{si}$) across firms generated by the increase in β_{Ks} (or β_{Ls}). The logic of the indirect effect is as follows. By lowering the cost of capital and labor, political connections act as a third factor of production that increases the degree of homogeneity of the profit function. In our model, because the production function is constant returns to scale in capital and labor, the profit function becomes of increasing returns to scale in capital, labor and political spending (but the model is well behaved as long as the negative slope of the demand functions is large enough, $(\sigma - 1) \gamma_s < 1$). A higher elasticity of subsidies to political connections is then akin to a lower curvature in the firm revenue function –see equation (12)– and hence the exogenous differences in firm productivity A_{si} or firm ability to connect Z_{si} are amplified in terms of firm size. Because the isoelastic model predicts that the expenditure share in political connections is the same across all firms within the same sector –see equation (11)– an increase in the dispersion of firm sizes also increases the dispersion of spending in political connections and hence the dispersion of wedges and marginal revenue products. Because both the direct and the indirect effects are positive, an increase in either β_{Ks} or β_{Ls} increases the dispersion of both wedges. This result is stated in the following proposition:[16]

Proposition 1. *The first derivative of the variance of log capital wedges and of log labor wedges, $Var[\log(1+\tau_{Ksi})]$ and $Var[\log(1+\tau_{Lsi})]$, with respect to both β_{Ks} and β_{Ls}, is positive.*

Further to the previous result, the increase in the dispersion of capital wedges generated by an increase in β_{Ks} or β_{Ls} is larger on those sectors with larger β_{Ks} or larger β_{Ls} (and the same is true for the increase in the dispersion of labor wedges). This is stated formally in the following Proposition:

Proposition 2. *The second derivative of the variance of log capital wedges and of log labor wedges, $Var[\log(1+\tau_{Ksi})]$ and $Var[\log(1+\tau_{Lsi})]$, with respect to both β_{Ks} and β_{Ls}, is positive, and so is the cross derivative with respect to β_{Ks} and β_{Ls}.*

Note that Propositions 1 and 2 are consistent with the empirical findings in Section 4.1. The positive first derivative of wedge dispersion with respect to β_{Ks} and β_{Ls} can be interpreted in two ways. The first interpretation is that sectors more prone to cronyism display more dispersion in firm productivities. The second interpretation is that an increase in cronyism (or a decline in institutional quality) increases dispersion in firm productivities. The positive second derivative can be interpreted as follows: an increase in

[16]The proofs of this and the next propositions are in Appendix B

cronyism (or a decline in institutional quality) generates larger increases in productivity dispersion on already more crony sectors. We can make this statement more formally as follows:

Corollary 1. *Let's define $\beta_{Ks} \equiv \lambda\hat{\beta}_{Ks}$ and $\beta_{Ls} \equiv \lambda\hat{\beta}_{Ls}$ where $\lambda > 0$ is the inverse of the general level of institutional quality, β_{Ks} and β_{Ls} are the actual elasticities of political connections to subsidies, and $\hat{\beta}_{Ks}$ and $\hat{\beta}_{Ks}$ are some fundamental elasticities. Then, the first and second derivatives of the variance of log capital wedges and of log labor wedges, $Var[\log(1+\tau_{Ksi})]$ and $Var[\log(1+\tau_{Lsi})]$, with respect to λ are always positive.*

5.2 Estimation

In order to use the model to make quantitative statements we need to estimate β_{Ks}, β_{Ls}, σ^2_{As}, σ^2_{Zs}, and σ_{AZs} for every sector. We do so by asking the model to match second moments of the distribution of wedges and productivity. In particular, following derivations similar to the ones in Section 5.1, the model allows to obtain the following analytical expression for the variance of firm TFP, the variance of wedges, and their covariance:

$$\begin{aligned}
\text{Var}[\log A_{si}] &= \sigma^2_{As} && (18)\\
\text{Var}[\log(1+\tau_{Ksi})] &= \beta^2_{Ks}\left(\sigma^2_{Z_s} + \text{Var}[\log M_{si}] + 2\,\text{Cov}[\log M_{si}, \log Z_{si}]\right) && (19)\\
\text{Var}[\log(1+\tau_{Lsi})] &= \beta^2_{Ls}\left(\sigma^2_{Z_s} + \text{Var}[\log M_{si}] + 2\,\text{Cov}[\log M_{si}, \log Z_{si}]\right) && (20)\\
\text{Cov}[\log(1+\tau_{Ksi}), \log A_{si}] &= \beta_{Ks}\left(\sigma_{AZs} + \text{Cov}[\log M_{si}, \log A_{si}]\right) && (21)\\
\text{Cov}[\log(1+\tau_{Lsi}), \log A_{si}] &= \beta_{Ls}\left(\sigma_{AZs} + \text{Cov}[\log M_{si}, \log A_{si}]\right) && (22)
\end{aligned}$$

where $\text{Var}[\log M_{si}]$, $\text{Cov}[\log M_{si}, \log Z_{si}]$, and $\text{Cov}[\log M_{si}, \log A_{si}]$ are given by equations (15)-(17). The left hand sides of equations (18)-(22) come from the data. We recover firm TFP, A_{si}, and the capital and labor wedges, τ_{Ksi} and τ_{Lsi}, for each firm from our firm-level data as it is standard in the literature and construct the second moments while correcting for measurement error, see Appendix A.5 for details. In Panel A of Table 4 we report the average and standard deviation of these moments across the 500 4-digit sectors. As already discussed in Section 3.1, we can see that there is much more dispersion in capital wedges than in labor wedges: the variance of the log of capital wedges is 1.61 while the one for capital wedges is 0.21. Furthermore, the covariance between firm productivity and capital and labor subsidies is negative, and it is larger in absolute value for capital (-0.42) than for labor (-0.17). This means that more productive firms tend to have smaller capital and labor shares than their sector average, and this is more pronounced for capital than for labor.

Table 4: Estimation: 2000

Panel A: empirical moments			Panel B: estimated parameters				
moment	mean	sd	param.	mean	sd	corr	se
$\text{Var}[\log A_{si}]$	0.71	0.24	σ^2_{As}	0.61	0.24	0.09	0.05
$\text{Var}[\log(1+\tau_{Ksi})]$	1.61	0.52	σ^2_{Zs}	10.89	2.46	1.51	0.36
$\text{Var}[\log(1+\tau_{Lsi})]$	0.21	0.14	σ_{AZs}	-1.93	0.71	-0.31	0.13
$\text{Cov}[\log(1+\tau_{Ksi}), \log A_{si}]$	-0.42	0.24	β_{Ks}	0.32	0.05	0.02	0.01
$\text{Cov}[\log(1+\tau_{Lsi}), \log A_{si}]$	-0.17	0.11	β_{Ls}	0.10	0.04	0.03	0.01
			γ_s	0.18	0.02	0.02	0.01

Notes. Column "mean" is the average over the 500 sectors, column "sd" is the standard deviation across the 500 sectors, column "corr" is the regression coefficient of the given sector-level variable on the BPI, and column "se" is the standard error of the estimation of this last regression coefficient.

