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Capital and labour (mis)allocation  
in the euro area:  
some stylized facts and determinants

**CompNet** The Competitiveness Research Network



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This paper presents research conducted within the Competitiveness Research Network (CompNet). The network is composed of economists from the European System of Central Banks (ESCB) - i.e. the 29 national central banks of the European Union (EU) and the European Central Bank – a number of international organisations (World Bank, OECD, EU Commission) universities and think-tanks, as well as a number of non-European Central Banks (Argentina and Peru) and organisations (US International Trade Commission). The objective of CompNet is to develop a more consistent analytical framework for assessing competitiveness, one which allows for a better correspondence between determinants and outcomes.

The research is carried out in three workstreams:

- 1) Aggregate Measures of Competitiveness;
- 2) Firm Level;
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## Abstract

We analyse the evolution of capital and labour (mis)allocation across firms in five euro-area countries (Belgium, France, Germany, Italy and Spain) and eight main sectors of the economy during the period 2002-2012. Three key stylized facts emerge. First, in all countries with the exception of Germany, capital allocation has worsened over time whereas the efficiency of labour reallocation has not changed significantly. Second, the observed increase in capital misallocation has been particularly severe in services as opposed to industry. Third, misallocation of both labour and capital dropped in all countries in 2009 and again for some country-sectors in 2011-2012. We next take stock of the possible drivers of input misallocation dynamics in a standard panel regression framework. Controlling for demand conditions and for the initial level of misallocation, heightened uncertainty, restrictive bank credit standards and tight product and labour market regulation are found to have boosted input misallocation, whereas the Great Recession *per se* exerted a cleansing effect.

**JEL codes:** D24, D61, O47

**Keywords:** total factor productivity, allocative efficiency, capital, labour, Great Recession

## Non-technical summary

Poor total factor productivity (TFP) growth has been a key issue in the euro area over the last years and analysing its determinant is crucial from a policy perspective. At the sectorial level, TFP growth depends, almost equally, on technology improvements within firms (within-firm TFP growth) and on the efficiency with which production factors are (mis)-allocated across firms (between-firm TFP growth). The focus of this paper is on the latter and in particular on misallocation of labour and capital in eight macro-sectors (which include manufacturing and services) for five large euro-area countries (Belgium, France, Germany, Italy and Spain) during the period 2002-2012.

Using the Hsieh and Klenow (2009) misallocation indicator, we uncover three stylized facts. First, in all countries, with the exception of Germany, capital allocation across firms within sectors has worsened over time since 2002 whereas the efficiency of labour allocation has not changed as dramatically. Second, the observed increase in capital misallocation at the country level has been driven by the developments of services rather than industry, suggesting that analyses focused solely on manufacturing may be grossly underestimating misallocation dynamics and cross-sector heterogeneity. Third, misallocation of both labour and capital dropped in the acutest year of the Great Recession (2009) in all countries but recovered thereafter.

The paper then investigates the potential determinants of changes in input misallocation by looking at traditional structural determinants, namely restrictive product and labour market regulations. We find that strict product market regulations correlates negatively with capital misallocation while both restrictive product and labour market regulations affect labour misallocation dynamics. This is line with the idea that regulations that shelter firms from competition might result in poor allocation of resources because low productive firms will keep operating instead of downsizing or exiting. Similarly, stringent labour market regulation, in the form of high hiring and firing costs, might also thwart resource allocation in sectors characterised by high job churning rates and risky technologies, where firms need to scale up or down quickly after a demand or technological shock.

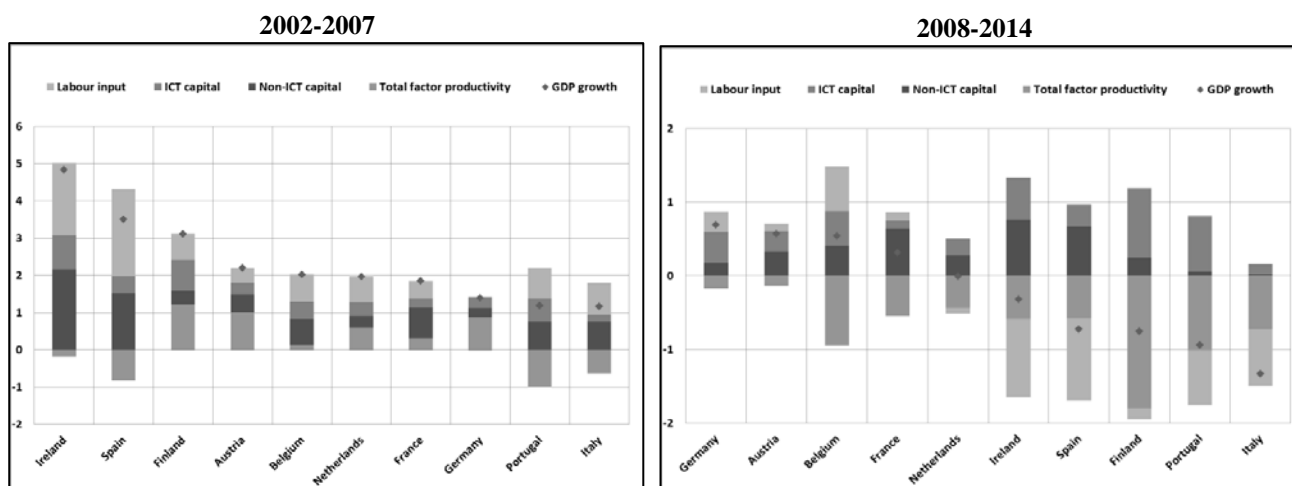
Based on recent literature, we also consider two demand-related indicators, namely realized demand and demand uncertainty, and credit market frictions. We find that boom periods are associated with an increase in misallocation of both capital and labour. Most importantly, we find that uncertainty explains a large part of the observed capital misallocation dynamics. A potential explanation for this finding is that more productive firms are those firms with “more to lose”. Conversely, zombie firms have “nothing to lose”. As a result, when uncertainty is high, productive firms do not expand and unproductive firms do not contract. The adoption of such a wait-and-see strategy shuts off much of the productivity-enhancing reallocation. Finally, credit market distortions are also positively correlated with capital misallocation suggesting that they might prevent productive firms from obtaining the resources needed to expand, so that input choices differ systematically across firms in ways that are unrelated to their productivity. Finally, once controlling for all these factors, a crisis dummy enters our capital and labour misallocation growth regressions negatively, suggesting a cleansing effect of the Great Recession.

From a policy perspective, the evidence suggests that in addition to structural factors, such as product market regulation, TFP growth in the euro area can be boosted also via measures that reduce macroeconomic uncertainty faced by firms.

## 1. Introduction

Poor total factor productivity (TFP) growth has been a key issue in the euro area over the last years. During 2002-2007, TFP dynamics dampened real GDP growth in Italy, Portugal and Spain, whereas they boosted output performance in the Northern euro-area countries (Figure 1; left hand side panel). Following the start of the Great Recession, however, TFP negatively contributed to real GDP growth in all euro-area countries, albeit to a greater extent in the Southern countries (Figure 1; right hand side panel). Cross-country empirical analysis is therefore required to better understand the factors behind the diverging TFP performance of euro-area countries.

**Figure 1. Contributions of production factors to real GDP growth**  
(annual average growth rates)



Source: Conference Board.

Aggregate TFP growth depends both on technology improvements within firms (within-firm TFP growth) and on the efficiency with which production factors are allocated across firms (between-firm TFP growth). If technology and knowledge flow freely and quickly across firms and countries (Comin and Hobijn 2010) we would expect a convergence in cross-country within-firm productivity growth rates and possibly also in levels. Therefore remaining cross-country differences in TFP growth would be explained by differences in so-called allocative efficiency, or the efficiency with which resources are allocated across heterogeneous firms (Bartelsman, Haltiwanger and Scarpetta 2013). Recent OECD research (Adalet McGowan et al. 2015), however, has pointed out that technology diffusion has slowed down since the early 2000s. Moreover, Comin and Mestrieri (2014) show that even if new technologies spread quickly across countries, they spread slowly to all firms in a given economy. Lastly, cross-country differences in within-firm productivity growth may also be explained by additional factors other than technology.<sup>1</sup> Hence, there is currently a consensus that observed differences in aggregate TFP growth across countries respond to both differences in within-firm and between-firm productivity growth. This paper focuses on the between-firm factor.

The two components of TFP growth – technical efficiency and reallocation of resources – are not mutually exclusive and are both important sources of aggregate growth, in the short and in the long run. However, it is difficult to pin down a magnitude for their relative contributions, as these are highly dependent on the country, sector, period and decomposition methodology employed. For example, at the two extremes, Foster, Haltiwanger and Krizan (2006) find that

<sup>1</sup> There are many other determinants that may explain differences in within-firm productivity, such as differences in management, in the quality of labour and capital or in firms' organizational structure (see Foster, Haltiwanger and Krizan 2001 and Syverson 2011 for detailed surveys).

aggregate productivity growth in the U.S. retail sector is almost exclusively due to the exit of less efficient firms which would contribute to a better allocation of resources, whereas Schmitz (2005) estimates that productivity growth in the U.S. iron mining sector is driven almost entirely by within-firm efficiency improvements. A plausible estimate of the relative magnitude of within-firm and between-firm productivity growth in manufacturing for example is approximately 50 per cent for each component, figure which is obtained as an average of estimates provided in selected studies and summarised in Table 1.

**Table 1. Contribution of within vs. between productivity growth to manufacturing TFP growth, selected studies**  
(percentage shares)

	Baily, Hulten and Campbell (1992)	Aw, Chen and Roberts (1997)*	Foster, Haltiwanger and Krizan (2006)	De Loeker and Konings (2006)	Petrin, White and Reiter (2011)
Reference					
Country	<b>US</b>	<b>Taiwan</b>	<b>US</b>	<b>Slovenia</b>	<b>US</b>
Years	1972-1987	1981-1991	1977-1987	1995-2000	1977-1996
<b>Within-firm productivity growth</b>	37	63	57	62	45
<b>Reallocation</b>	63	37	44	38	55

Note: All figures refer to manufacturing. (\*) Median growth rates.

Resources are reallocated across firms operating in the same sector, or in different sectors, as a result of firm expansion and contraction as well as firm entry and exit. In this paper, and due to data limitations, we are not able to disentangle the contribution of net entry from the shift of resources across incumbent firms operating within the same sector.<sup>2</sup> Furthermore, we disregard movements of resources between sectors.<sup>3</sup> On this point, however, Davis and Haltiwanger (1991) report that, across a variety of studies, only about 10 per cent of resource reallocation reflects shifts of employment opportunities across industries, suggesting that within-sector reallocation is the most important channel.<sup>4</sup> In Annex A we further argue why across-sector reallocation is less relevant than within-sector movements on the basis of firm-level data for selected euro-area countries.

The degree of misallocation of resources across firms operating in the same sector may be measured in several ways. The two most popular measures have been put forth by Hsieh and Klenow (2009) and Olley and Pakes (1996). Hsieh and Klenow (2009) show that under certain assumptions resource misallocation can be measured by the within-sector dispersion in the marginal productivity, in value terms, of factors of production (i.e. the change in total revenue earned by a firm that results from employing one more unit of capital or labour). Alternatively, following the Olley and Pakes decomposition (1996), allocative efficiency can be captured by the covariance between within-industry firm size and productivity. In this paper we choose the within-sector dispersion in marginal productivity as our preferred measure of misallocation, although we then check the robustness of our findings by employing the Olley-Pakes measure. Furthermore, we also compute the indicator of resource misallocation proposed by Petrin and Sivadasan (2013), which

<sup>2</sup> See Bartelsman, Lopez-Garcia and Presidente (2016) for a focus on the contribution to labour productivity growth of the expansion and contraction of incumbent firms in selected euro-area countries.

<sup>3</sup> A recent paper on between-sector reallocation of labour in twenty advanced economies over the past forty years is Borio et al. (2015), to which we refer.

<sup>4</sup> The reallocation of resources between sectors was particularly important in previous historical periods when inputs flowed from the less productive agriculture sector to the more productive manufacturing sector. For example, see Broadberry, Giordano and Zollino (2013) for the contribution of labour reallocation based on a shift-share analysis of Italy's labour productivity growth in the years 1861-2010 or, for a focus on more recent periods since the 1970s and on a cluster of countries, see OECD (2003).

relaxes the assumption of equal marginal costs across firms underlying Hsieh and Klenow's (2009) framework.

According to the recent empirical literature stemming from Hsieh and Klenow (2009) and referring to European countries, misallocation of resources has been observed in euro-area countries over the past 15 years, partially explaining their poor TFP performance. In particular, Gopinath et al. (2015) show that the dispersion in the marginal revenue productivity of capital within the manufacturing sector in Italy and Spain increased during 1999-2014, with an acceleration during the Great Recession years. Garcia-Santana et al. (2015) consider several sectors in Spain other than manufacturing during the period 1995-2007 and show that within-sector productivity dispersions increased in the period under analysis, particularly in industries characterized by larger State intervention (e.g. through licensing or regulations). They also find that small and young firms in Spain faced higher market distortions than large and mature firms. Calligaris (2015) finds that during the period 1993-2011 the significant and increasing input misallocation in the Italian manufacturing branches was higher for firms located in Southern Italy, for those characterized by low-technological intensity, as well as for small or young enterprises. Finally, Dias, Robalo Marques and Richmond (2014) find that input misallocation in Portugal increased during the period 1996-2011, particularly in services.

As seen, the existing evidence on resource misallocation is limited in terms of either country (mainly one) or sector (mainly manufacturing) coverage. Moreover, these studies often cover solely capital misallocation (e.g. Gopinath et al. 2015) or do not disentangle the different types of input misallocation (e.g. Calligaris 2015). Based on CompNet data, this paper instead provides a comprehensive analysis of both capital and labour misallocation across the main service and industrial sectors in five euro-area countries (Belgium, France, Germany, Italy and Spain) during the period 2002-2012. To our knowledge, this is the first paper in the literature on core euro-area countries with such a wide country and/or sector coverage.<sup>5</sup> The cross-country coverage of the analysis is crucial to identify common patterns, if any, in input misallocation and the role played to explain those patterns by cyclical conditions and structural policies.

Our analysis reveals three stylized facts. First, in all countries, with the exception of Germany, capital allocation has worsened over time since 2002 whereas the efficiency of labour allocation has not changed as dramatically. This piece of evidence confirms the importance of analysing labour and capital misallocation trends separately. Second, the observed increase in capital misallocation at the country level has been driven by the developments of services rather than industry, suggesting that analyses focused solely on manufacturing may be grossly underestimating misallocation dynamics and cross-sector heterogeneity. Third, misallocation of both labour and capital dropped in the acutest year of the Great Recession (2009) in all countries but recovered thereafter, although falling again in some country-sectors in 2011-2012, when the sovereign debt crisis erupted.

The paper then investigates the potential determinants of changes in input misallocation: a better knowledge of the obstacles to within-sector reallocation processes is essential in order to design sound and effective policies. As pointed out by the literature, strict product market regulations, particularly those sheltering firms from international or new firm competition, might result in poor allocation of resources because low-productivity firms will keep operating instead of downsizing or exiting (Schiantarelli 2008; Restuccia and Rogerson 2013; Andrews and Cingano 2014). Stringent labour market regulation, in the form of high hiring and firing costs, might also thwart resource allocation in sectors characterised by high job churning rates and risky technologies, where firms need to scale up or down quickly after a demand or technological shock (Haltiwanger, Scarpetta and Schweizer 2014; Bartelsman, Gautier and de Wind 2011). Although we consider these structural determinants in our empirical analysis, all indicators capturing developments in these variables have generally improved or remained stable over the timespan

<sup>5</sup> A similarly wide country and sector coverage is found in Gamberoni et al. (2016) but this analysis refers to a sample of Central-Eastern European countries.

considered, suggesting that other factors may be at play in explaining developments in input misallocation, especially referred to capital. Moreover, these market distortions may not be necessary to explain the observed within-sector dispersion in the marginal productivity in inputs, as argued by Asker, Collard-Wexler and De Loecker (2014), who prove that, in the case of capital at least, adjustment costs and demand shocks are sufficient to induce this dispersion.

We therefore consider two demand-related indicators, namely realized demand and demand uncertainty which to some extent take Asker, Collard-Wexler and De Loecker's (2014) critique into account. Slackness in demand could result in an improved reallocation of resources because job destruction increases to a larger extent than the reduction in job creation. Most importantly, the probability of exiting or downsizing is larger for less productive firms (Davis and Haltiwanger 1990; Caballero and Hammour 1994; Mortensen and Pissarides 1994). Uncertainty has also been put forward as a potential determinant of capital misallocation (Bloom et al. 2014; Riley, Rosazza-Bondibene and Young 2015), suggesting that it is the more productive firms that defer investment rather than the less productive units. The effect of uncertainty on employment is more ambiguous. In times of high uncertainty, hiring is risky because it is costly, yet firms may also become more reluctant to fire workers, as it would be costly to search for new workers in the case of a rise in future demand (Schaal 2015; Guglielminetti 2016). To our knowledge, the impact of uncertainty on within-sector input misallocation has never been explored thus far.

The recent literature further underscores the role of credit market distortions. Indeed, the existence of frictions in the financial markets might prevent productive firms from obtaining the resources needed to expand, so that input choices differ systematically across firms in ways that are unrelated to their productivity (Gilchrist, Sim and Zakrajsek 2015). One indication of the existence of such credit market distortions is provided by Banerjee and Moll (2009), who show that small firms in developing countries borrow at very high interest rates compared to both larger firms in the same sector and country and small firms in the same sector in advanced economies. This suggests a higher marginal return of capital relative to larger firms. Using Korean, Colombian and Chinese data, Midrigan and Xu (2014) however find that it is difficult to attribute the bulk of the large TFP losses from within-sector input misallocation to financial frictions, owing to the fact that the most efficient firms accumulate internal funds over time and grow out of their financing constraints; financial frictions instead are found to have sizable negative effects on the number of producers that operate as well as on the level of technology that producers adopt. Finally, Schivardi, Sette and Tabellini (2016) have shown that the increase in input misallocation in Italy during the crisis years is positively correlated with the combined presence of a large number of both weak firms and weak banks, with the latter tending to lend and to therefore support the former. In order to test the role of financial constraints in our set of countries, we thus also consider the cost of credit in our empirical analysis which, to the extent that it also captures firms' demand conditions, is also a way to control for another demand variable in the direction of Asker, Collard-Wexler and De Loecker's (2014) paper.

Our results are the following. The reduction in the stringency in both product and labour market regulations over the period under analysis contributed to dampen input misallocation growth. Conversely, demand variables played a large role in explaining the observed rise in capital misallocation. The increase in demand uncertainty was particularly important in explaining this type of misallocation, especially during the recent recessionary years. Increases in the cost of credit or, in alternative, the tightening of non-cost credit standards, also affected capital misallocation dynamics positively. Once controlling for all these factors, a crisis dummy enters our capital and labour misallocation growth regressions negatively, suggesting a cleansing effect of the Great Recession.