The right hand sides of equations (18)-(22) come from the model and, given calibrated values for σ and α_s, they are function of the 5 parameters to be estimated: β_{Ks}, β_{Ls}, σ^2_{As}, σ^2_{Zs}, and σ_{AZs}. Hence, for every sector we have a system of 5 equations in 5 unknowns that can be estimated by GMM. We report the model fit of equations (19)-(22) in Figure C.1 in Appendix C. In Panel B of Table 4 we report the average and standard deviation of the estimated parameters across the same 500 4-digit sectors. There are three important results from the estimation. First, cronyism is more effective in extracting capital subsidies than labor subsidies: the average across sectors of the estimated β_{Ks} is 0.32, three times as big as the average of estimated β_{Ls}, which is 0.10. Empirically, the reason for this result is that both the variance of wedges and the (absolute value of the) covariance of wedges with firm TFP is larger for capital than for labor. This result is consistent with the notion that *Cajas de Ahorros* may have given credits to connected firms and were hence an instrument of cronyism. Indeed, Cunat and Garicano (2010) show that politically controlled *Cajas de Ahorros* had very significantly worse loan performance. The second important result from the estimation is that the covariance between firm productivity and ability to connect to the public sector is negative ($\sigma_{AZs} < 0$), which is the result of the negative sign in the covariance between the wedges and firm TFP. In the model this correlation is exogenous, but one can easily think of possible mechanisms to generate it. In a model of occupational choice *a la* Lucas (1978) with two talents, we may obtain a negative correlation among entrepreneurs because of selection even if these two talents were independently distributed in the general population. Also, as argued by Akcigit, Baslandze, and Lotti (2017), entrepreneurs may need to choose how much to invest in improving firm productivity (for instance investing in R&D) *vs* in lobbying regulators. Finally, in Panel B of Table 4 we also report the correlation between each parameter and the level of cronyism. In particular we regress the estimated parameter against the BPI across sectors and report the slope coefficient and the standard deviation of the estimation. We first note that our estimated measures of cronyism at sector level, β_{Ks} and β_{Ls}, as well as their weighted average, γ_s, are larger in sectors with higher BPI and that the slope is statistically significant. Second, we also observe that both the variance in firm productivity, σ_A^2, and the variance in the ability to connect to public sector, σ_Z^2, are also positively and significantly correlated to the BPI index. Hence, according to our estimates, more crony sectors as identified by the BPI have higher returns to investing in connections and more dispersion in underlying firm productivity and ability to connect to the public sector.

5.3 Misallocation in 2000

We can assess the impact of cronyism in the 2000 economy by use of our estimated model economy. In the first column of Table 5 we report severals statistics of interest for this economy. We find that overall TFP losses due to misallocation are large: a counterfactual economy with no role for cronyism ($\beta_{Ks} = \beta_{Ls} = 0$) would experience an increase in aggregate TFP of 79%. We note that the relative large losses of misallocation come from an important rank reversal in firm sizes: the correlation between firm TFP and firm size is only 0.67 (it should be 1 in the efficient economy), and the rank correlation between firm size in the benchmark economy and the efficient one is 0.65. This means that a substantial number of firms that employ large (small) amounts of capital and labor in the benchmark economy —due to their large (small) ability to connect to the pubic sector— should be smaller (larger) in an efficient allocation.

Both heterogeneity in firm productivity and ability to connect to public sector contribute to the aggregate losses of cronyism. To measure the role of each level of heterogeneity we solve for two counterfactual economies, one in which $\sigma_{Zs}^2 = 0$ and hence only heterogeneity in firm productivity remains (second column in Table 5), and another one in which $\sigma_{As}^2 = 0$ and hence only heterogeneity in firm ability to connect remains (third column in Table 5). We see that with heterogeneity only in firm productivity firm dispersion in MRPK and MRPK halves but there are still important losses of misallocation: aggregate TFP could be 37% higher if cronyism was eliminated. In this economy cronyism does not generate any rank-reversal: the rank correlation of firm sizes between the crony

Table 5: Model economy: 2000

	Benchmark	Het. in A_{si}	Het. in Z_{si}
Var $(\log \text{MRPK}_{si})$	1.61	0.80	3.30
Var $(\log \text{MRPL}_{si})$	0.21	0.11	0.43
TFP Gain	0.79	0.37	1.58
Rank correlation	0.65	1.00	0.00
Corr $(\log P_{si}Y_{si}, \log A_{si})$	0.67	1.00	0.00
Share of emp by the top 10%	0.73	0.91	0.85

Notes. Statistic from model economies. The first column refers to the benchmark economy with the estimated parameters in Panel B of Table 4. The second column refers to the economy with $\sigma^2_{Zs} = 0$. The third column refers to the economy with $\sigma^2_{As} = 0$.

and the efficient economy is one, and firm size and firm productivity are perfectly correlated. The inefficiency in this economy arises because more productive firms invest more in cronyism than less productive ones, generating too much firm size dispersion: large firms are too large and small firms are too small. In particular, 91% of employment is in the 10% largest firms, in contrast to 73% in the benchmark economy. Firm dispersion and misallocation losses are larger for the economy which retains only heterogeneity in ability to connect but where all firms are equally productive. The TFP Gain of eliminating cronyism would be massive: a 158% increase. In this economy there is a large rank reversal by construction: the correlation of firm TFP and firm size, and the rank correlation of firm sizes between the crony and the efficient economy are both zero. The inefficiency in this economy arises because all firms, having the same productivity, should be of the same size in the first best but the heterogeneity in ability to connect creates large firm size heterogeneity.

Finally, note that the potential TFP Gain of the two counterfactual economies add up to much more than the potential TFP Gain of the benchmark economy. The reason for this is that the estimated negative correlation between firm productivity and ability to connect is negative, that is, $\sigma_{AZs} < 0$. Other things equal, more productive or better connected firms invest too much in cronyism, but because these two characteristics are negatively correlated in the cross-section of firms, they partly offset each other.