The structure of the paper is as follows. Section 2 describes the intuition underlying the Hsieh and Klenow (2009) model, which is used to derive our preferred measure of resource misallocation, also in comparison with alternative measures of misallocation, the Olley-Pakes gap and the Petrin and Sivadasan (2013) indicator. Section 3 presents descriptive evidence on the evolution of labour and capital misallocation over time and across sectors in Belgium, France, Germany, Italy and Spain. Within a standard panel regression framework, Section 4 explores the



empirical relationships between key cyclical and structural variables and the observed changes in input misallocation. Section 5 concludes.

## 2. The measurement of input misallocation

The paper adopts the theoretical approach developed by Hsieh and Klenow (2009), which shows that changes in sectorial TFP are proportional to changes in the within-sector dispersion of the marginal revenue product of capital and labour (MRPK and MRPL, respectively). The authors build a model of monopolistic competition with firm heterogeneity à la Melitz (2003), where firms face the same marginal cost of inputs but differ in terms of their physical TFP. In their setting, firms also face different potential input constraints. These constraints lead firms to produce different amounts than what would be optimal according to their different capital-labour ratios.

Intuitively, in the absence of constraints and in a static context, the returns to capital and labour should be similar across firms operating within the same sector, given that the marginal cost of labour and capital they face is the same. In other words, the allocation of resources across firms would depend only on the physical level of firm-specific TFP: in an efficient setting, differences in physical TFP across firms are fully compensated by firm price differentials leading to an equalization of MRPK and MRPL across firms. If dispersion in the marginal productivity of inputs is observed instead, this could be attributed, at least partially, to constraints impeding the efficient flow of resources across units of production. The extent of input misallocation is worse the greater the within-sector dispersion of marginal products of inputs across firms.

Hsieh and Klenow's (2009) model is outlined in Annex B. The key equations of interest, derived therein, are the following:

$$(1) MRPL_{si} = (1 - \alpha_s) \frac{\sigma - 1}{\sigma} \frac{P_{si} Y_{si}}{L_{si}} = w_s \frac{1}{1 - \tau_{Ysi}}$$

where  $MRPL_{si}$  is the marginal revenue productivity of labour of firm  $i$  in sector  $s$ ,  $\alpha_s$  is the share of capital in a Cobb-Douglas production process,  $\sigma > 1$  is the constant elasticity of substitution across varieties of goods,  $P_{si} Y_{si}$  is the nominal value added of firm  $i$ ,  $L_{si}$  is the labour employed by firm  $i$ ,  $w_s$  is the wage faced by all firms in sector  $s$  and  $\tau_{y,si}$  denotes distortions that affect output in firm  $i$ . If the economy is frictionless and therefore  $\tau_{Ysi} = 0$ ,  $MRPL_{si}$  is equal to the sector-specific marginal cost of labour. Similarly:

$$(2) MRPK_{si} = \alpha_s \frac{\sigma - 1}{\sigma} \frac{P_{si} Y_{si}}{K_{si}} = r_s \frac{1 + \tau_{Ksi}}{1 - \tau_{Ysi}}$$

where  $r_s$  is the cost of capital in sector  $s$  and  $\tau_{Ksi}$  refers to the distortions affecting the level of capital in firm  $i$ . If capital and output distortions are absent,  $MRPK_{si}$  is equal to the sector-specific cost of capital.

By combining equations 1 and 2, we can express revenue total factor productivity  $TFPR_{si}$  as follows:

$$(3) TFPR_{si} \propto MRPK_{si}^{\alpha_s} MRPL_{si}^{1 - \alpha_s} \propto \frac{(1 + \tau_{Ksi})^{\alpha_s}}{1 - \tau_{Ysi}}$$

Finally, under certain normality assumptions, Hsieh and Klenow (2009) show that sectorial (log)TFP is negatively related to the variance in (log) $TFPR_{si}$ . In other terms, sectorial TFP is lower the higher the dispersion in TFPR across firms, which is in turn a function of the dispersion in MRPK and in MRPL (and their covariance), and ultimately a result of capital and/or labour distortions.<sup>6</sup>

<sup>6</sup> In following Hsieh and Klenow (2009) we only consider the reallocation of two production factors, labour and capital, disregarding intermediate inputs. As Basu and Fernald (1997) and Jones (2013) argue, using a value added production function will misclassify growth coming from the reallocation of intermediate inputs as within-firm productivity growth, thereby understating the role of reallocation in explaining aggregate TFP growth. Moreover, adjustment costs may be lower for intermediate inputs relative to capital and labour, thereby implying that the dispersion in the marginal revenue product of these inputs is less subject to the critique put forward by Asker, Collard-Wexler and de Loecker (2014) which we will discuss further on. CompNet data, which we use in this paper, referring to the marginal productivity of raw materials are in fact not available. This is because, as explained in Annex C, the firm-level marginal

One must be aware that distortions might not be the only explanation behind the observed dispersion in TFPR. Indeed, Hsieh and Klenow's (2009) model is based on restrictive assumptions on preferences and on the production technology. TFPR dispersion could be the result of firms setting firm-specific, as opposed to fixed, mark-ups (see, for example, Peters 2013). Additionally, the Cobb-Douglas assumption might be too demanding. In this respect, Bartelsman, Haltiwanger and Scarpetta (2013) show that the within-sector dispersion in labour productivity is larger than the within-sector dispersion in TFP. This finding is difficult to reconcile with a Cobb-Douglas production function and the assumption that profit-maximizing firms equate their MRPL to wages since these two conditions would imply that there is no dispersion in labour productivity. Furthermore, Asker, Collard-Wexler and De Loecker (2014) show that in a dynamic setting with capital adjustment costs the within-sector dispersion in MRPK can be largely explained by changes in the volatility of productivity across sectors, suggesting the role of distortions may be negligible. In other terms, resource allocation may seem inefficient in a static sense (i.e. since the dispersion in MRPK is different from zero) even in an undistorted economy, but actually be efficient in a dynamic sense.<sup>7</sup>

In order to verify the soundness of the information on input misallocation stemming from Hsieh and Klenow's (2009) model, we also consider alternative measures of input misallocation, namely, the Olley and Pakes (1996) gap and the Petrin and Sivadasan (2013) wedge between the marginal revenue productivity and marginal cost of an input, which takes into account the possibility that the marginal cost is not equal across firms in a given sector.<sup>8</sup>

Regarding the Olley and Pakes' (1996) indicator, the intuition is the following (the algebraic formula is shown in Annex B): the (log) labour productivity of an industry is equal to the weighted average of the labour productivity of firms active in the industry, where the weights are the firm's share in total industry's employment. The industry's labour productivity can be then decomposed into two parts: *a*) the unweighted average of firm-level productivity and *b*) the within-industry cross-sectional covariance between the relative productivity of a firm and its relative weight, given by its size (the so-called OP gap). Given the unweighted industry mean, the higher the covariance the larger the contribution of the allocation of resources across firms to the industry productivity level, relative to a situation in which resources had been allocated randomly across firms (in that instance, the covariance would be zero).

Being grounded on a statistical decomposition, the OP gap has the advantage of being simple to compute and, according to Bartelsman, Haltiwanger and Scarpetta (2013), quite robust to mismeasurement. Additionally, it is easy to interpret, given that it provides the gain (in log points) in sectorial labour productivity stemming from the actual allocation of resources, relative to that obtained if resources were allocated randomly. On the other hand, the indicator also presents some disadvantages. Without the standard assumptions on the production function and/or demand curvature, the OP gap would be maximum if all resources were concentrated within the most efficient firm. But given that there are preferences for product variety, this would not be welfare-optimising. Secondly, the decomposition is cross-sectional and does not accommodate entry and exit, in the sense that it does not decompose aggregate productivity changes into components that are driven by entry and exit. However, regarding the latter Melitz and Polanec (2015) have recently

productivity of an input is calculated as the average industry coefficient of the input multiplied by the average productivity of the input at the firm level. The input coefficients are retrieved from the estimation of a Cobb-Douglas production function where the value added, defined as turnover minus raw materials, is the dependent variable. Hence the input coefficients of raw materials are not explicitly estimated.

<sup>7</sup> Hopenhayn (2014) also discusses the issue of adjustment costs, building upon Asker, Collard-Wexler and De Loecker (2013).

<sup>8</sup> There are other proxies for resource misallocation that we do not consider in this paper. For example, Bartelsman, Lopez-Garcia and Presidente (2016), following Foster, Grim and Haltiwanger (2014), estimate the productivity-enhancing reallocation of labour across firms looking at the elasticity of employment growth to initial productivity relative to that of the other firms in the sector. Results referring to labour misallocation in that paper are anyhow consistent with the stylised facts on labour we report herein.

proposed a dynamic OP gap able to account for the contribution of net entry to industry productivity growth. Lastly, Bartelsman, Haltiwanger and Scarpetta (2013) show that in the presence of overhead costs,<sup>9</sup> the covariance between productivity and size is not zero, thereby suggesting that cross-country differences in the OP gap could be reflecting cross-country differences in overhead costs rather than differences in allocative efficiency.

Regarding the other measure of input misallocation here considered, Petrin and Sivadasan (2013) start from a microeconomic optimisation problem at the firm level and show that the wedge between the value of the marginal product and of the marginal cost of the input at the firm level equals the increase in aggregate output resulting from the use of one extra unit of input by the firm. Hence, the average wedge, in absolute terms, across firms equals the average productivity gain from adjusting the input by one unit in the optimal direction, that is, from a low-wedge firm to a high-wedge firm. The larger the average wedge the larger the input misallocation because the larger the potential gains from reshuffling resources. As explained in more detail in Annex D, given our data limitations we cannot exactly reproduce Petrin and Sivadasan's (2013) indicator of allocative inefficiency although we are able to sufficiently approximate it, at least for the capital input.<sup>10</sup> In order to compute the average absolute capital wedge, we assume that each sector has five representative firms, one for each size class, and then take the average of the absolute value of those five wedges in each of the sectors considered. We proxy the average marginal cost of capital with the average implicit interest rate paid by the firm on its stock of debt (total interest payments divided by stock of debt).

### **3. Developments in labour and capital misallocation in selected euro-area countries**

#### **3.1 The data**

This section looks at trends in input misallocation in large euro-area countries (Belgium, France, Germany, Italy and Spain) for which we have comparable data, taken from the Competitiveness Research Network of the Eurosystem (CompNet) database and described in Annex C, on a representative sample of firms with more than 20 employees. Our analysis covers eight sectors at the one-digit industry level (according to NACE rev. 2): manufacturing, construction and six service sectors (wholesale and retail trade; information and communication; transportation and storage; food and accommodation services; professional, scientific and technical services; administrative and support services). The period under study is 2002-2012, hence we are able to analyse whether there are any significant changes in misallocation also during the Great Recession years. Some sectors or years are however missing for some countries.<sup>11</sup>

Using CompNet data in Figure 2 we are able to broadly replicate the main trends in national account TFP growth reported in Figure 1. The chart shows the average annual growth rate of median TFP considering all firms with at least one employee operating in the business economy.<sup>12</sup> With the exception of the very low, but positive, TFP growth recorded in Spain during the pre-crisis and the somehow larger TFP growth of Belgium, both the country rankings and orders of magnitude are quite similar despite the different nature of the data underlying national account statistics and the CompNet dataset: as more thoroughly explained in Annex C, CompNet data do

<sup>9</sup> Overhead costs are expenses that are necessary for the continued functioning of the business but cannot be immediately associated with the products or services being offered, that is, they do not directly generate profits, differently to labour, materials or capital expenses. They include among others accounting fees, advertising, insurance, interest, legal fees, labour burden, rent, repairs, supplies, taxes, telephone bills, travel expenditures and utilities. They are generally fixed costs, so they are incurred even in the absence of sales, but are positively correlated with size.

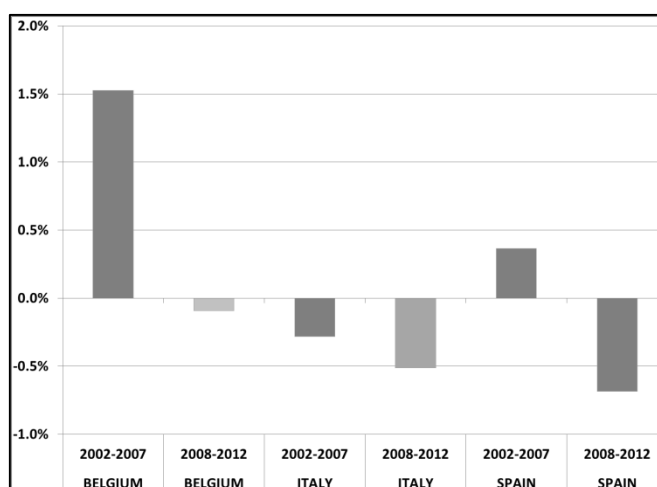
<sup>10</sup> The available labour data do not allow us to construct reliable estimates of this indicator.

<sup>11</sup> In particular, data for 2012 are missing for Belgium. Concerning sectors, food and accommodation services are missing for both Germany and Belgium and administrative and support services are missing for Germany.

<sup>12</sup> We only report the countries with good coverage of firms with less than 20 employees. Note that in the paper we use the sample of firms with at least 20 employees which are population weighed in all countries, and therefore representative of the underlying population of firms in terms of sector and size distribution.

not cover the agriculture, mining, finance, insurance and public sectors. Moreover, self-employed workers are excluded to ensure maximum comparability across country samples.

**Figure 2. TFP growth rates based on CompNet data**  
(annual average growth rates)



Source: Authors' calculations based on CompNet data full sample data.

Notes: Weighted averages, where the weights are the country-specific sectorial value added shares. Data for France cover 2004-2012, data for Belgium cover 2003-2010, data for Germany cover 2003-2012.

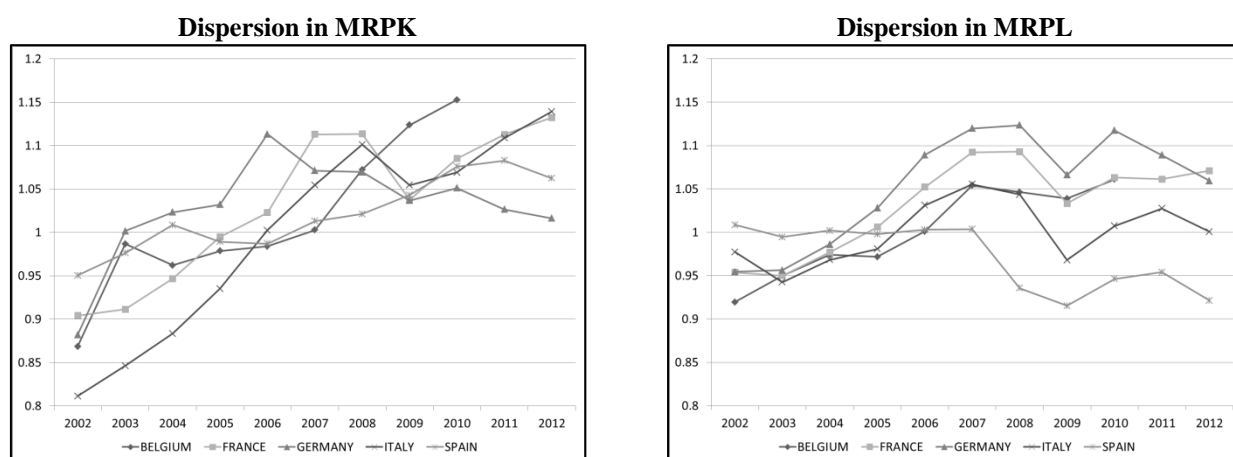
### 3.2 Developments in input misallocation

In order to examine the average total-economy evolution of resource misallocation since 2002 in the countries under analysis, we weighted sector-level input productivity dispersions with their corresponding country-specific time-varying sectorial shares in total value added. According to this aggregated indicator of misallocation, dispersion in MRPK has been on an upward trend since 2002 in all countries, with the exception of Germany, where the trend reversed in 2006 (Figure 3, left hand side panel). The trend reversal in the latter country was entirely driven by a decline in capital misallocation in industry, which weighs significantly in this country, whereas allocative inefficiency remained stable or continued to increase after 2006 in all service sectors. Dispersion in MRPL, on the other hand, grew significantly less over time in all countries, albeit starting from higher initial levels than MRPK dispersion (Figure 3, right hand side panel). These findings are consistent with those found in the recent empirical literature discussed in the Introduction, such as Gopinath et al. (2015), Garcia-Santana et al. (2015) and Calligaris (2015).

Moreover, it is noteworthy that growth in both MRPK and MRPL dispersion turned abruptly negative in 2008 or 2009 across all countries. In other terms, the pace of productivity-enhancing resource reallocation picked up during the Great Recession relative to “normal” times, albeit temporarily, as seen by subsequent growth rates which generally turned positive once again. At the onset of the sovereign debt crisis (2011-2012), especially labour misallocation fell again in some countries.

In Annex D we provide the correlations between the depicted changes in capital and labour misallocation in each country: although positively related, correlation is weak (below 0.6), suggesting that the determinants underlying growth in the two kinds of input misallocation are potentially different. Interestingly, after 2008 the correlation between changes in MRPL and MRPK dispersions increases slightly, suggesting a similar effect of the crisis years on both production factors. Moreover, in Annex E, we show that the hypothetical losses in TFP resulting from the reported developments in capital misallocation are much larger than those stemming from labour misallocation, although the reported estimates are subject to large measurement uncertainty.

**Figure 3. Total-economy average dispersion in MRPK and MRPL by country**  
(weighted averages)



Source: Authors' calculations based on CompNet data.

Notes: Weighted averages, where the weights are the country-specific time-varying sectorial value added shares. The value added series for Belgium ends in 2010.

An increase in the total-economy dispersion in MRPK, as depicted in Figure 3 for most countries under analysis, may be explained by a rise in the within-sector dispersion in MRPK within each sector, i.e. a “pure” misallocation effect, and/or by an increase in the weight of sectors where dispersion in MRPK is higher relative to that in shrinking sectors. To explore this issue we use 2002-2012 average country-specific sectorial value-added weights to neutralize the effect of the changing structural composition of the economy in order to appraise the “pure” within-sector misallocation effect in two sub-periods (2002-2007 and 2008-2012; Table 2). Focusing on capital misallocation (panel A), it is mainly the variation in within-sector dispersion in MRPK that drives the variation in total-economy misallocation. The structural change of the economy, according to the period and to the country, has generally amplified capital misallocation compared to a constant economic structure scenario, albeit to a small extent. Also in the case of labour misallocation there is a predominant role of “pure” within-sector changes in misallocation in explaining aggregate misallocation trends (panel B). However, if the five countries had kept their economic structure constant over time, the pre-crisis increase in the dispersion in MRPL recorded in all countries would have been more contained.