5.4 Change in misallocation between 2000 and 2007

As we argued in Section 4.1, there has been a decline in the quality of institutions in Spain over the period, leading to a more severe problem of cronyism. In this Section we

Table 6: Model economy: 2000 to 2007

	Data	$\lambda = 1.049$	$\lambda = 1.020$	$\lambda = 1.050$	$\lambda = 1.100$
Correl	0.1012	0.1012	0.0389	0.1034	0.2292
Δ Var $(\log \text{MRPK}_{si})$	0.60	0.27	0.11	0.28	0.60
Δ Var $(\log \text{MRPL}_{si})$	0.10	0.04	0.01	0.04	0.08
Δ TFP Gain	0.24	0.14	0.06	0.15	0.32
Δ Rank correlation		-0.05	-0.02	-0.05	-0.09
Δ Corr $(\log P_{si}Y_{si}, \log A_{si})$	-0.03	-0.04	-0.02	-0.04	-0.10
Δ Share of emp by the top 10%	0.01	0.02	0.01	0.02	0.05

Notes. Statistic from data (first column) and model economies (second to last columns). The second column refers to the counterfactual 2007 economy in which there is an increase in cronyism to match the differential increase in misallocation between more and less crony sectors (that is, to match the regression coefficient in the first column, second row of Table 2). Columns three to five refer to model economies with increasing levels of cronyism.

want to use our model to quantify the effects of this increase in cronyism in misallocation and in aggregate productivity. In terms of the model, we think of the institutional decline as follows: the returns on investing in political connections increased over the period in all sectors and for all factors. That is, β_{Ks} and β_{Ls} increased in the same proportion in all sectors. In order to perform our counterfactual exercise we multiply β_{Ks} and β_{Ls} by a constant λ until it reproduces the differential increase in misallocation between sectors of different levels of cronyism. That is to say, we calibrate λ to match the regression coefficient of ΔTFP Gain between 2000 and 2007 on the BPI reported in Table 2. This gives us $\lambda = 1.049$.

In Table 6 we report the main statistics of this new economy (second column) and compare them to the data (first column). The main result is that the ΔTFP Gain for the counterfactual economy is equal to 0.14 log points, which is a large number compared to the 0.24 log points measured in the data with the standard HK methodology (see Section 3.2). In other words, according to the standard HK methodology, the increase in misallocation erased an annual 3.1% of productivity growth between 2000 and 2007; our estimated model implies that the increase in misallocation due to institutional decline erased an annual 1.9% of productivity growth, more than half the decline implied by increased misallocation measured in the data.

Looking at the origin of this increase in misallocation, we find that our model generates increases in the dispersion of both the marginal revenue products of capital and labor. As in the data, the model generates a larger increase in the dispersion of the marginal revenue product of capital than in the dispersion of the marginal revenue product of labor, which is the result of the estimated $\beta_{Ks} > \beta_{Ls}$ and of Proposition 2. Furthermore, the institutional decline generates a small increase in the concentration of employment in the biggest firms (two percentage points) and a small decline of the correlation between firm size and firm productivity (0.04 log points) that are similar to the ones observed in the data between 2000 and 2007 (1 percentage point and 0.03 log points respectively).

Finally, the third to fifth rows in Table 6 show results for counterfactual economies with λ equal to 1.02, 1.05, and 1.10 respectively. We can see how dispersion of productivities, average TFP Gain, and differential TFP Gain between more and less crony sectors all increase monotonically as the institutional decline becomes more severe.

6 Concluding Remarks

Spanish growth during the 1995-2007 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 show that the source of negative TFP growth was the increase in the within-sector misallocation of production factors across firms. Furthermore, we find that the increase in misallocation was significantly higher in those industries in which the influence of the public sector is more important for business success.

Motivated by these empirical findings, we develop a model in which the source of misallocation is heterogenous firms spending different amounts of resources in order to become politically connected. This model delivers predictions on how the level and the changes in cronyism affect the evolution of within-sector misallocation and hence of TFP. Our quantitative analysis implies that more than half of the increase in TFP losses imputed to misallocation in Spain during the boom years can be accounted for by an increase in cronyism.

The specific channels through which firms take advantage of their political connections remain to be explored. In our simple model, these connections increase profits by decreasing firms' cost of capital and labor. The arbitrary interest rates charged by Spanish savings banks (*Cajas de Ahorros*), which were mostly controlled by local politicians, or the fraudulent assignment of public procurement projects might be potential instruments that politicians use to favor more connected firms.

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A Model details

A.1 Optimization problems

Production of final output. There is a representative firm that produces the final good and sells its output Y in a competitive market at price P, which we normalize to one. The firm buys the intermediate goods Y_s also in competitive markets at prices P_s. Therefore,

$$\max_{Y_s} \left\{ \prod_{s=1}^{S} Y_s^{\theta_s} - \sum_{s=1}^{S} P_s Y_s \right\} \tag{A.1}$$

which gives the standard FOC for each good Y_s, $P_s Y_s = \theta_s Y$

Production of sectoral output. In each sector s there is a representative firm that produces sectoral output Y_s by aggregating output from each variety si of goods within the sector. This firm sells output at price P_s in a competitive market and buys each variety at price P_{si}, which is also taken as given. Therefore,

$$\max_{Y_{si}} \left\{ P_s \left(\sum_{i=1}^{N_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} - \sum_{i=1}^{N_s} P_{si} Y_{si} \right\} \tag{A.2}$$

which gives the standard FOC for each good Y_{si},

$$P_s \left(\sum_{i=1}^{N_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}-1} Y_{si}^{\frac{\sigma-1}{\sigma}-1} = P_{si} \tag{A.3}$$

Dividing two such equations,

$$\frac{P_{si}}{P_{sj}} = \left(\frac{Y_{sj}}{Y_{si}} \right)^{1/\sigma} \quad \Rightarrow \quad \frac{P_{si} Y_{si}}{P_{sj} Y_{sj}} = \left(\frac{P_{si}}{P_{sj}} \right)^{1-\sigma} \tag{A.4}$$

we obtain the standard condition stating that the ratio of expenditure shares depends on the relative price between the goods and the elasticity of substitution. Since the firm has constant returns to scale and it operates in competitive markets it makes zero profits, so it must be the case that,

$$\sum_{i=1}^{N_s} P_{si} Y_{si} = P_s Y_s \tag{A.5}$$

Substituting equation (A.4) into this zero profit condition we obtain

$$\frac{P_{si}Y_{si}}{P_sY_s} = \left(\frac{P_{si}}{P_s}\right)^{1-\sigma} \quad \Rightarrow \quad P_{si}Y_{si} = \theta_s Y \left(\frac{P_{si}}{P_s}\right)^{1-\sigma} \tag{A.6}$$

which states that the expenditure demand for variety si depends on the aggregate demand for output of sector s, $\theta_s Y$, the relative price of variety si, $\frac{P_{si}}{P_s}$, and the elasticity of substitution σ. It will useful to use this expression to derive a demand curve for the firms producing variety si in terms of price, equation (6), or in terms of revenue

$$P_{si}Y_{si} = \left(\frac{\theta_s Y}{P_s^{1-\sigma}}\right)^{1/\sigma} Y_{si}^{\frac{\sigma-1}{\sigma}} \tag{A.7}$$