**Table 2. A decomposition of developments in total-economy capital and labour misallocation**  
(percentage changes)

**A. Capital misallocation**

		1	2	3
		<b>Actual MRPK dispersion</b>	<b>Fixed-weights MRPK dispersion</b>	<b>Sectorial composition effect</b>
<b>Belgium</b>	2002-2007	15.45%	12.87%	2.58%
	2008-2010	7.52%	7.70%	-0.18%
<b>France</b>	2002-2007	23.11%	22.93%	0.19%
	2008-2012	1.71%	1.45%	0.26%
<b>Germany</b>	2002-2007	21.46%	22.17%	-0.71%
	2008-2012	-4.97%	-5.22%	0.25%
<b>Italy</b>	2002-2007	29.97%	29.84%	0.13%
	2008-2012	3.47%	4.55%	-1.08%
<b>Spain</b>	2002-2007	6.58%	6.55%	0.03%
	2008-2012	4.03%	2.87%	1.16%

**B. Labour misallocation**

		1	2	3
		<b>Actual MRPL dispersion</b>	<b>Fixed-weights MRPL dispersion</b>	<b>Sectorial composition effect</b>
<b>Belgium</b>	2002-2007	14.65%	10.58%	4.07%
	2008-2010	1.41%	1.00%	0.41%
<b>France</b>	2002-2007	14.53%	12.85%	1.69%
	2008-2012	-2.01%	-2.09%	0.07%
<b>Germany</b>	2002-2007	17.30%	16.06%	1.24%
	2008-2012	-5.71%	-5.71%	0.00%
<b>Italy</b>	2002-2007	7.99%	5.63%	2.36%
	2008-2012	-4.10%	-4.45%	0.36%
<b>Spain</b>	2002-2007	-0.48%	-1.16%	0.68%
	2008-2012	-1.51%	-0.83%	-0.68%

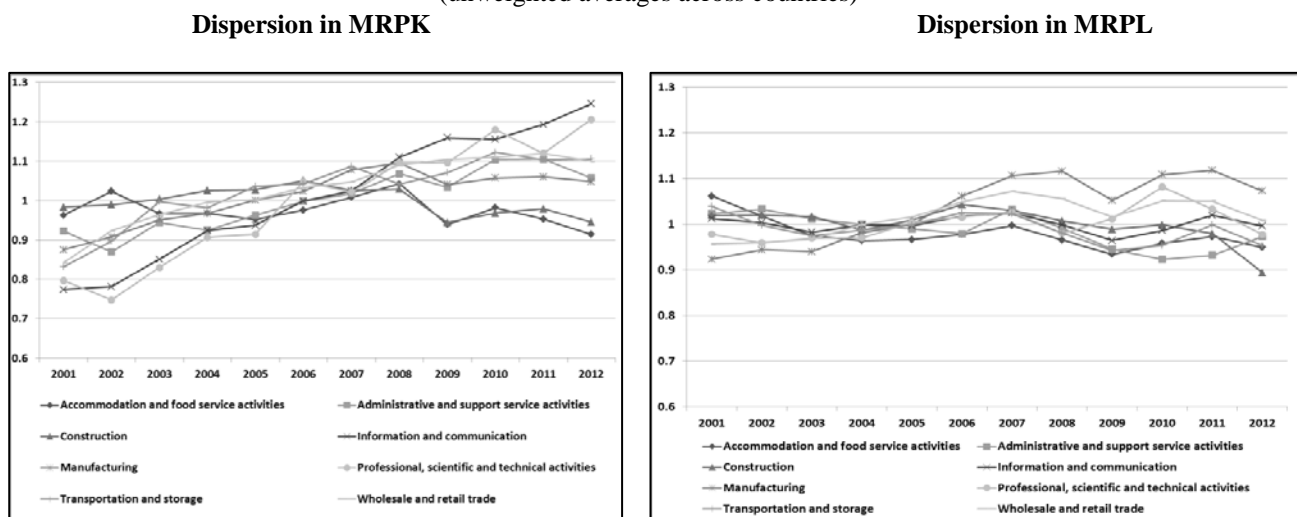
Source: Authors' calculations on CompNet data.

Notes: Whereas column 1 depicts the cumulative (2002-2007 and 2008-2012) changes in MRPK(L) dispersion given the actual structure of the economy, columns 2 shows the cumulative changes in MRPK(L) dispersion when country-specific weights are fixed at the 2002-2012 average. Column 3 is computed as the difference between column 1 and column 2.

In order to analyse sectorial developments we next compute the (unweighted) averages of sectorial dispersions in MRPL and in MRPK across the five countries (Figure 4). In services the

dispersion in MRPK has been more markedly upward-trending since the early 2000s than in industry, thereby suggesting that analyses focused solely on manufacturing, such as Gopinath et al. (2015) may be misleading. This upward trend is particularly pronounced for the information and communication sector and for professional and administrative activities. This is a worrying finding for two reasons. First, if the weight of services continues to grow in the economy, as is likely, then high capital misallocation in services will also exert a drag on future aggregate TFP growth. Second, resource misallocation and therefore low productivity growth in upstream service sectors indirectly dampens productivity growth also in downstream industrial sectors. With respect to dispersion in MRPL instead, we observe broadly stable developments across the service sectors, whereas labour misallocation in manufacturing modestly increased over the entire period *vis-à-vis* a decline in construction. The temporary drop in MRPL dispersions in 2009 was however common to most sectors. In Annex D we show the (again quite low) correlations between changes in labour and capital misallocation by sector, as well as reporting input misallocation dynamics across 2-digit industries within the heterogeneous manufacturing sector.<sup>13</sup>

**Figure 4. Input misallocation by sector**  
(unweighted averages across countries)

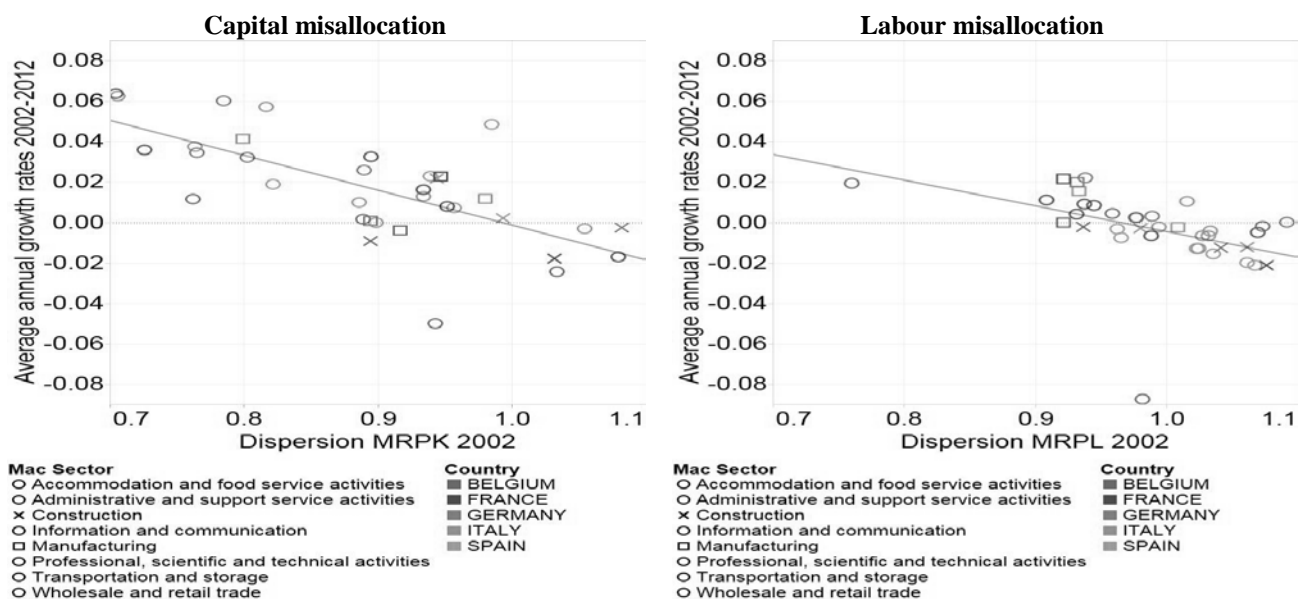


Source: Authors' calculations based on CompNet data.

Gamberoni et al. (2016) have found that for a sample of Central and Eastern European countries there is evidence of convergence in both capital and labour misallocation or of their inverse, allocative efficiency. We too find descriptive evidence of a negative correlation between the initial level of dispersion in 2002 and subsequent growth rates at the country-sector level (Figure 5), in particular for capital misallocation. However, amongst others, Quah (1993) has emphasised that this type of convergence, generally known as  $\beta$ -convergence, can be the result of a more general statistical, not economic, phenomenon of regression to the mean, so that one should actually focus on the so-called  $\sigma$ -convergence, i.e. the reduction in the dispersion of the cross-sectional distribution of country performance.  $\beta$ -convergence is a necessary, but not sufficient condition for  $\sigma$ -convergence. Figure 6 shows that the average cross-country dispersion across sectors in capital misallocation, a component of TFP growth, has indeed gone down until 2007, suggesting that the observed  $\beta$ -convergence in capital misallocation has resulted in  $\sigma$ -convergence, at least until the outbreak of the global financial crisis. The dispersion in labour misallocation, on the contrary, seems to have risen in all sectors, which is consistent with the weaker correlation found in Figure 5. We will further investigate these convergence hypotheses in our empirical analysis.

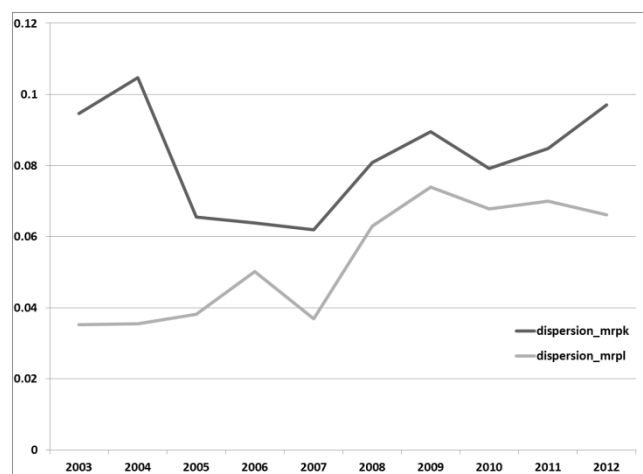
<sup>13</sup> These data are not strictly comparable to the one-digit measures employed in this paper: the former are raw, whereas the latter are de-trended (see Annex C for details).

**Figure 5. Yearly growth in input misallocation versus initial level of misallocation**



Source: Authors' calculations on CompNet data.

**Figure 6. Average cross-country and cross-sector standard deviation in misallocation**



Source: Authors' calculations on CompNet data.

Our descriptive analysis conducted thus far should not be biased by the fact that we are only considering firms with more than 20 employees. Indeed in Annex D we show that the developments described thus far are robust to the inclusion of smaller firms, for those countries for which the full sample of firms with employees is representative of the population (Belgium, Italy and Spain). Another robustness check we conducted refers to the underlying data employed in this paper. Using the same CompNet methodology described in Annex C, we computed the dispersion in MRPK and in MRPL on alternative data sourced from Amadeus. Given the burdensome data collection process involved, we focused solely on one case-study (the full sample of firms in manufacturing in Spain) and we confirm that developments in both MRPK and MRPL dispersion are similar to those



reported in this paper (Annex D).<sup>14</sup> Lastly, we checked the robustness of our results to the fact that firms in the same sector do not necessarily face the same marginal costs, as assumed in Hsieh and Klenow's (2009) model. To that end, we computed the Petrin and Sivadasan (2013) average wedges by sector and country and plotted their evolution over time (Annex D), obtaining similar trends to those uncovered in this section.

Table 3 compares the evolution of all the different measures of input misallocation discussed in Section 2 in order to confirm the soundness of the highlighted stylised facts across alternative measures. To be able to compare the dynamics of all indicators, we compute their relative cumulative growth since 2001, setting the value equal to 1 in 2001 and taking the average of the value of the index in the pre-crisis and the crisis period. Note that whereas an increase in the dispersions and in the capital wedge reported in the first three columns signals a rise in input misallocation, an increase in the OP gap provided in the fourth column suggests a fall in labour misallocation. The dispersion in MRPL and the OP gap convey consistent information over time, except for a small discrepancy in the case of Spain and Italy. In the former country, the modest decline in labour misallocation during the Great Recession is documented only by the slight fall in the MRPL dispersion measure and not by the alternative OP gap indicator. In the latter country, growth rates in MRPL dispersions remained substantially invariant while the OP gap indicator signals an improvement in labour misallocation. Lastly, the change in the average wedge between marginal productivity and marginal cost of capital varies in a similar way to the dispersion in MRPK. On the whole, our analysis based on the dispersion in marginal revenue products of inputs across countries appears therefore to be robust also to alternative measures of factor misallocation.

**Table 3. Evolution of different measures of input misallocation**

(average indices in two sub-periods; 2001=1 but for Italy where 2002=1)

	MRPL dispersion	MRPK dispersion	Capital wedge	OP gap
<b>Belgium</b>				
2002-2007	1.08	1.11	0.88	0.85
2008-2010	1.15	1.29	1.22	0.61
<b>France</b>				
2002-2007	1.03	1.09	1.00	1.21
2008-2012	1.09	1.22	1.08	0.67
<b>Germany</b>				
2002-2007	1.11	1.12	1.05	0.65
2008-2012	1.18	1.14	1.19	0.37
<b>Italy</b>				
2003-2007	1.02	1.16	1.19	1.03
2008-2012	1.03	1.35	1.45	1.08
<b>Spain</b>				
2002-2007	0.97	1.09	NA	0.83
2008-2012	0.90	1.17	1.13	0.71

Source: Authors' calculations on CompNet data.

Notes: A rise in the OP gap signals a decrease in misallocation. There are no data on capital costs, necessary to compute the capital wedge, for Spain before 2008.

<sup>14</sup> A further confirmation of the robustness of CompNet data is given by the fact that our stylized facts on input misallocation are in line with those tracked in the other papers we previously discussed, based on Amadeus or other firm-level data.

## 4. The determinants of input misallocation: panel regression analysis

### 4.1 The empirical model

In this section we investigate the potential determinants of changes in the dispersion in MRPK and MRPL, respectively, at the country-sector level in a standard panel regression framework. The difference in the variation of the two types of input misallocation, highlighted in Section 3, could possibly suggest that capital-specific factors rather than common shocks were mainly at work in the period under study. Similarly to Gamberoni et al. (2016), we adopt a conditional convergence model, based on Barro and Sala-i-Martin (2004), which takes the following form:

$$(4)\Delta var(MRPI)_{t,i,j} = \alpha_{t,i,j} + \beta var(MRPI)_{t0,i,j} + \mu_{t,i,j}$$

where  $I$  denotes either capital (K) or labour (L),  $\Delta$  indicates annual average growth rates<sup>15</sup>,  $i$  indicates the country,  $j$  indicates the sector,  $t$  the time dimension and  $\mu_{t,i,j}$  are shocks reflecting changes in production conditions or consumers' preferences. Owing to the conditionality of the model, input misallocation also depends on variables that affect the steady state. Ideally in equilibrium the dispersion in the marginal revenue in levels would equal zero. However, owing to the presence of distortions, in equilibrium changes in input misallocation are affected by country and sector-specific variables that determine  $\alpha_{t,i,j}$  in equation 4.

In our full empirical specification, as well as initial conditions in misallocation, we consider various types of shocks to the business environment. As suggested by the literature, we first examine the role of two structural factors, i.e. changes in both product and labour market regulations. In the presence of high barriers to entry, unproductive firms are able to survive and therefore retain productive resources which are not shifted to the most efficient firms in a given industry (Schiantarelli 2008; Restuccia and Rogerson 2013; Andrews and Cingano 2014). Furthermore, more stringent employment regulation might prevent firms from adjusting their workforce to optimal levels, therefore hampering the efficient reallocation of workers across firms (Haltiwanger, Scarpetta and Schweizer 2014; Bartelsman, Gautier and de Wind 2011). Moreover, in the labour misallocation regressions we also include an interaction term between the changes in product and labour market regulations. The employment effect of interactions between the two sets of policies is still an open issue.<sup>16</sup> Using a general equilibrium model, Blanchard and Giavazzi (2003) find that combining product and labour market deregulation allows workers to counteract the decline in total – and also their – rents with the gains as consumers and that introducing product market deregulations is a means to pave the way for subsequent labour market deregulation, since total rents decline and workers may appropriate lower shares of rents as a result. More recently, Fiori et al. (2012) empirically show that employment gains from product market deregulation are largest in situations where labour market settings provide strong bargaining power to workers, so that product and labour market policies are considered as “economic substitutes”. The effects of product market liberalization on employment become even stronger over time since, by increasing competition and creating downward pressures on total rents, it also reduces incentives for workers to defend high levels of bargaining power through stricter labour market settings. In this respect product and labour market regulations are considered as “political complements” as product market reforms lead to labour market deregulation.<sup>17</sup> To our knowledge, no study has however analysed the interaction of product and labour market policies on labour misallocation.

Next, we also consider business-cycle conditions: changes in realized demand and demand uncertainty, as well as a crisis dummy variable that equals one from 2008 onwards. The inclusion of

<sup>15</sup> We drop the 2003/2002 annual average rate owing to the inclusion of the 2002 level of capital misallocation as a regressor, which could therefore lead to a potential endogeneity bias.

<sup>16</sup> To our knowledge, none of this literature has focused on the effects on investment.

<sup>17</sup> On the evolution of the relationship between workers' bargaining power and of firms' mark-ups by sector in Italy, for example, see Giordano and Zollino (2016).

these variables is also a way of controlling for Asker, Collard-Wexler and De Loecker's (2014) critique that the dispersion in MRPK, at least in a given point of time, is the result of demand shocks to firms that cannot adjust instantaneously. Regarding demand conditions, we include changes in sectorial real turnover to capture booms and busts at the sectorial level. Slackness in demand could result in an improved reallocation of resources because job destruction increases to a larger extent than the reduction in job creation, given that the costs of job creation are lower owing to a high supply of unemployed labour. Moreover, the probability of exiting or downsizing is larger for less productive firms (Davis and Haltiwanger 1990; Caballero and Hammour 1994; Mortensen and Pissarides 1994). Heightened uncertainty can also affect allocation of capital as most productive firms might be more risk-averse than less productive ones (as potential losses are larger) and therefore decide to postpone their investments to a larger extent. For example, Bloom et al. (2014) show that input misallocation increases in the economy in response to an uncertainty shock. In the absence of uncertainty, unproductive firms contract and productive firms expand. But when uncertainty is high, firms reduce expansion and contraction, adopting a wait-and-see strategy to gather more information on the external environment (the so-called "real option channel") and therefore shut off much of this productivity-enhancing reallocation. Riley, Rosazza-Bondibene and Young (2015) report low risk appetite and high uncertainty as being significant factors explaining the lack of external restructuring among the largest (and possibly the most productive) firms during the Great Recession in the U.K.. Moreover, using U.S. data, both Schaal (2015) and Guglielminetti (2016) show that uncertainty can significantly dampen employment, although to our knowledge there is yet no study that specifically explores the link between uncertainty and within-sector labour misallocation.<sup>18</sup>

Finally, we also control for the cost of bank credit, another possible way of controlling for firms' demand conditions in the direction of Asker, Collard-Wexler and De Loecker (2014). The key role of financial systems is to acquire information about investment opportunities and facilitate the allocation of resources into viable entrepreneurial projects (Levine 2005). Therefore, difficult access to external finance for certain types of firms (young or small firms, for example) or loose credit standards due to weak screening of borrowers can lead to input misallocation. More in detail, our full empirical specification is the following:

$$(5) \Delta var(MRPI)_{t,i,j} = \beta_0 + \beta_1 var(MRPI)_{2002,i,j} + \beta_2 crisis + \beta_3 uncertainty_{t-1,i,j} + \beta_4 \Delta real\ turnover_{t,i,j} + \beta_5 \Delta creditcost_{t,i,j} + \beta_6 \Delta PMR_{t,i,j} + \beta_7 \Delta EPL_{t,i,j} + \gamma_j + \theta_i + \varepsilon_{t,i,j}$$

where I is either K or L,  $\gamma_j$  and  $\theta_i$  are respectively country and sector fixed effects and  $\Delta$  denotes changes in  $t/t-1$ .<sup>19</sup>

#### 4.2 Description and measurement of the explanatory variables

In this section we describe the construction of the covariates employed in our regression analysis and their evolution in the period under study. A summary table is provided in Annex F.

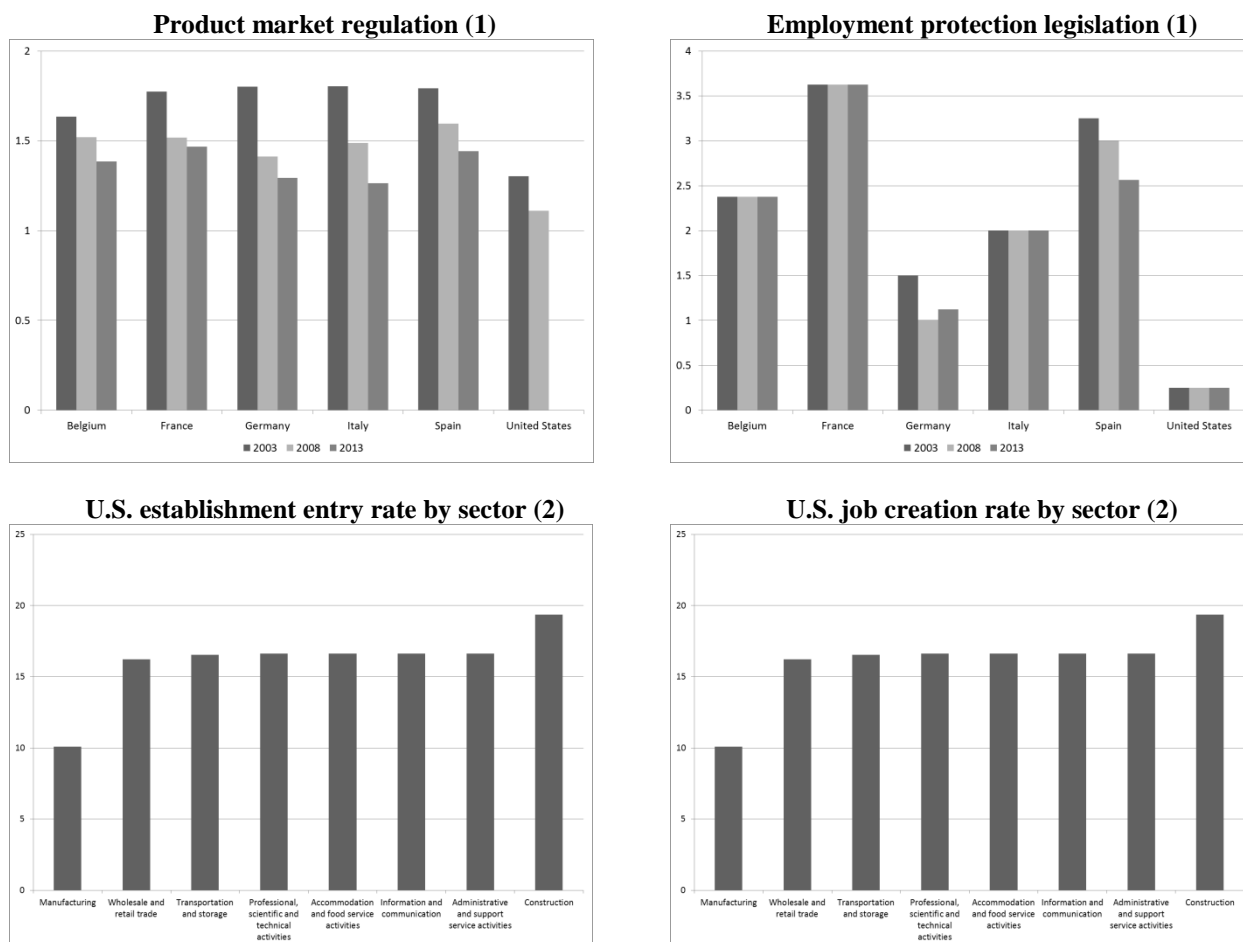
First, we consider the OECD product market regulation (PMR), which captures *ex ante* anti-competitive practices. This indicator is available for 1999, 2003, 2008 and 2013. PMR has decreased across the entire period considered in the countries under study, although a small rise may be observed between 2008 and 2013 in Belgium and in Spain (Figure 6, top left hand side panel). This indicator is available at the aggregate level. To disentangle its sector-specific impact

<sup>18</sup> Changes in sectorial turnover are potentially endogenous. If allocation deteriorates in a sector, other things equal we will have lower turnover, giving rise to a negative correlation between the two, where causality however goes in the other direction. As we will see, however, regression results provide for the opposite coefficient, which is good. Similar reasons apply to the uncertainty variable. For this reason, the empirical specifications include the lag of this variable.

<sup>19</sup> As we shall see, country and sector fixed effects also proxy for the interaction terms (sectorial and country-level variables) used to construct the credit, product market regulation and labour market regulation variables. In a robustness check, documented in Annex G, we also show results obtained with year fixed effects in lieu of the crisis dummy.

we adopt the difference-in-difference approach pioneered by Rajan and Zingales (1998) and employed in this specific context by Andrews and Cingano (2012). We use the U.S. establishment entry rate, sourced from the Census Bureau’s Longitudinal Business Database as an index of “natural” sectorial exposure to entry barriers (since industries with high natural entry barriers will also present low entry).<sup>20</sup> The sectors with the highest establishment rate are transportation and storage, followed by all other service sectors (Figure 7, bottom left hand side panel). We use U.S. figures to proxy sectorial technologically-driven entry rates because the U.S. is a country with lower PMR relative to the considered euro-area countries. We then interact the aggregate PMR with the sector-specific U.S. entry rate to obtain sectorial exposure of PMR for the selected euro-area countries.<sup>21</sup> Moreover, in order to expand the time coverage of our PMR indicator, we interpolate the measure available every four/five years with the year-on-year dynamics of the OECD Regulatory Impact Indicator, available annually for each country and sector considered.<sup>22</sup> In this manner we obtain a series of sectorial PMR for 1999-2013 for each country under study, which more than covers the whole period of interest in this paper.

**Figure 7. Total-economy regulation and sectorial degree of exposure to regulation**



Source: OECD and authors’ calculations on Census Bureau’s Longitudinal Business Database.

- (1) A higher value of the indicators signals tighter regulation.
- (2) 2002-2007 averages.

<sup>20</sup> In Annex F we show similarly to Bassanini et al. (2009), via a simple analysis of variance, that most of the variance in the U.S. firm entry rates is due to the variation across industries rather than over time.

<sup>21</sup> We use the time-invariant 2002-2007 firm entry rate average to net out any time effects.

<sup>22</sup> The OECD Regulatory Impact Indicator computes the impact on 39 sectors of regulation in a number of non-manufacturing sectors producing inputs, taking into account the relative weight of each of those inputs in the production process. By using this interpolation method, we are assuming that the regulatory impact of upstream sectors is similar to the country-wide regulation dynamics.

Another possible driver of input misallocation put forward by the literature refers to strict and complex employment protection legislation (EPL). We consider the OECD indicator for temporary employment which measures the strictness of regulation on the use of fixed-term and temporary work agency contracts. Differently to the PMR indicator, this measure is available for the whole period under study. Compared to the initial value in 2003, we observe very little variation over time with a marked decrease standing out only for Spain (Figure 7, top right hand side panel). The indicator is again not available at the sector level. We therefore exploit the fact that for some industries, particularly those with a higher “natural” rate of job churning, EPL is more binding than for others. In the vein of the recent literature,<sup>23</sup> we use the U.S. sectorial job creation rate (sourced from the Census Bureau’s Longitudinal Business Database) as an exogenous measure of the propensity to implement staff changes through new job hires in a specific industry, resulting purely from its idiosyncratic technological characteristics (such as the technological features of production processes and the type of knowledge management required by production activities), and not by country-specific determinants and the level of regulation itself. Given that the U.S. is considered a frictionless country, with little regulation compared with euro-area countries, we consider its sector-specific job churning rates the “natural” rates.<sup>24</sup> The sector with the highest job creation rate is construction, followed by all the service sectors (Figure 7, bottom right hand side panel). We then interact the U.S. sectorial job creation rate with the total-economy EPL indicator referred to the selected euro-area countries to obtain the indicator of sectorial exposure to labour market regulation included in our regressions.

We next look at the cost of bank credit.<sup>25</sup> In Figure 8 we plot the evolution of the average interest rate on bank loans to firms by country, sourced from the European Central Bank: in the run-up to the global financial crisis the cost of credit spiked in all countries and hiked again in Italy and in Spain in particular at the onset of the sovereign debt crisis. The employed credit variable however refers to the total economy. To disentangle its sector-specific effect, we consider that the cost of credit has a different impact on firms depending on the average external finance dependence of the sector where it operates. Hence, we interact the cost of credit with a measure of sector-specific demand for external finance first introduced by Rajan and Zingales (1998). The latter indicator is constructed as the share of capital expenses not financed by the cash-flow from operations of large listed U.S. firms (i.e. the amount of desired investment that cannot be financed through internal cash flows generated by the same business) and is built on the assumptions that: *i*) in highly developed financial markets, such as the U.S., industry differences in this share reflect underlying technological differences among industries and *ii*) technological differences across sectors (such as the scale of projects, cash harvest periods, the need for continuing investment) are common across countries. We build these measures by using the S&P IQ Capital database.<sup>26</sup> Differently to Rajan and Zingales (1998) and Bena and Ondko (2012), where this dependence indicator is constructed only for the manufacturing sector, we constructed measures for all of the eight sectors considered in this paper. To prevent excessive weight being given to the large firms, industry values are calculated as medians.<sup>27</sup> According to this measure, information and communication and professional, scientific and technical services are the most dependent sectors on external finance (Figure 9).

<sup>23</sup> See Bassanini et al. (2009), Andrews and Cingano (2012), Pellegrino and Zingales (2014) and Haltiwanger, Scarpetta and Schweiger (2014).

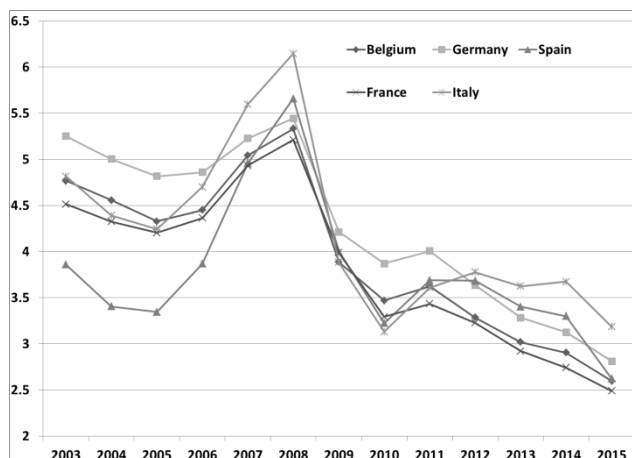
<sup>24</sup> Again, we use the average 2002- 2007 exposure rate. In Annex F we show that most of the variance in the U.S. job creation rates is due to the variation across industries rather than over time.

<sup>25</sup> Due to data availability we only consider bank lending as a source of external finance for firms. In the countries under study the dependence on bank loans is anyhow high relative to non-banking finance.

<sup>26</sup> As mentioned in Rajan and Zingales (1998), considering only listed companies has two advantages. First, large publicly traded firms typically face the least frictions in accessing finance. Secondly, disclosure requirements imply that the data on financing are comprehensive.

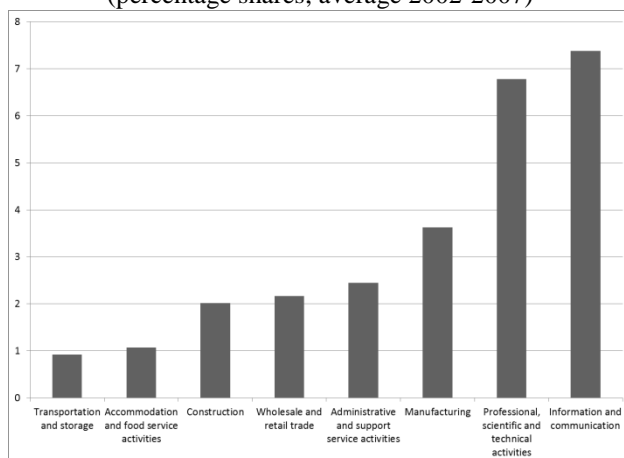
<sup>27</sup> Moreover, to fully capture the extent of dependence by sector isolating year-specific effects, we take the average of the 2002-2007 values.

**Figure 8. Average cost of bank credit to firms**  
(percentage values)



Source: ECB.

**Figure 9. Median external dependence on finance**  
by sector  
(percentage shares; average 2002-2007)



Source: Authors' calculations on S&P IQ Capital data.

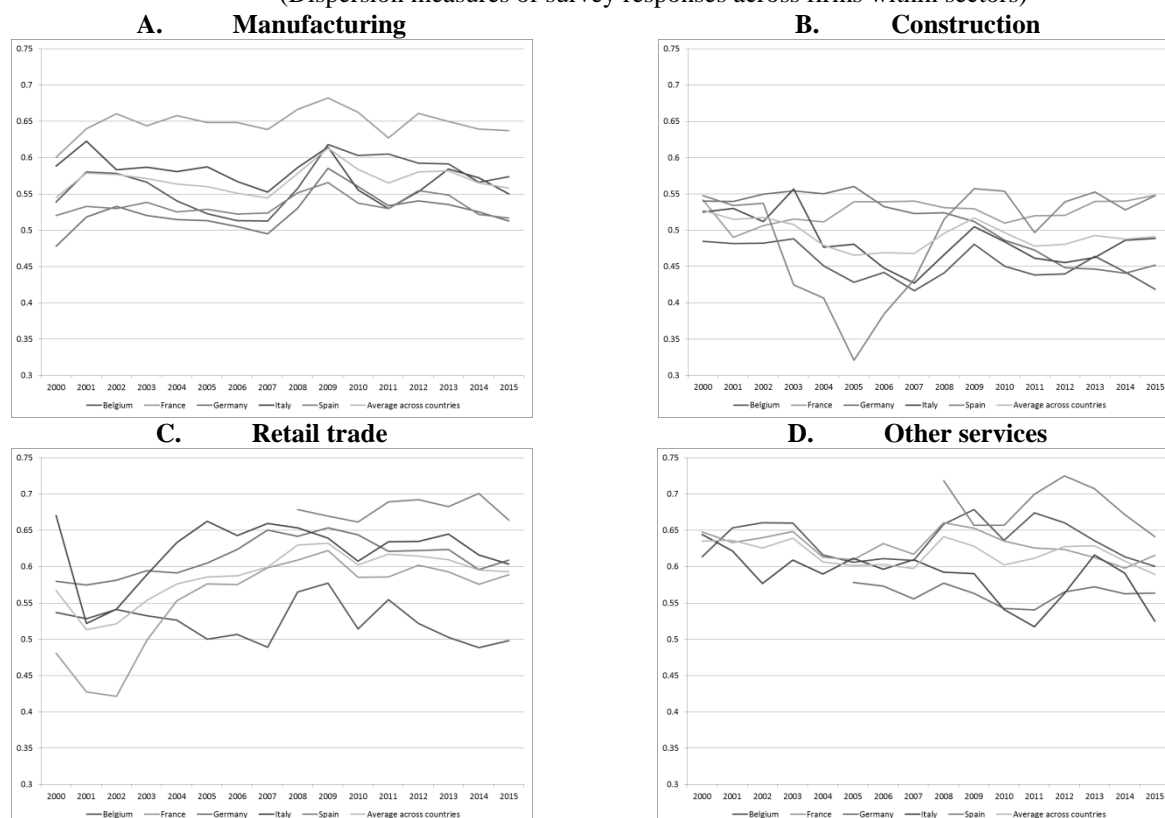
In our regressions we also control for changes in real demand and demand uncertainty. As mentioned previously, sectorial demand is captured by sectorial average real turnover across firms sourced from CompNet. Moreover, we introduce for the first time in the literature a comparable cross-country sector-specific survey-based uncertainty measure for sectors other than manufacturing. Following Fuss and Vermeulen (2008), Bachmann, Elstner and Sims (2014) and Buseti, Giordano and Zevi (2016), we proxy demand uncertainty with the cross-sectional dispersion in the expectations of firms interviewed in the monthly European Commission Business Survey. The measure is computed as  $\sqrt{\frac{frac_t^+ + frac_t^-}{2} - (\frac{frac_t^+ - frac_t^-}{2})^2}$ , where  $frac_t^+$  and  $frac_t^-$  are the fractions of firms with “increase” and “decrease” responses at time  $t$ , and varies between 0 and 1.<sup>28</sup> The questions we consider are those referring to future production/demand expectations of the firms relative to the current situation,<sup>29</sup> taking yearly averages of the computed monthly dispersion measures. Our dispersion measures are therefore both time-varying and forward-looking.<sup>30</sup> Data are available for four macro-sectors of the economy: manufacturing, construction, retail trade and other services. From a sectorial perspective, during 2001-2014 uncertainty in both manufacturing and construction displayed very similar patterns, which were also comparable to those observed in “other services” (Figure 10). The dispersion measure in the retail sector instead registered an upward trend until 2009 driven by all countries for which retail data are available, with the exception of Belgium. Focusing on the most recent period, uncertainty faced by firms significantly increased in all countries and in all sectors in 2008-2009. Another spike in uncertainty was recorded during the sovereign debt crisis in 2011-2013 according to the country, with the exception of Germany where uncertainty has been declining roughly since 2009 in all sectors with the exception of “other services”. The second general hike in uncertainty was driven mainly by manufacturing and “other services”.

<sup>28</sup> This measure is the cross-sectional standard deviation of survey responses when the “increase” response is coded as 1, the neutral response as 0 and the “decrease” response as -1.