Production of varieties. The optimization problem of the firm producing variety si can be stated formally as,

$$\max_{L_{si},K_{si},M_{si}} \left\{P_{si}Y_{si} - (1+\tau_{Lsi})^{-1}\, w\, L_{si} - (1+\tau_{Ksi})^{-1}\, r\, K_{si} - P_M M_{si}\right\} \tag{A.8}$$

$$\begin{aligned} \text{subject to} \qquad & P_{si}Y_{si} = \left(\frac{\theta_s Y}{P_s^{1-\sigma}}\right)^{1/\sigma} Y_{si}^{\frac{\sigma-1}{\sigma}} \\ & Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s} \\ & (1+\tau_{Ksi}) = (Z_{si}\, M_{si})^{\beta_{Ks}} \\ & (1+\tau_{Lsi}) = (Z_{si}\, M_{si})^{\beta_{Ls}} \end{aligned}$$

This yields the first order conditions (1), (2), and (11).

Firm size. Combining the FOC we find that the optimal firm's price is given by:

$$P_{si} = \frac{\sigma}{\sigma-1} c_s(w,r) \frac{1}{A_{si}} \frac{1}{(1+\tau_{Ksi})^{\alpha_s} (1+\tau_{Lsi})^{1-\alpha_s}} \tag{A.9}$$

where $c_s(w,r) \equiv \left(\frac{r}{\alpha_s}\right)^{\alpha_s} \left(\frac{w}{1-\alpha_s}\right)^{1-\alpha_s}$. This is the standard equation stating that the price of firm's output equals a mark-up $\frac{\sigma}{\sigma-1}$ over the marginal cost, but corrected with subsidies.

Next, substitute firm price in (A.9) into the firm demand (6) to obtain the optimal output:

$$Y_{si} = \left(\frac{\theta_s Y}{P_s^{1-\sigma}}\right) \left[\frac{\sigma-1}{\sigma} \frac{1}{c_s(w,r)} A_{si} (1+\tau_{Ksi})^{\alpha_s} (1+\tau_{Lsi})^{1-\alpha_s}\right]^{\sigma} \tag{A.10}$$

Hence, total revenues can be expressed as,

$$P_{si}Y_{si} = \left(\frac{\theta_s Y}{P_s^{1-\sigma}}\right)\left[\frac{\sigma-1}{\sigma}\frac{1}{c_s\left(w,r\right)}A_{si}\left(Z_{si}M_{si}\right)^{\gamma_s}\right]^{\sigma-1} \tag{A.11}$$

where the idiosyncratic wedges have been substituted by their production function. Finally, plugging equation (11) in this last expression we get equation (12) characterizing firm size in terms of revenues as function of A_{si} and Z_{si} only.

Revenue productivities. Total factor productivity revenue of firm i is defined as:

$$\text{TFPR}_{si} \equiv P_{si}A_{si} \tag{A.12}$$

Therefore, substituting equation (A.9) into equation (A.12):

$$\text{TFPR}_{si} = \frac{\sigma}{\sigma-1}c_s\left(w,r\right)\left(\frac{1}{1+\tau_{K_{si}}}\right)^{\alpha_s}\left(\frac{1}{1+\tau_{L_{si}}}\right)^{1-\alpha_s} \tag{A.13}$$

and using the FOC (1) and (2) we can write TFPR_{si} as a function of MRPK_{si} and MRPL_{si}:

$$\text{TFPR}_{si} = \frac{\sigma}{\sigma-1}\left(\frac{\text{MRPK}_{si}}{\alpha_s}\right)^{\alpha_s}\left(\frac{\text{MRPL}_{si}}{1-\alpha_s}\right)^{1-\alpha_s} \tag{A.14}$$

Capital to labor ratio. Dividing the FOC conditions for capital and labor we obtain:

$$\frac{K_{si}}{L_{si}} = \frac{\alpha_s}{1-\alpha_s}\frac{w}{r}\frac{\left(1+\tau_{Ksi}\right)}{\left(1+\tau_{Lsi}\right)} \tag{A.15}$$

Hence, relative factor use only depends on the economy-wide ratio of factor prices, w/r, the sectoral capital share, α_s, and the firm-level distortions τ_{Ksi} and τ_{Lsi}. In the standard model with exogeneous wedges firm productivity A_{si} does not affect the ratio of factors because it increases equally the productivity of each factor. However, note that in our model the ratio of wedges is given by,

$$\frac{\left(1+\tau_{Ksi}\right)}{\left(1+\tau_{Lsi}\right)} = \left(Z_{si}M_{si}\right)^{\beta_{Ks}-\beta_{Ls}} \tag{A.16}$$

Hence, if say $\beta_{Ks} > \beta_{Ls}$ then larger firms will have larger capital to labor ratios because larger firms invest more in political connections and those turn out to be more useful in obtaining privileged access to credit.

Factor demands. Using the FOC equations (1), (2), the production function (5), and the optimal price (A.9), one can express optimal factor demands for each firm as:

$$K_{si} = \frac{\alpha_s}{r} c_s(w,r)\frac{Y_{si}}{A_{si}}\left(\frac{1+\tau_{Ksi}}{1+\tau_{Lsi}}\right)^{1-\alpha_s} \tag{A.17}$$

$$L_{si} = \frac{1-\alpha_s}{w} c_s(w,r)\frac{Y_{si}}{A_{si}}\left(\frac{1+\tau_{Lsi}}{1+\tau_{Ksi}}\right)^{\alpha_s} \tag{A.18}$$

Different from the standard model the wedges are endogenous. One can easily substitute the ratio of wedges in equation (A.16), the optimal demand of M_{si} from equation (11), and the optimal output supply from equation (A.10).