<sup>29</sup> In particular for manufacturing we consider the question “production expectations for the months ahead”, for construction “employment expectations over the next 3 months”, for retail trade “orders expectations over the next 3 months” and for other services “expectation of the demand over the next 3 months”.

<sup>30</sup> For this reason in our regressions we lagged our uncertainty measures by one year. Moreover, these measures are based on expectations of changes in demand and are, therefore, included as levels in the regressions, since they already reflect changes.

**Figure 10. Demand uncertainty by country and by sector**  
(Dispersion measures of survey responses across firms within sectors)



Source: Authors' calculations on European Commission Business Survey data.  
Notes: See main text for details on how the measures were constructed.

### 4.3 Regression results

We next measure the estimated relationships between capital (Table 4) and labour (Table 5) misallocation dynamics, respectively, and each of the discussed potential determinants. Our results point to the following findings. We broadly confirm the descriptive evidence shown in Figure 5 that growth in within-sector capital misallocation is negatively correlated with its initial level at the beginning of the period under study, also when controlling for other covariates,<sup>31</sup> thereby pointing to the existence of a conditional convergence process in capital allocative (in)efficiency within country-sectors. Next, we find that real turnover growth boosts growth in the dispersion in MRPK in line with the idea that misallocation increases during booms and declines during busts.<sup>32</sup> As well as the “first moment” of growth in demand being found to be positively associated with capital misallocation, its “second moment”, proxied by demand uncertainty, is also found to foster capital misallocation growth. As we shall see further on, this measure of demand uncertainty is not statistically significant instead in the labour misallocation regressions. One possible explanation is that, relative to labour, capital presents higher adjustment costs and a larger degree of irreversibility, thereby confirming the role of demand in explaining the dispersion in MRPK as argued by Asker, Collard-Wexler and De Loecker (2014). In the face of heightened uncertainty, whereas high and low uncertainty firms do not seem to adjust their workforce to a different extent, this seems instead

<sup>31</sup> The variable is marginally significant at a 15 per cent confidence level.

<sup>32</sup> The turnover variable might be capturing also mark-ups. However, results available upon request show that the demand variable coefficient remains positive and significant also once we include the average profit margin growth across firms as a proxy for mark-ups.

to be the case for capital, in which less productive, and possibly less risk-averse, firms are more willing to incur in fixed investment costs in order to survive in the market.

All discussed capital misallocation results are robust to the inclusion of market distortions, i.e. to regulatory and credit constraints. In particular, both the strictness of PMR and the tightening of credit standards are found to hinder the ability of reallocating resources to most efficient producers on average in the country-sectors under study. While the results for PMR are in line with the expectations provided by the literature, the expected effect of a higher cost of credit on efficient resource allocation is *a priori* ambiguous. Our findings suggest that a rise in the cost of credit positively correlates with capital misallocation growth. This result has been found for example in cases when banks, in a context of credit rationing, tend to lend to firms with more collateral (i.e. tangible fixed assets) rather than to the more efficient firms in the sectors (which may, for example, have invested more in intangible assets). Similarly, Schivardi, Sette and Tabellini (2016) find that in Italy during the crisis years both the combination of a large number of “zombie” firms and of a large share of weak banks (i.e. banks with low capital ratios), which lent to the former firms, gave way to a rise in the dispersion in revenue-based TFP. Our results are instead not in line with those in Gopinath et al. (2015), who find that capital misallocation in Spain increased in the pre-crisis period as the result of huge and badly allocated capital inflows. It must be noted however that their model is unable to explain the observed continuation of the upward trend in the dispersion in MRPK in the crisis years. Moreover, as we shall see, our findings concerning the impact of the tightness in credit markets on capital misallocation are unchanged also when using a different credit variable, confirming the robustness of our result to alternative measures. The difference with respect to Gopinath et al.’s (2015) findings may be due to the fact that, in addition to manufacturing, our analysis also considers the service sectors, as well as a wider range of countries. Next, changes in EPL are found not to significantly affect the degree of efficiency with which capital is allocated across firms. Finally, controlling for all these factors, the Great Recession years are associated with an improvement in allocative efficiency.

**Table 4. Regression results: changes in the dispersion in MRPK**

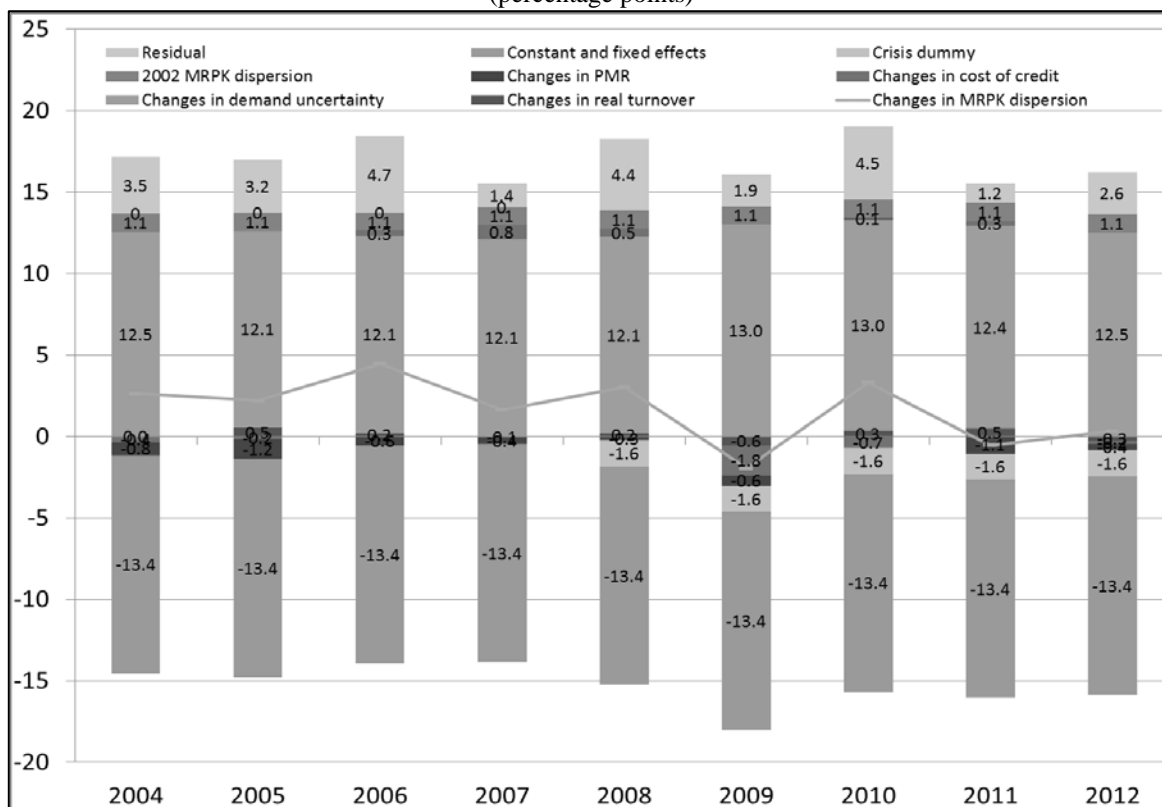
<b>Dependent variable: Changes in MRPK dispersion</b>			
	(1)	(2)	(3)
Dispersion in MRPK in 2002 (ln)	-0.090 0.06	-0.088 0.07	-0.090 0.07
Changes in real turnover (t/t-1)	0.124*** 0.04	0.127*** 0.04	0.125*** 0.04
Demand uncertainty (t-1)	0.205** 0.1	0.211** 0.1	0.206** 0.1
Changes in cost of credit (t/t-1)	0.361** 0.17	0.346** 0.16	0.336** 0.16
Changes in PMR (t/t-1)		0.211** 0.1	0.212** 0.1
Changes in EPL (t/t-1)			-0.082 0.08
Crisis dummy	-0.012 0.01	-0.016* 0.01	-0.015 0.01
Constant	-0.099* 0.06	-0.097* 0.06	-0.095* 0.05
Adjusted R-squared	0.096	0.107	0.106
N	283	283	283
* p<0.10, ** p<0.05, *** p<0.01			

Notes: Estimates are obtained via OLS with White’s correction for heteroskedasticity (standard errors are reported in small font). Country and sector fixed effects included but not reported. See footnotes 11 and 12 concerning the number of observations in our dataset.



We then use the estimated coefficients of our preferred specification (column 2 in Table 4), obtained by including only statistically significant explanatory variables, to compute the average contributions of the explanatory variables to the average change in capital misallocation in the years under study (Figure 11). The general decline in PMR over the period considered dampened capital misallocation dynamics, with a renewed vigour especially in 2011; the effect however is small. After the boost to capital misallocation exerted by the rising cost of credit in 2006-2008, the fall in interest rates, also a result of enacted monetary policy measures, helped slow growth in misallocation down; also this variable however exerts a small impact, in line with the findings in Midrigan and Xu (2014). The largest contribution stems from demand uncertainty: in 2009-2010 the significant, positive contribution of demand uncertainty reached its peak, remaining high until 2012.<sup>33</sup>

**Figure 11. Yearly contributions of covariates to changes in MRPK dispersion**  
(percentage points)



Turning to the results related to MRPL dispersion (Table 5), changes in real turnover have a similar effect on labour misallocation dynamics to that observed for capital. Moreover, the crisis had a cleansing effect on labour misallocation, slightly larger in magnitude to that seen for capital. The initial level of MRPL dispersion is instead not statistically significant, suggesting that in the period under study there was no convergence in labour misallocation across core euro-area countries. Stricter product market regulation is found to have led to higher labour misallocation growth. But we also find that more stringent labour market regulations positively correlate with labour misallocation growth, particularly in sectors characterized by more stringent product market regulations. Thus, these results support the idea that the positive effect of the tightness of PMR on labour misallocation growth is amplified if also EPL becomes more restrictive. Seen from an inverse perspective, the gains in the allocative efficiency of labour are larger if both kinds of

<sup>33</sup> Notwithstanding the sector and country heterogeneity seen in Figure 9, on average across countries and sectors demand uncertainty varied little over time, explaining its rather stable contribution.

regulation are jointly loosened. Finally, both the cost of credit and demand uncertainty do not seem to matter for labour misallocation dynamics. The latter result does not imply that uncertainty does not affect employment, but, as mentioned earlier, that we find no evidence of a differentiated impact between low- and high-productivity firms and thereby of a change in between-firm labour allocative efficiency.

**Table 5. Regression results: changes in the dispersion in MRPL**

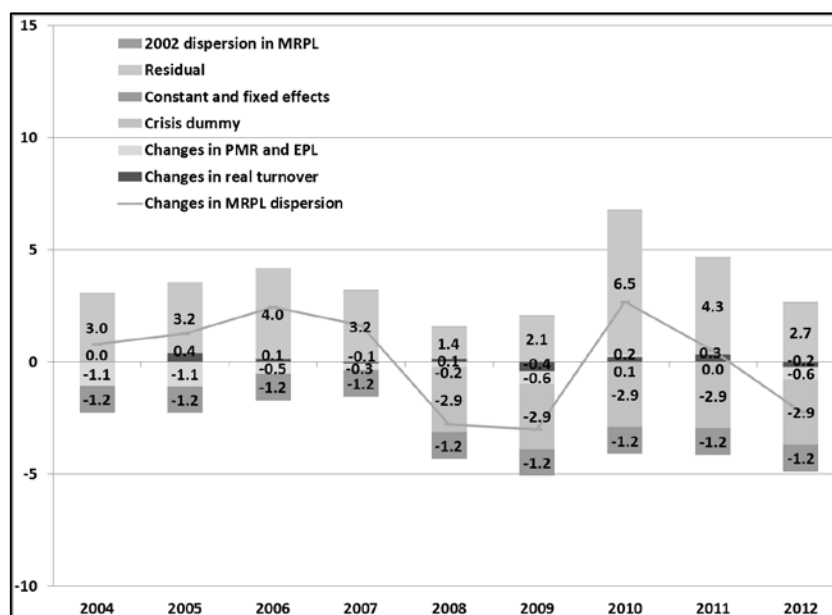
Dependent variable: Changes in MRPL dispersion	(1)	(2)	(3)	(4)	(5)
Dispersion in MRPL in 2002 (ln)	-0.139* 0.08	-0.142* 0.08	-0.141* 0.08	-0.145* 0.08	-0.147* 0.08
Changes in cost of credit (t/t-1)	0.061 0.11	0.05 0.11	0.05 0.11	0.011 0.11	
Changes in real turnover (t/t-1)	0.099*** 0.04	0.101*** 0.04	0.101*** 0.04	0.095*** 0.04	0.093*** 0.04
Demand uncertainty (t-1)	0.062 0.06	0.066 0.06	0.066 0.06	0.06 0.06	
Changes in PMR (t/t-1)		0.156** 0.07	0.156** 0.07	0.189*** 0.07	0.187*** 0.07
Changes in EPL (t/t-1)			-0.007 0.06	0.081 0.07	0.079 0.07
Changes in PMR*changes in EPL (t/t-1)				3.256** 1.36	3.303** 1.28
Crisis dummy	-0.024*** 0.01	-0.027*** 0.01	-0.027*** 0.01	-0.030*** 0.01	-0.029*** 0.01
Constant	-0.018 0.04	-0.017 0.04	-0.016 0.04	-0.011 0.04	0.022* 0.01
Adjusted R-squared	0.116	0.13	0.127	0.135	0.139
N	283	283	283	283	283
* p<0.10, ** p<0.05, *** p<0.01					

Notes: Estimates are obtained via OLS with White's correction for heteroskedasticity (standard errors are reported in small font). Country and sector fixed effects included but not reported. See footnotes 11 and 12 concerning the number of observations in our dataset.

Figure 12 plots the average contributions to changes in labour misallocation growth according to our preferred specification (Table 5, column 3), again selected as the most parsimonious specification. The joint effect of the loosening of both product and labour market regulation muted labour misallocation growth in most years and, in particular during the recent recessionary years, in 2009 and 2012, although the combined effect was small. The crisis played a significant labour-cleansing role.<sup>34</sup>

<sup>34</sup> In the case of the labour regressions the contribution of the residual is much larger than in the capital misallocation regressions. This is also linked to the more parsimonious specification used.

**Figure 12. Yearly contributions of covariates to changes in MRPL dispersion**  
(percentage points)



#### 4.4 Robustness and sensitivity analysis

We further conducted a battery of robustness checks. First, we replaced the crisis dummy with year fixed effects (Table G1 in Annex G). The signs of all the estimated coefficients remain in line with those reported in the baseline specifications but statistical significance is lost for the PMR variable in the capital misallocation regressions, probably due to its limited time variation.<sup>35</sup> Concerning the coefficient of the year dummies, 2009 is associated with a negative coefficient in both labour and capital misallocation regressions. In the case of MRPL dispersion, also 2008 and 2012 were years in which a cleansing effect was exerted.

Secondly, in addition to country and sector fixed effects, we also include country-sector fixed effects (results available upon request). All baseline findings hold, including the statistical significance of the PMR and EPL variables, although demand uncertainty becomes only marginally significant in the capital misallocation regressions.<sup>36</sup>

Thirdly, we check that our baseline results are robust to changes in the sample. Results available on request, obtained by dropping one country at a time from the sample, show a remarkable stability in the sign of the estimated coefficients reported in the previous section. Statistical significance is, however, sometimes lost, suggesting that some countries may be driving some specific results in our panel analysis, mainly referring to the effects of regulation and of demand uncertainty.

Fourthly, we replace the initial (2002) value of dispersion in both MRPK and MRPL with their lagged values. Our findings mimic the baseline results (Table G2).

Next, we look at the effects of the covariates on the OP gap, which proxies labour misallocation dynamics with an inverted sign (Table G3). Albeit not always statistically significant, the signs of the variables are in line with the results obtained in the baseline regressions related to changes in labour misallocation.

Furthermore, we check the robustness of results by exploring alternative explanatory variables in our preferred specifications (Tables 6 and 7). First, we replace the EPL sub-indicator on temporary workers with the EPL strictness of employment protection considering individual and

<sup>35</sup> The cost of credit variable also loses significance; however, an alternative proxy for financial constraints (i.e. changes in credit standards applied to banks), which we will discuss further on, is statistically significant.

<sup>36</sup> Naturally, in these regressions the initial level of misallocation, defined at the country-sector level, is omitted.

collective dismissals, again taken from OECD (column 1 in Table 6 and 7). Although this variable *per se* marginally loses significance in the labour misallocation specification, its interaction with the PMR variable is still significant and positive. As an alternative proxy to PMR, we employ the changes in median sectorial profit margins sourced from CompNet, assuming that the stricter barriers to entry in product markets, the higher the firms' mark-ups in the sector, the higher the profits. Results reported in Tables 6 and 7 (columns 2) point to increases in profit margins significantly boosting both capital (at a 13 per cent confidence level) and labour misallocation growth.

In columns 3 and 4 of both tables we adopt an alternative measure of uncertainty, i.e. the disagreement across GDP growth forecasts published by Consensus Economics, available for all countries except Belgium, plotted in Annex G. A similar measure has been employed, for example, in Bulligan and Emiliozzi (2013) focused on Italy. We employ both the standard deviation and the interquartile range across forecasts, published in year  $t$ , referring to GDP growth in year  $t$ .<sup>37</sup> Changes in uncertainty, thus measured, are also found to boost capital misallocation dynamics, as well as labour misallocation growth, suggesting therefore that the effect of uncertainty on the latter variable could also be statistically significant and positive.

Finally, as an alternative to the cost of credit, we consider various measures of firms' ability to access external finance related to bank supply-side constraints (Table 6, columns 5 to 9). For each country we consider banks' responses to the Eurosystem Bank Lending Survey, introduced in 2003 and conducted at a quarterly frequency, concerning questions related to credit supply conditions. In particular, we consider the various survey questions concerning: *a*) loan size, which usually decreases in presence of credit tightening; *b*) loan maturity, which tends to be reduced in the presence of credit tightening; *c*) non-interest charges, which tend to increase in presence of credit tightening; and *d*) collateral requirements, which become more burdensome for the firm in the presence of credit tightening. The replies provided by the banks are then used to produce net percentages, i.e. the difference between the share of banks responding "tightened considerably" and "tightened somewhat", and the share of banks responding "eased somewhat" and "eased considerably". The survey further provides a diffusion index, which we use in our main baseline regressions, defined as the net percentage weighted according to the intensity of the response, giving lenders who have answered "considerably" a weight twice as high (score of 1) as lenders having answered "somewhat" (score of 0.5). In addition to considering the four credit variables separately, we construct a synthetic indicator of credit standards, given by the first component of a principal component analysis conducted on these variables. All measures are then interacted with the external finance dependence indicator shown in Figure 9. A rise in the measure signals a tightening of credit standards, which was particularly evident after the outbreak of the global financial crisis, in particular in Spain, and again during the sovereign debt crisis, especially in Italy (see Annex G). We find that the tightening of standards referring to loan size is significant and positively correlated with capital misallocation dynamics.

<sup>37</sup> Consensus forecasts are available at a monthly frequency; yearly averages were taken and refer to the total economy.

**Table 6. Baseline regression results for capital misallocation with alternative covariate measures**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dispersion in MRPK in 2002 (ln)	-0.089 0.07	-0.096 0.07	-0.102 0.01	-0.102 0.01	-0.088 0.07	-0.086 0.06	-0.089 0.07	-0.089 0.07	-0.090 0.06
Changes in real turnover (t/t-1)	0.135*** 0.04	0.107*** 0.04	0.094** 0.05	0.098** 0.05	0.136*** 0.04	0.138*** 0.04	0.132*** 0.04	0.130*** 0.04	0.135*** 0.04
Demand uncertainty (t-1)	0.196* 0.1	0.186* 0.1			0.171* 0.1	0.179* 0.1	0.167* 0.1	0.169* 0.1	0.171* 0.1
Changes in cost of credit (t/t-1)	0.363** 0.16	0.308* 0.17	0.256* 0.15	0.271* 0.15					
Changes in PMR (t/t-1)	0.177* 0.1		0.128 0.09	0.128 0.09	0.219** 0.1	0.211** 0.1	0.222** 0.1	0.221** 0.1	0.222** 0.1
Changes in EPL - alternative definition (t/t-1)	0.787** 0.4				0.410 0.480				
Crisis dummy	-0.015 0.01	-0.005 0.01	-0.026*** 0.01	-0.026*** 0.01	-0.026*** 0.01	-0.028*** 0.01	-0.024** 0.01	-0.023** 0.01	-0.023** 0.01
Changes in profit margins (t/t-1)		0.054 0.04							
Changes in EPL (t/t-1)		-0.084 0.08							
Demand uncertainty - standard deviation across GDP forecasts (t-1)			0.109* 0.06						
Demand uncertainty - interquartile range of GDP forecasts (t-1)				0.081* 0.05					
Changes in credit standards - synthetic indicator (t/t-1)					0.08 0.07				
Changes in credit standards - loan size (t/t-1)						0.030* 0.02			
Changes in credit standards - collateral (t/t-1)							0.013 0.02		
Changes in credit standards - maturity (t/t-1)								0.004 0.02	
Changes in credit standards - non interest rates (t/t-1)									0.015 0.02
Constant	0.074* 0.04	0.068* 0.04	0.002 0.02	0.003 0.02	0.077** 0.04	0.077** 0.04	0.074* 0.04	0.074* 0.04	0.073* 0.04
Adjusted R-squared	0.115	0.097	0.102	0.100	0.093	0.099	0.092	0.09	0.091
N	283	283	270	270	283	283	283	283	283

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01

Notes: Estimates are obtained via OLS with White's correction for heteroskedasticity (standard errors are reported in small font). Country and sector fixed effects included, but not reported.

**Table 7. Baseline regression results for labour misallocation with alternative covariate measures**

	(1)	(2)	(3)	(4)
Changes in real turnover (t/t-1)	0.094*** 0.03	0.073** 0.03	0.096*** 0.04	0.094*** 0.04
Changes in PMR (t/t-1)	0.182*** 0.07		0.072 0.08	0.071 0.07
Changes in EPL- alternative definition (t/t-1)	0.350 0.5			
Crisis dummy	-0.024*** 0.01	0.010 0.01	-0.040** 0.01	-0.040** 0.01
Changes in profit margins (t/t-1)		0.108** 0.02		
Changes in EPL (t/t-1)		-0.013 0.04	0.068 0.07	0.088 0.07
Changes in PMR (t/t-1)*Changes in EPL alternative definition (t/t-1)	19.283** 7.48			
Changes in profit margins (t/t-1)*Changes in EPL (t/t-1)		0.741* 0.41		
Changes in PMR (t/t-1)*Changes in EPL (t/t-1)			2.630** 1.38	3.770*** 1.36
Demand uncertainty - standard deviation across GDP forecasts (t-1)			0.185*** 0.05	
Demand uncertainty - interquartile range of GDP forecasts (t-1)				0.161*** 0.04
Constant	0.036*** 0.01	0.028*** 0.01	0.007 0.01	0.006 0.01
Adjusted R-squared	0.119	0.15	0.21	0.22
N	351	351	270	270

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01

Notes: Estimates are obtained via OLS with White's correction for heteroskedasticity (standard errors are reported in small font). Country and sector fixed effects included, but not reported.

The sectorialized variables represent interaction terms between a time-variant country level variable and a time-invariant sector specific variable. The baseline regressions include sector and country fixed effects which absorb the individual effect of the separate terms, owing to the low variability of the product and labour market regulation indicators. However, as an additional robustness check, we re-estimate the baseline regressions by replacing the country fixed effects with the PMR, EPL, and the cost of credit variables in the main specifications. Concerning the changes in MRPK dispersions, results are confirmed with the only exception of the sectorialized variables that captures changes in product market regulation, which turns significant only at the 15 percent level, and the crisis dummy which loses significance. Results are confirmed in the specification related to the changes in the MRPL dispersion.

In a last robustness check we have also considered the possibility that using U.S. sectorial weights does not allow the correct measurement of the technological characteristics that determine the industry-specific degree of exposure to regulation or the need for external finance. Ciccone and Papaioannou (2010) indeed caution against using a benchmark country to derive exposure indices, in that if there is an idiosyncratic component that differentiates the benchmark country's exposure to the frictionless exposure, then regressions including the interacted variables may lead to biased results. The authors therefore suggest running auxiliary regressions on actual country-specific sectorial exposure rates to derive the frictionless exposure. Owing to data availability, we were able to construct sectorial exposure indicators only to gauge the impact of credit standards. Results, which are consistent with our baseline findings, are discussed in Annex G.

## 5. Conclusions

TFP growth has been lagging behind in some euro-area countries, in particular in Spain and Italy, since the early 2000s at least. In all countries TFP growth has decelerated since 2007. Given the importance of TFP growth for economic development, understanding the drivers of cross-country differences in TFP growth is at the top of the policy agenda. This paper approaches the issue focusing on the role of the allocation of production resources across firms within sectors. Indeed, aggregate or sector-specific TFP growth can be explained by the increase in TFP within each firm operating in a given market, resulting from investment in human capital, innovation or better management. But it can also be influenced by the efficiency with which given resources are allocated across production units. An efficient allocation of resources is facilitated by the flow of resources from the least to the most productive firms in the market.

We use micro-aggregated data from the CompNet database to track labour and capital allocative efficiency over time and across five euro-area countries and eight macro-sectors. To our knowledge, this is the first paper with such wide country-sector coverage within the euro area. We uncover a set of stylized patterns that are common across Belgium, France, Germany, Italy and Spain. First, in all countries, with the exception of Germany, capital allocation has worsened over time whereas labour allocation has not changed significantly. This piece of evidence confirms the importance of analysing labour and capital misallocation trends separately, which many papers in the recent empirical literature do not do. Second, the observed increase in capital misallocation at the country level has been driven by the developments of services rather than industries, suggesting that analyses focused solely on manufacturing, such as Gopinath et al. (2015), may be underestimating dispersion dynamics. Third, misallocation of both labour and capital dropped temporarily during the most acute phases of the crisis but recovered thereafter.

The paper next aims at shedding some light on the possible drivers of input misallocation in the set of countries analysed. As well as the standard market distortions considered in the recent empirical literature (i.e. restrictive regulation), we also consider demand factors which can explain dispersion in the marginal productivity of capital in particular, for which adjustment costs are high, in the direction of Asker, Collard-Wexler and De Loecker (2014). Whereas some factors explain both capital and labour misallocation dynamics, such as growth in sectorial demand (which enters positively in our regressions), changes in PMR (which also enters positively) and a crisis dummy

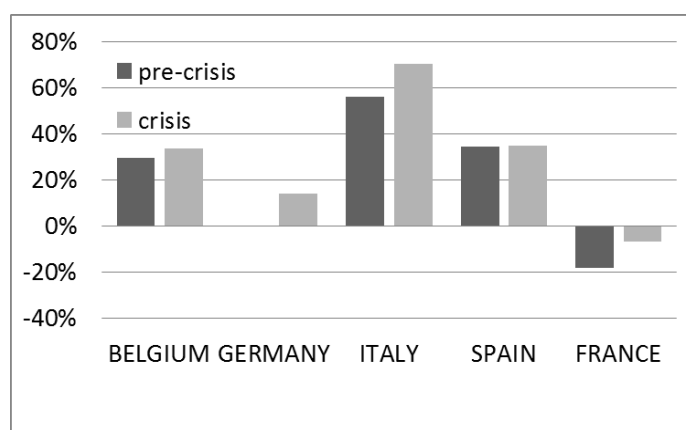
(which enters negatively, suggesting a cleansing effect), other determinants are input-specific. In particular, the rise in capital misallocation growth was fostered by increases in the cost of credit and in demand uncertainty, especially in the years in the run-up to the global financial crisis and in 2009-2010, respectively. In the case of labour, less restrictive EPL, jointly with loosened PMR, were a significant dampener on labour misallocation growth. Baseline results are robust also to alternative measures of all our explanatory variables and of our dependent variables, as well as to additional sensitivity analysis.

Our results therefore suggest that in order to foster a more efficient within-sector allocation of inputs across firms structural reforms, such as those lowering entry barriers for firms, removing size-contingent regulations that prevent firms from reaching their optimal size and enhancing bankruptcy regulations that facilitate the exit of unproductive firms, would be warranted. The loosening of PMR and EPL in recent years in some countries has proven to dampen misallocation dynamics, yet there is still room for further reductions, as shown for example when comparing the level of regulation with that in the U.S.. Credit policies aimed at better matching the supply of credit to the most productive firms would also lower capital misallocation. Structural reforms however are known to take time to deploy their beneficial effects. Given the significant role found for demand uncertainty in explaining capital misallocation, TFP growth would also benefit from demand-side policies. Actions in the latter area should aim, as well as ensuring a stable and transparent regulatory environment, also at creating an effective macro-policy environment to boost business confidence, as for example already suggested by Bloom, Kose and Terrones (2013). In conclusion, to the extent that euro-area economies are far from perfectly frictionless, policies that reduce both the cyclical and structural distortions singled out in this paper may have large effects on aggregate TFP growth via the channel of a more efficient reallocation of production factors.

## Annex A. The reallocation of resources from the non-tradable to the tradable sectors

Policy-makers often invoke the need for countries to reallocate resources from the non-tradable to the tradable sector. The underlying defining assumption is that all firms belonging to the non-tradable sector are not exposed to international competition (and vice-versa). Along these lines, manufacturing, ICT, agriculture, and transport are usually regarded as tradable sectors while construction, hotels and restaurants, business services, and the public sector are generally considered non-tradable sectors. Since the average productivity of the tradable sector is generally larger than that of the non-tradable sector in selected euro-area countries (Figure A1), aggregate productivity growth would be boosted if the tradable part of the economy gained more weight.

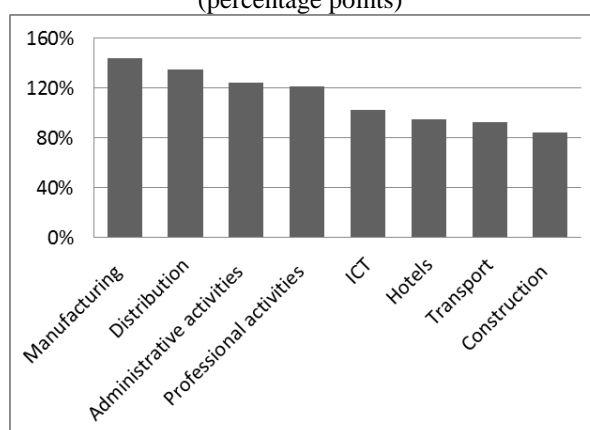
**Figure A1. Differences in average productivity of firms in tradable relative to non-tradable sectors, before and during the crisis**  
(percentage points)



Source: Authors' calculations on CompNet data.

Note: Tradables here include manufacturing, wholesale and retail distribution, transport and storage and ICT. Non-tradables include construction, hotels and restaurants, professional and administrative services. Data refer to non-financial corporations with at least 20 employees. The pre-crisis period refers to 2001-2007 and the crisis period to 2008-2012.

**Figure B1. Differences in average productivity of firms in the upper quintile relative to firms in the lower quintile within a given sector**  
(percentage points)



Source: Authors' calculations on CompNet data.

Note: Data refer to non-financial corporations with at least 20 employees. We show the productivity differences, in percentage, between the firm in the 80<sup>th</sup> decile and the 20<sup>th</sup> decile of the productivity distribution within each sector. Unweighted averages across countries.

However, this traditional split of the economy suffers from two drawbacks. First, non-exporting firms might support or provide inputs to exporting firms in a given sector and, therefore, contribute to serve foreign demand. One example could be restaurants in tourist areas of countries, which contribute decisively to the exports of tourism services. Additionally, the increasing presence of firms in global value chains means that many firms might import most of the inputs for their exports. Moreover, the degree to which this is the case is very country-specific. In this context, only input-output table analysis can account for all the trade of intermediate goods and services between sectors and across countries. These data allow determining what part of the sector value added serves foreign demand (i.e. is exported) and what part serves domestic demand (see for example Zeugner 2013). Table A1 shows that the “tradability” of each of the macro-sectors according to this measure is largest in manufacturing and smallest in public services. Yet, a large part of the value added of traditionally non-tradable sectors, like hotels and restaurants or real estate, is also exported.



**Table A1. The share of exported value added in selected euro-area countries**  
(percentage values)

Sector	Agriculture & fishing	Mining & utilities	Manufacturing	Construction	Trade, hotels, transport & similar	Financial & real estate	Public & social services	All sectors
ISIC code	A,B	C,E	D	F	G,I	J,K	L-P	Total
Belgium	77	21	88	11	37	32	5	33
France	43	13	52	2	16	15	3	16
Germany	28	18	58	5	22	23	5	24
Spain	30	15	40	2	14	22	4	15
Italy	18	17	46	4	16	14	2	16

Source: Zeugner (2013).

Second, increasingly available firm-level evidence has led to the additional finding that firms are very heterogeneous in terms of productivity within sectors: there are very productive and very unproductive firms in all sectors, whatever their degree of tradability. Most importantly, the productivity differences between the most and the least productive firms in a given sector are larger than the average productivity difference between tradables and non-tradables (Figure B1).

Given that all sectors are to a certain extent tradable, and that only the most productive firms in a given industry are able to bear trade costs and sell abroad (the average productivity premia of exporters within manufacturing is about 20 per cent; Berthou et al. 2015), policy-makers should aim at reallocating available resources to the most productive firms within the sector. This is the only way to increase the capacity of the economy to compete in international markets.

## Annex B. Hsieh and Klenow's (2009) model

Hsieh and Klenow (2009) consider an economy consisting of  $S$  sectors. Each sector is a CES aggregate of  $M$  differentiated products:

$$(B1) Y_s = \left( \sum_{i=1}^M Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where  $\sigma > 1$  is the elasticity of substitution across varieties of goods. The production function for each differentiated product/firm is given by the following Cobb-Douglas production technology:

$$(B2) Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}$$

where  $\alpha_s$  denotes the share of capital in the production process. Capital and labour shares are thus allowed to differ across industries (but not across firms within an industry) and sum to one, consistently with constant returns to scale. As in Melitz (2003) firms differ in terms of their productivity level  $A_{si}$ . Additionally, firms differ in the types of output and input constraints they face. Following Hsieh and Klenow (2009), we denote with  $\tau_{Y,si}$  distortions that affect output and  $\tau_{k,si}$  distortions that affect the absolute level of capital. Assuming that all firms in the same industry face the same wage ( $w_s$ ) and cost of capital ( $r_s$ ), profits are defined as:

$$(B3) \pi_{si} = P_{si} Y_{si} - (1 + \tau_{L,si}) w_s L_{si} - (1 + \tau_{K,si}) r_s K_{si}$$

Profit maximization yields the standard condition that the firm's output price is a fixed mark-up over its marginal cost:

$$(B4) P_{si} = \frac{\sigma}{(\sigma-1)} \left( \frac{r_s}{\alpha_s} \right)^{\alpha_s} \left( \frac{w_s}{1-\alpha_s} \right)^{(1-\alpha_s)} \frac{(1+\tau_{K,si})^{\alpha_s}}{A_{si}(1-\tau_{Y,si})}$$

Manipulations of the first order conditions for profit maximization yield the following expressions for the capital-labour ratio, labour and output:

$$(B5) \frac{K_{si}}{L_{si}} = \frac{\alpha_s}{(1-\alpha_s)} \frac{w_s}{r_s} \frac{1}{(1+\tau_{k,si})}$$

$$(B6) L_{si} \propto \frac{A_{si}^{\sigma-1} (1-\tau_{Y,si})^\sigma}{(1+\tau_{K,si})^{\alpha_s(\sigma-1)}}$$

$$(B7) Y_{si} \propto \frac{A_{si}^{\sigma-1} (1-\tau_{Y,si})^\sigma}{(1+\tau_{K,si})^{\alpha_s \sigma}}$$

The relative size of firms, and therefore allocative efficiency, depends therefore not only on firm productivity levels (with capital and labour increasing the more productive the firm), but also (negatively) on the labour and capital distortions firms face. This also translates into differences in the marginal revenue products of labour and capital across firms. Specifically, the marginal revenue product of labour ( $MRPL_{si}$ ) is proportional to revenue per worker:

$$(B8) MRPL_{si} = (1 - \alpha_s) \frac{\sigma-1}{\sigma} \frac{P_{si} Y_{si}}{L_{si}} = w_s \frac{1}{1-\tau_{Y,si}}$$

and the marginal revenue product of capital ( $MRPK_{si}$ ) is proportional to the revenue-capital ratio:

$$(B9) MRPK_{si} = \alpha_s \frac{\sigma-1}{\sigma} \frac{P_{si} Y_{si}}{K_{si}} = r_s \frac{1+\tau_{K,si}}{1-\tau_{Y,si}}$$

Hsieh and Klenow (2009) further define physical total factor productivity as  $TFPQ_{si} = A_{si}$  and the revenue total factor productivity as  $TFPR_{si} = P_{si} A_{si}$ . This distinction allows deriving an expression that links firm physical total factor productivity to the dispersion in the marginal product of capital and labour. Specifically, using equations B8 and B9, we can express  $TFPR_{si}$  as follows

$$(B10) TFPR_{si} \propto MRPK_{si}^{\alpha_s} MRPL_{si}^{1-\alpha_s} \propto \frac{(1+\tau_{K,si})^{\alpha_s}}{1-\tau_{Y,si}}$$

and the sectorial productivity  $A_s$  as follows:

$$(B11) A_s = \left( \sum_{i=1}^M \left( A_{si} \frac{\overline{TFPR}_s}{TFPR_{si}} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}}$$

where  $\overline{TFPR}_s$  is a geometric average of the average marginal revenue product of capital and labor in the sector. If marginal products were equalized across plants,  $TFPQ = \overline{A}_s = \left( \sum_{i=1}^M A_{si}^{\sigma-1} \right)^{\frac{1}{\sigma-1}}$ . When TFPQ and TFPR are jointly log-normally distributed, Hsieh and Klenow (2009) show that  $A_s$  can be expressed as:

$$(B12) \log A_s = \frac{1}{\sigma-1} \log \left( \sum_{i=1}^{M_s} A_{si}^{\sigma-1} \right) - \frac{\sigma}{2} \text{var}(\log TFPR_{si})$$

In this special case, the negative effect of distortions on sectorial TFP can be summarized by the variance of  $\log TFPR_{si}$ .