Sectoral prices. Using the zero profit condition for the producers of sectoral output we obtain an expression for the sectoral price P_s:

$$P_s = \sum_{i=1}^{N_s}\frac{P_{si}Y_{si}}{Y_s} = \sum_{i=1}^{N_s} P_{si}\left(\frac{P_{si}}{P_s}\right)^{-\sigma} \Rightarrow P_s = \left(\sum_{i=1}^{N_s} P_{si}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{A.19}$$

Next, we plug optimal firms' prices from equation (A.9) into (A.19):

$$P_s = \frac{\sigma}{\sigma-1} c_s(w,r)\left[\sum_{i=1}^{N_s}\left(\frac{1}{A_{si}}\frac{1}{(1+\tau_{Ksi})^{\alpha_s}(1+\tau_{Lsi})^{1-\alpha_s}}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$$

which we can rewrite as

$$P_s = \frac{\sigma}{\sigma-1}\left[\sum_{i=1}^{N_s}\left(\frac{1}{A_{si}}\left(\frac{\mathrm{MRPK}_{si}}{\alpha_s}\right)^{\alpha_s}\left(\frac{\mathrm{MRPL}_{si}}{1-\alpha_s}\right)^{1-\alpha_s}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{A.20}$$

or

$$P_s = \left[\sum_{i=1}^{N_s}\left(\frac{1}{A_{si}}\mathrm{TFPR}_{si}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{A.21}$$

A.2 Sectoral TFP

Let's start by defining the sectoral-wide marginal revenue products of capital and labor as the weighted harmonic means of each firm marginal revenue products:

$$\begin{aligned}\overline{\text{MRPK}}_s &\equiv \left[\sum_i^{N_s}\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)\frac{1}{\text{MRPK}_{si}}\right]^{-1} = r\left[\sum_i^{N_s}\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)(1+\tau_{Ksi})\right]^{-1}\\ \overline{\text{MRPL}}_s &\equiv \left[\sum_i^{N_s}\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)\frac{1}{\text{MRPL}_{si}}\right]^{-1} = w\left[\sum_i^{N_s}\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)(1+\tau_{Lsi})\right]^{-1}\end{aligned}$$

We can express the total amounts of capital and labor in industry s by aggregating over equations (A.17) and (A.18):

$$\begin{aligned}K_s &= \frac{\alpha_s}{r}\; c_s(w,r)\sum_{i=1}^{M_s}\frac{Y_{si}}{A_{si}}\left(\frac{1+\tau_{Ksi}}{1+\tau_{Lsi}}\right)^{1-\alpha_s}\\ L_s &= \frac{1-\alpha_s}{w}c_s(w,r)\sum_{i=1}^{M_s}\frac{Y_{si}}{A_{si}}\left(\frac{1+\tau_{Lsi}}{1+\tau_{Ksi}}\right)^{\alpha_s}\end{aligned}$$

Taking a geometric average:

$$K_s^{\alpha_s}L_s^{1-\alpha_s} = \left[\sum_{i=1}^{M_s}\frac{Y_{si}}{A_{si}}\left(\frac{1+\tau_{Ksi}}{1+\tau_{Lsi}}\right)^{1-\alpha_s}\right]^{\alpha_s}\left[\sum_{i=1}^{M_s}\frac{Y_{si}}{A_{si}}\left(\frac{1+\tau_{Lsi}}{1+\tau_{Ksi}}\right)^{\alpha_s}\right]^{1-\alpha_s}$$

Therefore, we can write output of sector S as a Cobb-Douglas production function

$$Y_s = A_sK_s^{\alpha}L_s^{1-\alpha} \tag{A.22}$$

with

$$A_s = \left(\left[\sum_{i=1}^{M_s}\frac{Y_{si}}{Y_s}\frac{1}{A_{si}}\left(\frac{1+\tau_{Ksi}}{1+\tau_{Lsi}}\right)^{1-\alpha_s}\right]^{\alpha_s}\left[\sum_{i=1}^{M_s}\frac{Y_{si}}{Y_s}\frac{1}{A_{si}}\left(\frac{1+\tau_{Lsi}}{1+\tau_{Ksi}}\right)^{\alpha_s}\right]^{1-\alpha_s}\right)^{-1} \tag{A.23}$$

Given the demand curve for firm products (6) we obtain:

$$A_s = \left(\left[\sum_{i=1}^{M_s}\left(\frac{P_{si}}{P_s}\right)^{-\sigma}\frac{1}{A_{si}}\left(\frac{1+\tau_{Ksi}}{1+\tau_{Lsi}}\right)^{1-\alpha_s}\right]^{\alpha_s}\left[\sum_{i=1}^{M_s}\left(\frac{P_{si}}{P_s}\right)^{-\sigma}\frac{1}{A_{si}}\left(\frac{1+\tau_{Lsi}}{1+\tau_{Ksi}}\right)^{\alpha_s}\right]^{1-\alpha_s}\right)^{-1}$$

that can be rewritten as

$$A_s = \left(P_s \left[\sum_{i=1}^{M_s} \left(\frac{P_{si}}{P_s} \right)^{1-\sigma} \frac{1}{\text{TFPR}_{si}} \left(\frac{1+\tau_{Ksi}}{1+\tau_{Lsi}} \right)^{1-\alpha_s} \right]^{\alpha_s} \left[\sum_{i=1}^{M_s} \left(\frac{P_{si}}{P_s} \right)^{1-\sigma} \frac{1}{\text{TFPR}_{si}} \left(\frac{1+\tau_{Lsi}}{1+\tau_{Ksi}} \right)^{\alpha_s} \right]^{1-\alpha_s} \right)^{-1}$$

Following equation (A.6) we can replace the terms $(P_{si}/P_s)^{1-\sigma}$ by relative revenues. In addition, we define $\overline{\text{TFPR}}_s \equiv A_s P_s$. Then,

$$\overline{\text{TFPR}}_s = \left(\left[\sum_{i=1}^{M_s} \left(\frac{P_{si}Y_{si}}{P_sY_s} \right) \frac{1}{\text{TFPR}_{si}} \left(\frac{1+\tau_{Ksi}}{1+\tau_{Lsi}} \right)^{1-\alpha_s} \right]^{\alpha_s} \left[\sum_{i=1}^{M_s} \left(\frac{P_{si}Y_{si}}{P_sY_s} \right) \frac{1}{\text{TFPR}_{si}} \left(\frac{1+\tau_{Lsi}}{1+\tau_{Ksi}} \right)^{\alpha_s} \right]^{1-\alpha_s} \right)^{-1} \tag{A.24}$$

And using the expression for TFPR_{si} in equation (A.13), we can rewrite:

$$\begin{aligned} \overline{\text{TFPR}}_s &= \frac{\sigma}{\sigma-1} c_s(w,r) \left(\left[\sum_{i=1}^{M_s} \left(\frac{P_{si}Y_{si}}{P_sY_s} \right) (1+\tau_{Ksi}) \right]^{\alpha_s} \left[\sum_{i=1}^{M_s} \left(\frac{P_{si}Y_{si}}{P_sY_s} \right) (1+\tau_{Lsi}) \right]^{1-\alpha_s} \right)^{-1} \\ &= \frac{\sigma}{\sigma-1} \left(\frac{\overline{\text{MRPK}}_s}{\alpha_s} \right)^{\alpha_s} \left(\frac{\overline{\text{MRPL}}_s}{1-\alpha_s} \right)^{1-\alpha_s} \end{aligned}$$

Dividing $\overline{\text{TFPR}}_s$ back by P_s in equation (A.20) we obtain the expression for A_s:

$$A_s = \left[\sum_{i=1}^{N_s} \left(A_{si} \left(\frac{\overline{\text{MRPK}}_s}{\text{MRPK}_{si}} \right)^{\alpha_s} \left(\frac{\overline{\text{MRPL}}_s}{\text{MRPL}_{si}} \right)^{1-\alpha_s} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{A.25}$$

or

$$A_s = \left[\sum_{i=1}^{N_s} \left(A_{si} \frac{\overline{\text{TFPR}}_s}{\text{TFPR}_{si}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{A.26}$$

These expressions clearly shows how within-industry misallocation of labor and capital yields a lower measured TFP in sector s. Without distortions marginal revenue products would be equal to the sectoral averages and optional TFP in sector s, denoted by an asterisk, would be:

$$A_s^* = \left[\sum_{i=1}^{N_s} A_{si}^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{A.27}$$

A.3 The log-normal case

There is a simple and well-known formula for the productivity losses due to misallocation when A_{si}, MRPK_{si}, and MRPL_{si} follow a joint log-normal distribution. In particular,

$$\log \frac{A_s^*}{A_s} = \frac{\sigma}{2} \mathrm{Var}\left(\log \mathrm{TFPR}_{si}\right) + \frac{\alpha_s \left(1-\alpha_s\right)}{2} \mathrm{Var}\left(\log \frac{\mathrm{MRPK}_{si}}{\mathrm{MRPL}_{si}}\right) \tag{A.28}$$

which can be re-expressed in terms of the dispersions of MRPK_{si} and MRPL_{si} as follows

$$\begin{aligned} \log \frac{A_s^*}{A_s} = {} & \frac{\sigma \alpha^2 + \alpha_s \left(1-\alpha_s\right)}{2} \mathrm{Var}\left(\log \mathrm{MRPK}_{si}\right) \\ + {} & \frac{\sigma \left(1-\alpha_s\right)^2 + \alpha_s \left(1-\alpha_s\right)}{2} \mathrm{Var}\left(\log \mathrm{MRPL}_{si}\right) \\ + {} & \left(\sigma - 1\right) \alpha_s \left(1-\alpha_s\right) \mathrm{Cov}\left(\log \mathrm{MRPK}_{si}, \log \mathrm{MRPL}_{si}\right) \end{aligned} \tag{A.29}$$

A.4 Aggregate TFP

Final output 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:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s} \tag{A.30}$$

where $\sum_{s=1}^{S} \theta_s = 1$. The Cobb-Douglas assumption implies that 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. Combining the aggregator (A.30) with sectoral outputs (A.22) we can express GDP as:

$$Y = \prod_{s=1}^{S} \left(A_s K_s^{\alpha_s} L_s^{\alpha_s}\right)^{\theta_s} = \mathrm{TFP} \left(\prod_{s=1}^{S} K_s^{\theta_s}\right)^{\alpha_s} \left(\prod_{s=1}^{S} L_s^{\theta_s}\right)^{1-\alpha_s} \tag{A.31}$$

where $\mathrm{TFP} \equiv \prod_{s=1}^{S} A_s^{\theta_s}$. Then, using equation (A.26) the aggregate observed TFP becomes:

$$\mathrm{TFP} = \prod_{s=1}^{S} \left[\left(\sum_{i=1}^{M_s} \left(A_{si} \frac{\overline{\mathrm{TFPR}}_s}{\mathrm{TFPR}_{si}} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \right]^{\theta_s} \tag{A.32}$$

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):

$$\text{TFP}^* = \prod_{s=1}^{S} \text{TFP}_s^{*\theta_s} = \prod_{s=1}^{S} \left[\left(\sum_{i=1}^{M_s} (A_{si})^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \right]^{\theta_s} \tag{A.33}$$

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.

A.5 Parameterization and building the second moments

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.[17] The industry-specific capital shares α_s are set to 1 minus the labor share in industry s in the US.

Given the Coubb-Douglas production function (5), the model-implied demand function (A.7), and the firm FOC for capital and labor, equations (1) and (2), we can obtain a firm-specific productivity term A_{si} and firm-specific distortions τ_{Ksi} and τ_{Lsi} from firm level measures of revenues $P_{si}Y_{si}$, capital stock K_{si} and labor bill wL_{si}:

$$1 + \tau_{Ksi} = \frac{rK_{si}}{P_{si}Y_{si}} \left[\alpha_s \frac{\sigma - 1}{\sigma} \right]^{-1} \tag{A.34}$$

$$1 + \tau_{Lsi} = \frac{wL_{si}}{P_{si}Y_{si}} \left[(1 - \alpha_s) \frac{\sigma - 1}{\sigma} \right]^{-1} \tag{A.35}$$

$$A_{si} = \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \kappa_s \tag{A.36}$$

where κ_s is an industry-specific constant that does not affect relative productivities within industry. Note that firms that have higher capital share (labor share) than the average of the sector are inferred to be enjoying a subsidy in capital (labor).

The existence of measurement error in firm inputs or revenues inflates the dispersion of wedges and creates spurious correlations between wedges and productivities. In particular, assume additive classical measurement error in the log of revenues, ε_{Ysi} , capital, ε_{Ksi}, and labor, ε_{Lsi}:

$$\log \widehat{P_{si}Y_{si}} = \log P_{si}Y_{si} + \log \varepsilon_{Ysi}$$
$$\log \widehat{K}_{si} = \log K_{si} + \log \varepsilon_{Ksi}$$
$$\log \widehat{L}_{si} = \log L_{si} + \log \varepsilon_{Lsi}$$

[17]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.

where a hat denotes the measured value and the no-hat denotes the true value. The variances of the log of measurement error are denoted by σ_{Ys}^2, σ_{Ks}^2, and σ_{Ls}^2. Hence, using equations (A.34)-(A.36) our measured firm level TFP and wedges can be expressed as,

$$\begin{aligned}
\log \widehat{A_{si}} &= \log A_{si} + \frac{\sigma}{\sigma-1}\log \varepsilon_{Ysi} - \alpha_s \log \varepsilon_{Ksi} + (1-\alpha_s)\log \varepsilon_{Lsi} \\
\log \widehat{(1+\tau_{Ksi})} &= \log(1+\tau_{Ksi}) + \log \varepsilon_{Ksi} - \log \varepsilon_{Ysi} \\
\log \widehat{(1+\tau_{Lsi})} &= \log(1+\tau_{Lsi}) + \log \varepsilon_{Lsi} - \log \varepsilon_{Ysi}
\end{aligned}$$