Turning instead to the labour productivity decomposition in Olley and Pakes (1996), from which we derive an alternative measure of labour misallocation, sectorial labour productivity  $lp_t$  can be decomposed in the following manner:

$$(B13) lp_t = \sum_{i=1}^N s_{it} lp_{it} = \overline{lp}_t + \sum_{i=1}^N \Delta s_{it} \Delta lp_{it}$$

where  $\overline{lp}_t$  represent the unweighted average productivity of all firms in the sector and the second term in the right-hand side represents the covariance between the relative size and productivity of the firm. The relative size, relative to the unweighted sector average, is given by  $\Delta s_{it} = s_{it} - \overline{s}_t$  where  $s_{it}$  is the employment of firm  $I$  and  $\overline{s}_t$  is the unweighted employment average. The relative productivity, again with respect to the unweighted sector average, is given by  $\Delta lp_{it} = lp_{it} - \overline{lp}_t$  where  $p_{it}$  is firm-level productivity.

## Annex C. The CompNet database and the measurement of input misallocation

The general description of the CompNet micro-aggregated database, which encompasses a very wide set of indicators related to competitiveness can be found in Lopez-Garcia et al. (2015). Data sources are heterogeneous although most countries rely on administrative data (firm registries) and few on surveys carried out by the national central banks. Despite this heterogeneity in terms of sources, target populations are defined in the same way across countries, aiming at private sector, non-financial corporations with employees, consistent with the definition of category S11 in the European System of Accounts (i.e., excluding sole proprietors). Table C1 below provides an overview of the country coverage and characteristics of the data employed in this paper.

**Table C1. CompNet data coverage**

Country	Exclusion rule?	Coverage <i>vis-a-vis</i> population of firms <sup>(1)</sup>		Coverage <i>vis-a-vis</i> national accounts <sup>(2)</sup>		Time and sector coverage	
		No. of firms	Employment	VA	Employment	Sample period	Sectors excluded (deviations from default)
Belgium	none	31%	76%	49%	39%	1996-2010	none
France	turnover >750,000€	7%	58%	42%	34%	1995-2012	Tobacco products
Germany	firms applying for a rating	3%	41%	32%	20%	1997-2012	Tobacco products, accommodation services, food and beverage services, information services, real estate services, veterinary services, administrative and support services
Italy	LLCs with employees	10%	53%	27%	30%	2001-2012	none
Spain	none	19%	47%	25%	32%	1995-2012	none

Notes: (1) OECD, Structural Business Statistics; 2004-2007 averages. (2) Eurostat, national accounts; coverage computed for 2005.

In order to deal with differences in cross-country data coverage, indicators were collected considering two different samples of firms: those with at least one employee (the “full” sample), and those with at least 20 employees (the “20E” sample). Due to the existence of exclusion rules in some countries, the 20E sample appears far more homogeneous and comparable across countries than the full sample. That is the reason why the main analysis is done using the 20E sample in this paper. Furthermore, the 20E samples are weighted so they are representative of the population of firms in terms of sector and size distribution.

In order to compute the dispersion in marginal productivity of inputs used in this paper as a proxy for input misallocation, we first estimate a Cobb-Douglas production function *à la* Levinsohn-Petrin-Wooldridge pooling all firms operating in a given country and 2-digit industry (according to NACE rev. 2) over the period of analysis. This methodology tackles the simultaneity bias emerging from the fact that the firm observes productivity and then chooses the amount of inputs to produce; that is, the choice of labour and capital depends on the unobserved (for the econometrician) productivity shock. To see the problem, consider the following Cobb-Douglas production function:

$$(C1) Y_{it} = A_{it} K_{it}^{\beta_K} L_{it}^{\beta_L}$$

where  $Y_{it}$  is value added of firm  $i$  at time  $t$ ,  $K$  and  $L$  are the two production inputs and  $A$  is the Hicksian neutral efficiency level of the firm.  $Y$ ,  $L$  and  $K$  are econometrically observed whereas  $A$  is not, although it is known by the firm.

Taking equation C1 in logs:

$$(C2) y_{it} = \beta_0 + \beta_k k_{it} + \beta_L l_{it} + \omega_{it} + u_{it}$$

$$\text{where } \ln(A_{it}) = \beta_0 + \omega_{it} + u_{it}$$

with  $\beta_0$  representing the mean-efficient level across firms and over time and  $\omega_{it} + u_{it}$  is a firm-specific deviation from that mean. The first component refers to an unobserved firm-level time-variant productivity level, known by the firm, and the second component is an i.i.d error term representing unexpected (by the firm) shocks, and therefore independent of the rest of explanatory variables. Equation C2 could be consistently estimated by OLS only if firm's variable input choices are independent of the unobserved shocks, including firm-level productivity. That is very unlikely to be the case since productivity is observed by the firm and therefore it will influence the choice of the optimal bundle of inputs. If this endogeneity issue is ignored, the technology coefficients of labour and materials will be upward biased. If labour is the only freely available input and capital being quasi-fixed (Levinsohn and Petrin 2003), the technology coefficient of capital will be downward biased.

One of the solutions provided for solving this problem was introduced by Olley and Pakes (1996), who proposed to use observed input choices to instrument for unobserved productivity. Although their initial choice was to use investment, Levinsohn and Petrin (2003) noted that the strict monotonicity of the investment function, with respect to productivity and capital, was broken given the many zeroes reported by firms. Hence they proposed as an alternative solution to proxy productivity with material inputs demand, that is  $m_{it} = h(k_{it}, \omega_{it})$ , which can be claimed to be strictly increasing in productivity and, therefore, can be inverted out to factor productivity. Moreover, there are few missing or zero observations in variables such as energy or some other intermediate input consumption at the firm level. Finally, Wooldridge (2009) implemented this approach in a GMM framework which can deliver more efficient estimators.

Having estimated the production function, where the real stock of capital is defined as the book value of fixed tangible assets deflated with the GDP deflator and labour as the full-time-equivalent average number of employees in year  $t$ , the firm-level marginal productivity of each input is then computed as the product of the respective input coefficient and the average productivity of the input. Indeed, the marginal productivity revenue of capital (MRPK) is equal to:

$$(C3) \text{MRPK}_i = \beta_k \frac{Y_i}{K_i}$$

and the marginal productivity revenue of labour (MRPL) is equal to:

$$(C4) \text{MRPL}_i = \beta_L \frac{Y_i}{L_i}$$

Next, we purge the time variation of the marginal productivity of the input at the firm level from developments common to all firms in the 2-digit industry (driven by price dynamics or technology improvements for example). After de-trending the firm-level MRPK and MRPL we compute the within-industry (defined at the 2-digit level) standard deviation of MRPK and MRPL. Lastly, we aggregate to the macro-sector level by taking the median dispersion across all 2-digit industries in each macro-sector.

## Annex D. Additional descriptive evidence on input misallocation

An issue to investigate is whether capital and labour misallocation are independent or vary jointly, possibly owing to common determinants. This preliminary analysis justifies the analysis of these two sources of input misallocation separately or combined. A simple correlation analysis provided in Table D1, referred to countries (left hand side panel) and to sectors (right hand side panel), suggests that the contemporaneous yearly growth rates of the two kinds of misallocation are generally positively correlated, although links are below 0.6 and negative in several cases before 2007. There is evidence of an increase in the correlation during the Great Recession across all countries and sectors (with the exception of the information and communication sector, the administrative support service, and the professional activities sectors). In conclusion, the low correlations between the two types of input misallocation suggest the usefulness of considering them separately in an empirical analysis of their determinants.

**Table D1. Correlation between changes in MRPL and MRPK dispersions...**

...by country

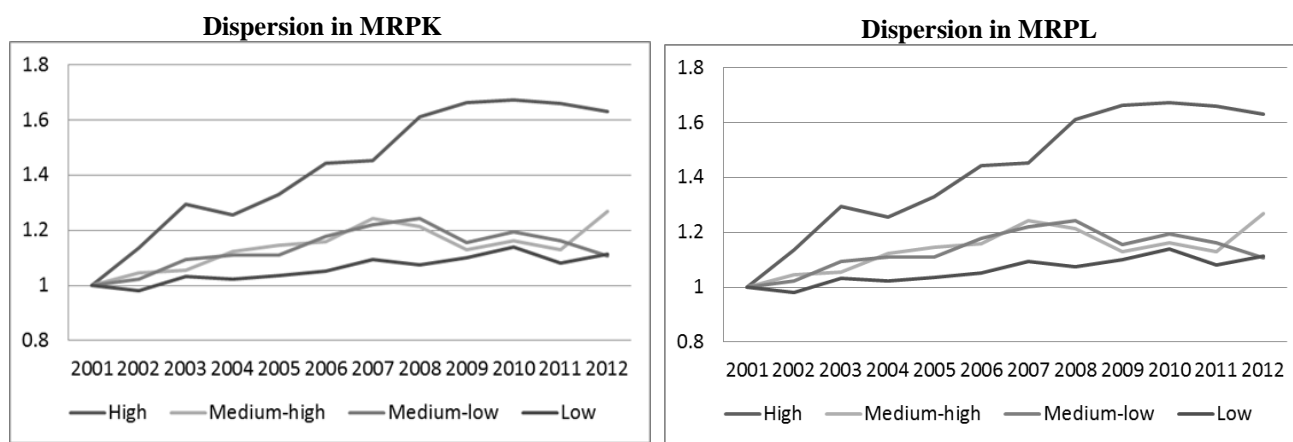
...by sector

		Correlation between MRPL and MRPK dispersions in growth rates
<b>Belgium</b>	2002-2007	-0.17
	2008-2010	-0.02
<b>France</b>	2002-2007	0.60
	2008-2012	0.96
<b>Germany</b>	2002-2007	-0.39
	2008-2012	0.92
<b>Italy</b>	2002-2007	0.48
	2008-2012	0.49
<b>Spain</b>	2002-2007	-0.09
	2008-2012	0.40
		<b>Correlation between MRPL and MRPK dispersions in growth rates</b>
<b>Manufacturing</b>		
2002-2007		-0.54
2008-2010		0.87
<b>Construction</b>		
2002-2007		0.18
2008-2012		0.38
<b>Wholesale and retail trade</b>		
2002-2007		-0.59
2008-2012		0.16
<b>Transportation and storage</b>		
2002-2007		-0.79
2008-2012		0.10
<b>Accommodation and food</b>		
2002-2007		0.21
2008-2012		0.44
<b>Information and communication</b>		
2002-2007		0.13
2008-2012		-0.67
<b>Professional, scientific and technical activities</b>		
2002-2007		0.26
2008-2012		0.12
<b>Administrative and support service activities</b>		
2002-2007		-0.29
2008-2012		-0.48

Source: Authors' calculations on CompNet data.

In order to investigate differentiated dynamics of input misallocation within the broadly defined manufacturing sector,<sup>38</sup> Figure D1 reports developments in average MRPL and MRPK dispersion in four groups of manufacturing branches, grouped according to their degree of technological intensity on the basis of the definition provided by Eurostat: high, medium-high, medium-low and low.<sup>39</sup> The upward trend in MRPK dispersion, and to a lesser extent in MRPL dispersion, is most evident in high-technology manufacturing industries, and least evident in low-technology sectors. In Section 3 we observed that the ICT sector displayed the clearest upward trend, at least regarding capital misallocation, too. This is consistent with the importance of credit access (these industries are most dependent on external finance) and of regulation given that high-technology high-risky industries might need to expand or downsize quickly after a radical innovation and are therefore more exposed to restrictive product and labour market regulations.

**Figure D1. Developments in the dispersion in MRPK and in MRPL within manufacturing**  
(2001=1)



Source: Author's calculations on CompNet data.

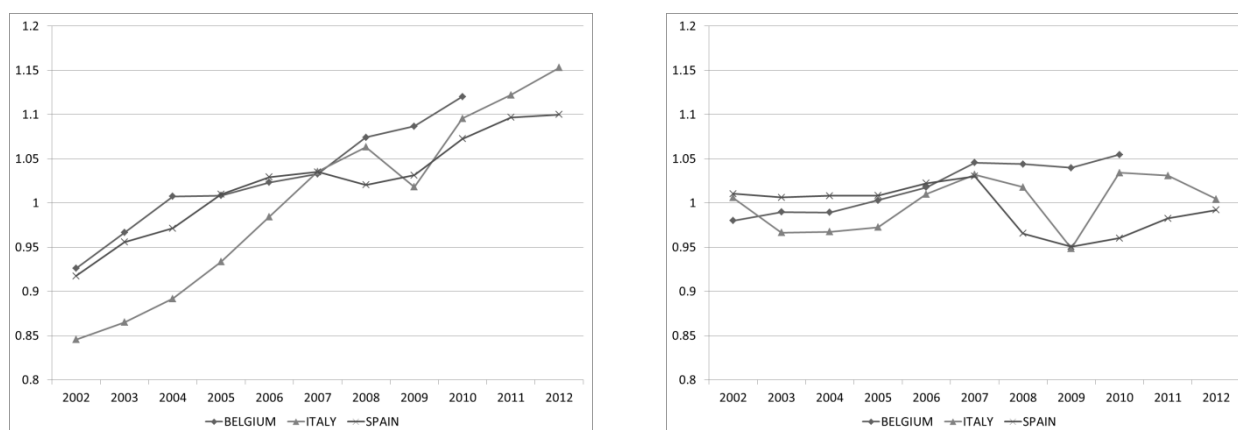
Note: Weighted averages, according to the branch-specific share in manufacturing value added, of MRPL and MRPK dispersion in each two-digit industry; then unweighted averages across the countries under analysis.

The paper has thus far focused on a sample of firms with more than 20 employees in order to include five countries in the analysis. Concerns around our results may stem from the large share of small firms in some of the countries considered, such as Italy and Spain, that are not captured when using the restricted sample. In order to address this concern, we check the robustness of our results by also considering the full sample for the countries for which these data are available (Belgium, Italy and Spain), as well as using Amadeus data (for a benchmark country-sector, in this case Spanish manufacturing). The main developments described in Section 3.2 are confirmed in Figures D2 and D3.

<sup>38</sup> Note that the CompNet database provides in addition to the de-trended one-digit industry aggregation of dispersion the full distribution and the standard deviation of the "raw or non de-trended" measures of dispersion in MRPK and MRPL in each two-digit industry, which is what we show here. The correlation between the de-trended and the raw data series, aggregated at the one-digit industry level, are quite similar (series available upon request).

<sup>39</sup> In particular, see [http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech\\_classification\\_of\\_manufacturing\\_industries](http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech_classification_of_manufacturing_industries).

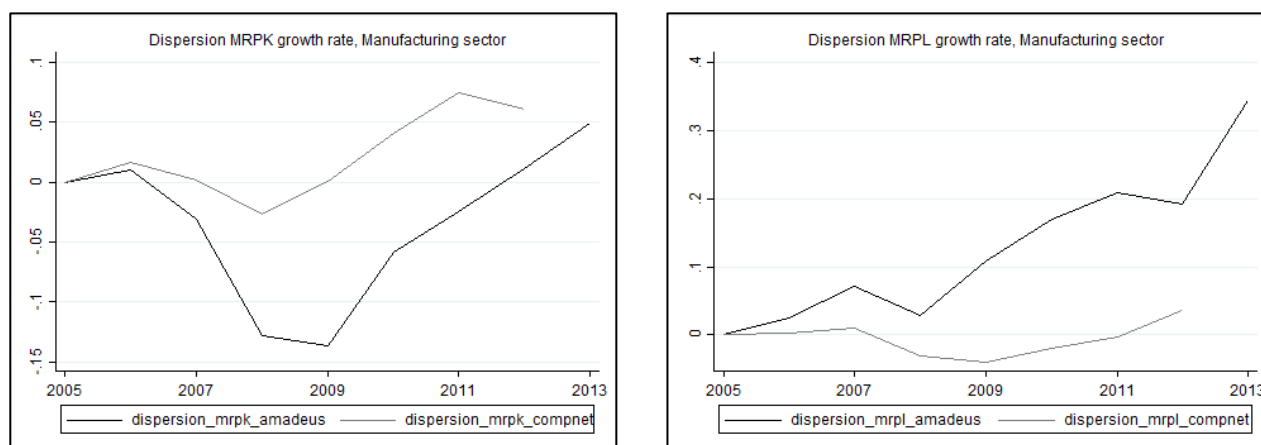
**Figure D2. Average dispersion in MRPK and MRPL**  
(full sample data; weighted averages)



Source: Authors' calculations based on CompNet data.

Notes: Weighted averages, where the weights are the country-specific sectorial value added shares. The value added series for Belgium ends in 2010.

**Figure D3. Comparison of trends in MRPK and MRPL dispersion in manufacturing in Spain based on CompNet and Amadeus data**  
(full sample)



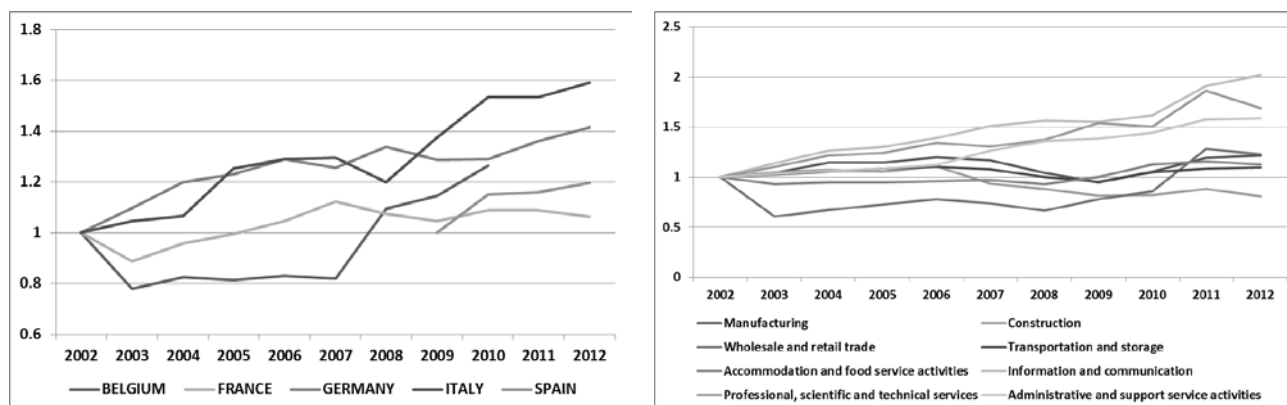
Source: Authors' calculations based on Compnet and Amadeus data.