Hence, the variances and covariances of the true wedges and productivity in the r.h.s. of equations (18)-(22) are given by the measured ones minus some terms accounting for the variances of measurement error in revenues and production factors,

$$\begin{aligned}
&\mathrm{Var}\left[\log A_{si}\right] &&= \mathrm{Var}\left[\log \widehat{A_{si}}\right] - \left(\frac{\sigma}{\sigma-1}\right)^2 \sigma_{Ys}^2 - \alpha_s^2\sigma_{Ks}^2 - (1-\alpha_s)^2\sigma_{Ls}^2 \\
&\mathrm{Var}\left[\log(1+\tau_{Ksi})\right] &&= \mathrm{Var}\left[\log \widehat{(1+\tau_{Ksi})}\right] - \sigma_{Ys}^2 - \sigma_{Ks}^2 \\
&\mathrm{Var}\left[\log(1+\tau_{Lsi})\right] &&= \mathrm{Var}\left[\log \widehat{(1+\tau_{Lsi})}\right] - \sigma_{Ys}^2 - \sigma_{Ls}^2 \\
&\mathrm{Cov}\left[\log(1+\tau_{Ksi}), \log A_{si}\right] &&= \mathrm{Cov}\left[\log \widehat{(1+\tau_{Ksi})}, \log \widehat{A_{si}}\right] + \frac{\sigma}{\sigma-1}\sigma_{Ys}^2 + \alpha\sigma_{Ks}^2 \\
&\mathrm{Cov}\left[\log(1+\tau_{Lsi}), \log A_{si}\right] &&= \mathrm{Cov}\left[\log \widehat{(1+\tau_{Lsi})}, \log \widehat{A_{si}}\right] + \frac{\sigma}{\sigma-1}\sigma_{Ys}^2 + (1-\alpha)\sigma_{Ls}^2
\end{aligned}$$

Now, to obtain estimates of the variance of the measurement errors we proceed as follows. We assume that (a) the US is an efficient economy and hence its true dispersion in MRPK and MRPL is close to zero so that its measured variance in MRPK and MRPL reflects measurement error only; (b) the variance of the measurement error in Spain is the same as in the US; and (c) the proportion of the variance in measured log MRPK and log MRPL that comes from measurement error in all sectors s in Spain is the same as in the aggregate. For the whole economy, the variance in measured log TFPR is around 0.2 in the US according to Hsieh and Klenow (2009) and 0.5 in Spain. This would imply that around 40% of the variance of measured log TFPR in every sector in Spain comes from measurement error. Because the variance in measured log MPRK is 0.79 in the US and 1.80 in Spain, this ratio is similar for MRPK and hence for MRPL. Hence, we consider that 40% of the variance of log MRPK and 40% of the variance of log MPRL in each sector is measurement error:

$$\begin{aligned} 0.4\mathrm{Var}\left[\log \widehat{\mathrm{MRPK}}_{si}\right] &= \sigma^2_{Ks} + \sigma^2_{Ys} \\ 0.4\mathrm{Var}\left[\log \widehat{\mathrm{MRPL}}_{si}\right] &= \sigma^2_{Ls} + \sigma^2_{Ys} \end{aligned}$$

Further assuming that $\sigma^2_{Ys} = 0$ this gives us values for σ^2_{Ks} and σ^2_{Ls}

B Proofs

Proposition 1

Proof. Let's start with the derivative of the dispersion of capital wedges with respect to β_{Ks}. Using equation (13) it can be written as

$$\begin{aligned}
\frac{\partial \mathrm{Var}\left[\log\left(1+\tau_{Ksi}\right)\right]}{\partial \beta_{Ks}} &= 2\beta_{Ks}\left(\sigma^2_{Z_s} + \mathrm{Var}\left[\log M_{si}\right] + 2\,\mathrm{Cov}\left[\log M_{si}, \log Z_{si}\right]\right) \\
&+ \beta^2_{Ks}\frac{\partial \gamma_s}{\partial \beta_{Ks}}\left(\frac{\partial \mathrm{Var}\left[\log M_{si}\right]}{\partial \gamma_s} + 2\frac{\partial \mathrm{Cov}\left[\log M_{si}, \log Z_{si}\right]}{\partial \gamma_s}\right) \qquad \text{(B.1)}
\end{aligned}$$

where the derivatives in the second term are given by,

$$\begin{aligned}
\frac{\partial \mathrm{Var}\left[\log M_{si}\right]}{\partial \gamma_s} &= 2\left(\frac{\sigma-1}{1-\tilde{\gamma}_s}\right)^2\left[\left(\frac{\sigma-1}{1-\tilde{\gamma}_s}\right)\left(\sigma^2_{As} + \gamma_s^2\sigma^2_{Zs} + 2\gamma_s\,\sigma_{AZ_s}\right) + \left(\gamma_s\sigma^2_{Zs} + \sigma_{AZ_s}\right)\right] \\
\frac{\partial \mathrm{Cov}\left[\log M_{si}, \log Z_{si}\right]}{\partial \gamma_s} &= \left(\frac{\sigma-1}{1-\tilde{\gamma}_s}\right)^2\left[\left(\gamma_s\sigma^2_{Zs} + \sigma_{AZs}\right) + \left(\frac{\sigma-1}{1-\tilde{\gamma}_s}\right)^{-1}\sigma^2_{Zs}\right]
\end{aligned}$$

which using equations (15) and (16) can be rewritten as,

$$\begin{aligned}
\frac{\partial \mathrm{Var}\left[\log M_{si}\right]}{\partial \gamma_s} &= 2\left(\frac{\sigma-1}{1-\tilde{\gamma}_s}\right)\left[\mathrm{Var}\left[\log M_{si}\right] + \mathrm{Cov}\left[\log M_{si}, \log Z_{si}\right]\right] \\
\frac{\partial \mathrm{Cov}\left[\log M_{si}, \log Z_{si}\right]}{\partial \gamma_s} &= \left(\frac{\sigma-1}{1-\tilde{\gamma}_s}\right)\left[\sigma^2_{Zs} + \mathrm{Cov}\left[\log M_{si}, \log Z_{si}\right]\right]
\end{aligned}$$

Hence, the term in brackets in the second term of the r.h.s. of equation (B.1) is given by

$$\left(\frac{\partial \mathrm{Var}\left[\log M_{si}\right]}{\partial \gamma_s} + 2\frac{\partial \mathrm{Cov}\left[\log M_{si}, \log Z_{si}\right]}{\partial \gamma_s}\right) = 2\left(\frac{\sigma-1}{1-\tilde{\gamma}_s}\right)\left(\sigma^2_{Zs} + \mathrm{Var}\left[\log M_{si}\right] + \mathrm{Cov}\left[\log M_{si}, \log Z_{si}\right]\right) \qquad \text{(B.2)}$$

With all these elements in place, and using again equation (13), we can rewrite:

$$\frac{\partial \mathrm{Var}\left[\log\left(1+\tau_{Ksi}\right)\right]}{\partial \beta_{Ks}} = 2\frac{1}{\beta_{Ks}}\mathrm{Var}\left[\log\left(1+\tau_{Ksi}\right)\right] + 2\alpha_s\left(\frac{\sigma-1}{1-\tilde{\gamma}_s}\right)\mathrm{Var}\left[\log\left(1+\tau_{Ksi}\right)\right] \qquad \text{(B.3)}$$

which is positive because $\beta_{Ks} \geq 0$, $\alpha_s \geq 0$, $\sigma > 1$, $\tilde{\gamma}_s > 1$ and $\mathrm{Var}\left[\log\left(1+\tau_{Ksi}\right)\right] \geq 0$. The derivative of the dispersion of the capital wedge with respect to β_{Ls} is given by,

$$\frac{\partial \mathrm{Var}\left[\log\left(1+\tau_{Ksi}\right)\right]}{\partial \beta_{Ls}} = \beta^2_{Ks}\frac{\partial \gamma_s}{\partial \beta_{Ls}}\left(\frac{\partial \mathrm{Var}\left[\log M_{si}\right]}{\partial \gamma_s} + 2\frac{\partial \mathrm{Cov}\left[\log M_{si}, \log Z_{si}\right]}{\partial \gamma_s}\right) \qquad \text{(B.4)}$$

which can be written as,

$$\frac{\partial \text{Var}\left[\log\left(1+\tau_{Ksi}\right)\right]}{\partial \beta_{Ls}} = 2\left(1-\alpha_s\right)\left(\frac{\sigma-1}{1-\tilde{\gamma}_s}\right)\text{Var}\left[\log\left(1+\tau_{Ksi}\right)\right] \tag{B.5}$$

and hence is also positive. The same analysis applies to the derivatives of the dispersion of labor wedges. □

Proposition 2

Proof. The first derivative of the dispersion of the capital wedge with respect to β_{Ks} is given by equation (B.3). The derivative with respect to β_{Ks} of the second term in the r.h.s. of equation (B.3) is positive because of Proposition 1 and because $\left(\frac{\sigma-1}{1-\tilde{\gamma}_s}\right)$ is increasing in γ_s. The derivative with respect to β_{Ks} of the first term in the r.h.s. of equation (B.3) is positive as the proof for $\frac{\partial \text{Var}[\log(1+\tau_{Ksi})]}{\partial \beta_{Ks}} > 0$ in Proposition 1 carries over to $\frac{\partial \text{Var}[\log(1+\tau_{Ksi})]/\beta_{Ks}}{\partial \beta_{Ks}}$ almost unchanged.

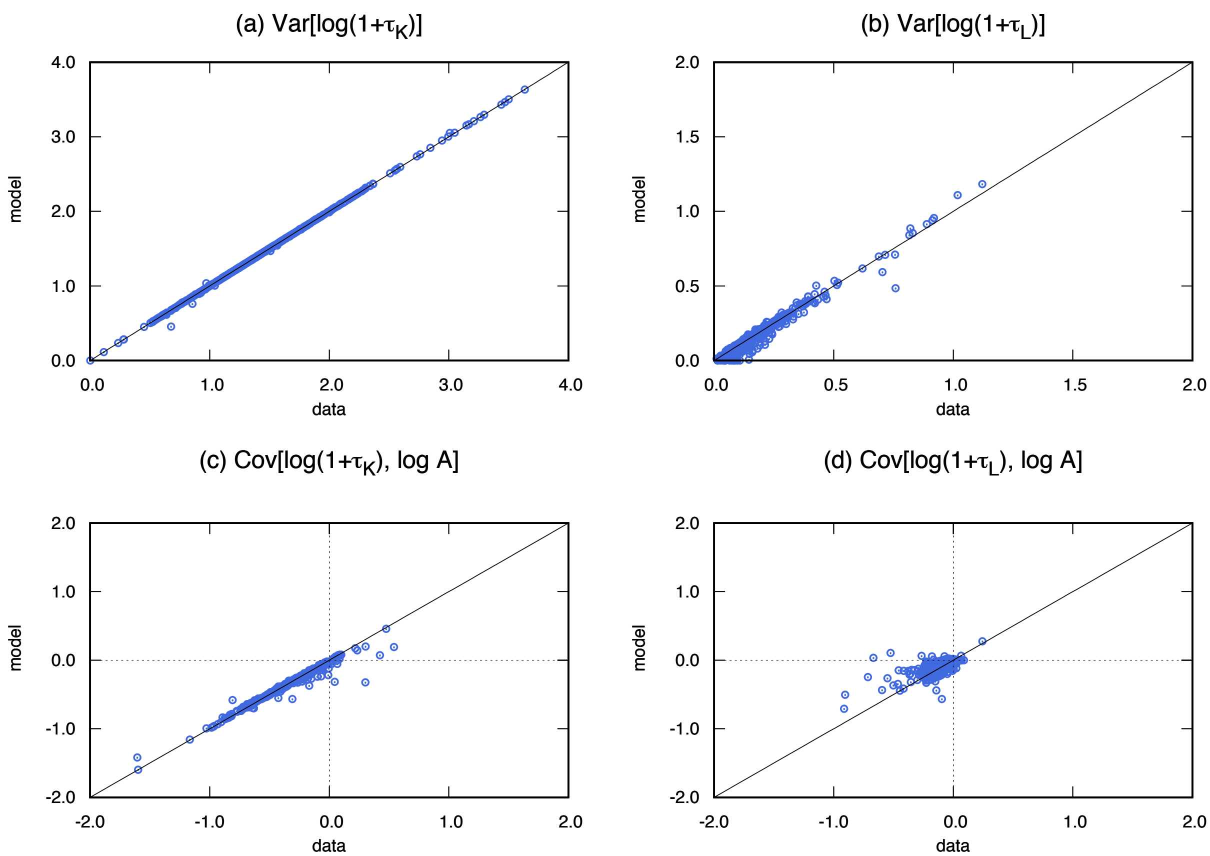
The first derivative of the dispersion of the capital wedge with respect to β_{Ls} is given by equation (B.5). The derivative of the r.h.s. of equation (B.5) with respect to β_{Ls} is positive because of the same reasons in the first part of the proof. Finally, the derivative of the first and second terms in the r.h.s. of equation (B.3) with respect to β_{Ls} is positive also because of the same arguments in the first part of the proof. □

Corollary 1

Proof. This follows from Proposition 1 and 2. □

C Extra Figures

Figure C.1: Model Fit



Notes. This Figure displays the left hand side (axis "data") and the right hand side (axis "model") of the moment conditions (19)-(22) *evaluated at the estimated parameters.*

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