Lastly, we have computed the average absolute wedge between the marginal productivity of capital and its marginal cost, as suggested by Petrin and Sivadasan (2013) in each macro sector and country on the 20E CompNet data. However, given data constraints some *caveats* of our approximation must be kept in mind. First, we do not have firm-level prices (nor can we use the production function residual as Petrin and Sivadasan 2013 do) to retrieve the nominal value of the marginal productivity of the input at the firm level, hence we opt for expressing the marginal productivity and the marginal cost in real terms, using the corresponding industry deflator. Second, we do not have information on the marginal cost of capital so we approximate it with the average implicit interest rate paid by the firm on its stock of debt (total interest payments divided by stock of debt) and third, we do not have the marginal productivity of the input and its average cost at the firm level but rather the median across firms in a given size class (five size classes in total) operating in the sector. We therefore assume that there are five representative firms (one in each size class) in each sector, compute their wedges in absolute terms and then average them.

Despite the fact that this is a quite imperfect approximation, Figure D4 below shows that capital misallocation (as measured by the wedge) has been increasing over time in all countries and that this trend is driven by services, which are the main stylized facts uncovered using Hsieh and Klenow's (2009) indicator of input misallocation.



**Figure D4. Country and sector trends in the average absolute wedge of marginal productivity and marginal cost of capital**  
(2002=1)



Source: Authors' calculations based on Compnet data.

Note: There are no data on the marginal cost of capital for Spain prior to 2008.

## Annex E. The impact of labour and capital misallocation on TFP growth: a counterfactual exercise

Based on the model presented in Section 2 and Annex B, we can gauge the hypothetical impact of the observed changes in either capital or labour misallocation on aggregate TFP growth in each country, assuming all things equal. In the vein of Gopinath et al. (2015), we first assume that the only driver of TFP growth is a change in the dispersion of MRPK (i.e. labour misallocation is assumed to remain constant), resulting from a change in  $(1 + \tau_{ist}^k)$  in equation C2. Then it can be shown that:

$$(E1) \Delta \log(TFP^K) = -(\alpha(\sigma\alpha + 1 - \alpha)/2)\Delta Var(\log MRPK_{ist})$$

Similarly, assuming that only changes in the dispersion in MRPL ( $1/(1 + \tau_{ist}^y)$ ) affect TFP growth, then:

$$(E2) \Delta \log(TFP^L) = -\left(\frac{(1-\alpha)(\sigma(1-\alpha)+\alpha)}{2}\right)\Delta Var(\log MRPL_{ist})$$

Finally, in order to compute changes in aggregate TFP in each country, we weight sectorial dispersions in marginal productivity of inputs by their share in value added.<sup>40</sup>

In order to compute the hypothetical changes in TFP stemming from those in input misallocation, considered one at a time, assumptions need to be made concerning the capital share  $\alpha$  (and the labour share, obtained as its complement to 1) and the elasticity of substitution across goods  $\sigma$  in equations E1 and E2. The existing literature mainly adopts fixed parameters equal to 0.35 and 3, respectively. These assumptions, however, disregard any possible country and/or sector variation. In order to overcome these limitations, we consider three alternative possibilities for the case of input shares: actual shares from the CompNet database,<sup>41</sup> actual shares from Eurostat national account data,<sup>42</sup> and input shares from the U.S., as derived from the U.S. Census Bureau, considered an exogenous benchmark. The two first alternatives allow for country and sector differences whereas the third one allows only for sector variation. Concerning elasticities of substitution, we derive sectorial and country-specific estimates from the sectorial and country-specific mark-up estimates in Christodopolou and Vermeulen (2012), as in Dias, Robalo Marques and Richmond (2014) and Garcia-Santana et al. (2015). We also derive estimates on the basis of U.S. sectorial mark-ups from the same dataset. We therefore consider twelve possible combinations of input shares and elasticity of substitution parameters.

These counterfactuals do not allow for measurement error or model misspecification. However, similarly to Garcia-Santana et al (2015), by focusing in the changes in hypothetical TFP

<sup>40</sup> CompNet provides data on the standard deviations and means of the marginal revenue products (in levels). To obtain the variance of the log (rather than the level) of MRPK and MRPL, we apply an approximation based on a Taylor expansion for a normal distributed variable according to which  $Var(\log X) = \frac{\sigma_X^2}{\mu_X^2}$ . This transformation is however valid only for variables with a small coefficient of variation (i.e. the ratio of the mean to the standard error). This assumption holds for the MRPL while variations in MRPK are large at times. Therefore, the results presented in this annex should be seen as rough approximation, especially in the case of changes in the MRPK dispersion.

<sup>41</sup> In this case, capital and labour shares do not necessarily sum up to one, as returns on scale are not assumed to be constant. As it is the case in all firm-level datasets relying on accounting information, capital shares estimated in CompNet are very small because capital is recorded at book value, or acquisition value, which does not reflect the amount of capital actually used in production. Moreover, capital book values taken from firms' balance sheets include different generations of capital (past investments) valued at different (historical) prices, so some comparability issues across firms may be expected. This measurement error in capital leads to downward biased capital shares, very often close to zero. In the CompNet dataset, production functions are estimated at the 2-digit as well as at the 1-digit industry levels. If the input coefficient estimated at the 2-digit level turned out not significantly different from zero, the coefficient of the macro-sector where the industry belonged was used instead.

<sup>42</sup> We average input shares over time when the national account data is considered in order to make them comparable to the CompNet estimates (which are averages over the analysis period). Moreover, we computed the share of total labour compensation in value added, and derived the capital share as its complement to one.

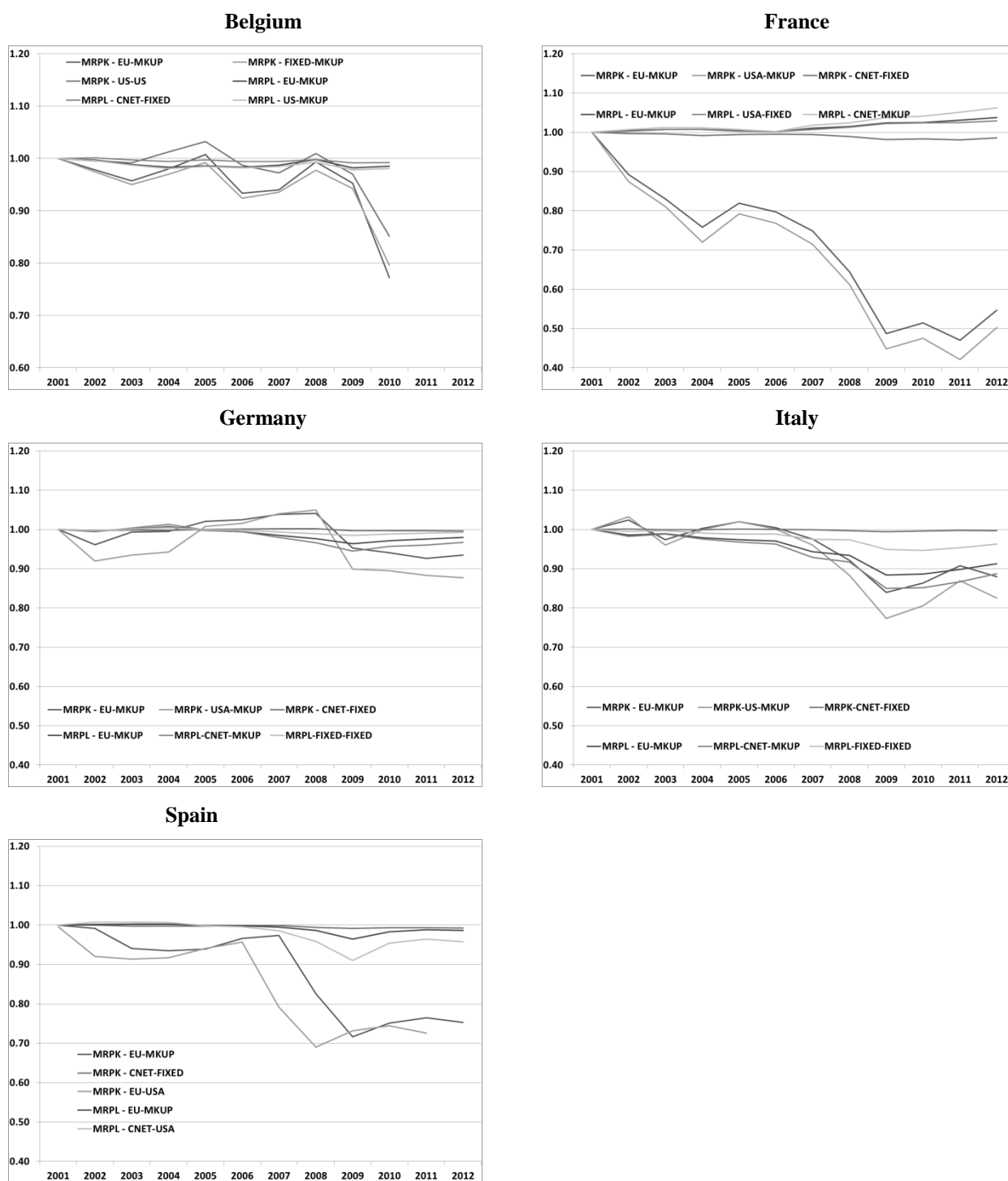
since 2001, and not on the levels, the only required assumption is that measurement error and model misspecifications do not vary over time, which we believe to be not too restrictive.

Our baseline exercise is conducted with input shares derived from Eurostat national accounts and elasticities of substitution based on estimated mark-ups in Christodopolou and Vermeulen (2012). This choice allows for differences in the parameters across countries and sectors. Furthermore, we also plot the country-specific minimum and maximum changes in TFP, obtained by adopting alternative parameter values, to get an idea of the confidence interval around our baseline estimates. We further aggregate the marginal revenue products of inputs at the country level using value added weights for the year 2006, a mid-point year in our analysis. This ensures that the weights reflect the specific structure of the economy while guaranteeing that the variation of TFP growth is driven only by changes in the dispersion in MPRK and MPRL and not by structural changes of the economy.<sup>43</sup>

Various results can be drawn from Figure E1. First, the observed changes in capital misallocation over the period considered have had a dampening effect on TFP growth in most cases. Generally, the dispersion in MRPK is the main drag on counterfactual TFP growth, producing in France (where the impact was the greatest) under the baseline scenario a cumulative decline over the entire 2001-2012 period of around 50 per cent. TFP losses were of a relevant magnitude also in Spain, Belgium and Italy, whereas they were contained in Germany. These results suggest that the potential TFP gains from a more efficient allocation of capital are large. Secondly, gains stemming from labour reallocation appear limited. This again seems to be a general finding for all countries under study. Third, the hypothetical TFP gains here reported are very sensitive to the choice of parameters, and the reported ranges (i.e. the difference between the maximum and minimum TFP estimates) are all but negligible. The max-min difference is, however, much smaller in the case of changes in labour misallocation when compared to capital. This is mostly due to the smaller observed changes in MRPL dispersion. Under the fixed-parameter scenario, for example, changes in MRPK led to a cumulative loss in TFP growth of about 20 per cent in France. Employing fixed values for capital shares and elasticity of substitution as done in most of the literature might lead to underestimating TFP losses stemming from misallocation.

<sup>43</sup> Similar results to those here presented are anyhow found when the actual time-varying weights are employed.

**Figure E1. Hypothetical changes in TFP growth**  
(TFP levels normalised to 1 in 2001)



Source: Authors' calculations based on CompNet, Eurostat, Bureau of Economic Analysis, Christopoulou and Vermeulen (2012) data.

Notes: The input shares can be defined as FIXED (0.35), CNET (CompNet source), EU (Eurostat source) and USA (USA shares); the elasticity of substitution can be defined as FIXED (3), MKUP (derived from mark-ups in Christopoulou and Vermeulen 2012) and USA (derived from U.S. mark-ups in Christopoulou and Vermeulen 2012). See text for further details.

## Annex F – Additional information on the determinants of changes in input misallocation

### Table F1. Explanatory variables-- definitions and sources

Final sector-level variables	Total economy-level variables	Sector-level indicators
<i>1. Cyclical conditions</i>		
<p><b>Average real turnover</b> across firms within sectors. Source: ECB CompNet database.</p> <p><b>Demand uncertainty.</b> It is a measure of disagreement across firms concerning their economic outlook. Source: calculations on the European Commission Business Survey data using the methodology described in Busetti, Giordano and Zevi (2016).</p> <p><b>Disagreement across professional forecasters (alternative indicator).</b> It is proxied by the standard deviation and by the interquartile range across GDP growth forecasts. Source: Authors' calculations on Consensus Economics.</p>		
<i>2. Regulation</i>		
<p><b>Sectorial PMR</b> is constructed by interacting the following total-economy and sectorial variables.</p> <p><b>Median profit margins</b> across firms within sectors (<b>alternative indicator</b>). Source: ECB CompNet database.</p> <p><b>Sectorial EPL</b> is constructed by interacting the following total-economy and sectorial variables.</p> <p><b>Sectorial EPL (alternative indicator)</b> is constructed by interacting the following total-economy and sectorial variables.</p>	<p><b>Product market regulation indicator.</b> Available years are interpolated using the Regulatory Impact Indicator. Source: calculations on OECD data.</p> <p><b>Employment protection legislation sub-indicator for temporary employment</b> which measures the strictness of regulation on the use of fixed-term and temporary work agency contracts. Source: OECD.</p> <p><b>Employment protection legislation sub-indicator of dismissals</b> which measures the strictness of employment protection considering individual and collective dismissals (regular contracts). Source: OECD.</p>	<p><b>U.S. business entry rate (average 2002-2007)</b> is defined as the number of firm establishments at time t divided by the average of firm establishments at t and t-1. Source: Census Bureau's Longitudinal Business Database.</p> <p><b>U.S. job creation rate (average 2002-2007)</b> is constructed as <math>100 * (\text{job\_creation} / \text{denom})</math>. Job_creation is the count of all U.S. jobs created within the sector every year. Denom is the Davis, Haltiwanger and Schuh (1996) denominator: for time t, it is the average of U.S. employment in t and t-1. This denominator attempts to prevent transitory shocks from creating a bias to the relationship between net growth from t-1 to t and size. Source: Census Bureau's Longitudinal Business Database.</p> <p>See above.</p>
<i>3. Credit constraints</i>		
<p><b>Sectorial cost of credit</b> is constructed by interacting the following total-economy and sectorial variables.</p> <p><b>Sectorial credit standards (alternative indicator)</b> are constructed by interacting the following total-economy and sectorial variables.</p>	<p><b>Interest rate on bank loans to firms.</b> Source: ECB.</p> <p><b>Diffusion indices of the questions on average loan size, maturity, collateral requirements and non-interest charges credit standards,</b> and the first component of a principal component analysis. Source: calculations on the ECB Bank Lending Survey data.</p>	<p><b>External financial dependence</b> is the average median from 2002 to 2007 of <math>(\text{capital expenditure} - \text{cash from operations}) / \text{capital expenditure}</math>. Source: Calculations on S&amp;P IQ Capital data using the methodology described in Rajan and Zingales (1998).</p> <p>See above.</p>

### Table F2. Percentage share of the variance of the mentioned variables explained by industry and time dummies

	Job-creation rate	Firm entry rate
Industry dummies	55.7	58.7
Time dummies	37.6	34.7
<i>Total explained variance</i>	93.2	93.5
<i>Number of observations</i>	88	88

Source: Authors' calculations on Census Bureau's Longitudinal Business Database.

## Annex G. Robustness checks

**Table G1. Regression results: baseline regressions with year fixed effects**

	MRPK				MRPL		
Changes in real turnover (t/t-1)	0.099** (0.04)	0.096** (0.04)	0.098** (0.04)	0.095** (0.04)	0.066** (0.03)	0.066** (0.03)	0.065** (0.03)
Demand uncertainty (t-1)	0.211** (0.01)	0.208** (0.01)	0.219** (0.01)	0.215** (0.01)	0.025 (0.06)	0.026 (0.07)	
Changes in cost of credit (t/t-1)	0.192 (0.28)	0.176 (0.28)					
Changes in credit standards PCA (t/t-1)			0.173* (0.09)	0.164* (0.09)			
Change in PMR (t/t-1)	0.145 (0.01)	0.135 (0.01)	0.14 (0.01)	0.131 (0.01)	0.124* (0.07)	0.139** (0.07)	0.110* (0.07)
Change in EPL (t/t-1)		-0.119 (0.08)		-0.11 (0.08)	-0.038 (0.04)	0.031 (0.06)	0.064 (0.06)
Changes in PMR (t/t-1)* Changes in EPL (t/t-1)						2.303* (1.38)	3.107** (1.4)
Dispersion in MRPK in 2002 (ln)	-0.091 (0.07)	-0.092 (0.06)	-0.09 (0.06)	-0.092 (0.06)			
Dispersion in MRPL in 2002 (ln)					-0.093 (0.08)	-0.095 (0.08)	
YEAR FIXED EFFECTS							
2005	-0.005 (0.02)	0 (0.02)	0.002 (0.02)	0.006 (0.02)	0.007 (0.01)	0.006 (0.01)	0.009 (0.01)
2006	0.025 (0.02)	0.031 (0.02)	0.033 (0.02)	0.038* (0.02)	0.025** (0.01)	0.024** (0.01)	0.020* (0.01)
2007	-0.017 (0.02)	-0.011 (0.02)	-0.005 (0.02)	-0.001 (0.02)	0.013 (0.01)	0.012 (0.01)	0.013 (0.01)
2008	0.003 (0.02)	0.009 (0.02)	-0.004 (0.02)	0.002 (0.02)	-0.023** (0.01)	-0.025** (0.01)	-0.034*** (0.01)
2009	-0.039 (0.02)	-0.034 (0.02)	-0.059** (0.02)	-0.053** (0.02)	-0.031** (0.01)	-0.032** (0.01)	-0.030*** (0.01)
2010	-0.005 (0.02)	0.001 (0.02)	-0.004 (0.02)	0.002 (0.02)	0.016 (0.01)	0.015 (0.01)	0.018 (0.01)
2011	-0.024 (0.02)	-0.023 (0.02)	-0.016 (0.02)	-0.015 (0.02)	-0.008 (0.01)	-0.014 (0.01)	-0.014 (0.01)
2012	-0.022 (0.02)	-0.014 (0.02)	-0.025 (0.02)	-0.017 (0.02)	-0.024** (0.01)	-0.025** (0.01)	-0.022** (0.01)
constant	-0.101* (0.06)	-0.104* (0.06)	-0.103* (0.06)	-0.106* (0.06)	-0.003 (0.04)	0.003 (0.04)	0.026** (0.01)
R2	0.121	0.123	0.129	0.13	0.164	0.167	0.179
N	283	283	283	283	307	307	351
* p<0.10, ** p<0.05, *** p<0.01							
Country and sector fixed effects included but not reported							

Notes: Estimates are obtained via OLS with White's correction for heteroskedasticity (standard errors are reported in brackets). See footnotes 11 and 12 concerning the number of observations in our dataset; moreover, the number of observations drop when the cost of credit is included in our sample, as it is unavailable for the first year of our sample, and when demand uncertainty is included, since this variable is missing in the initial years for some countries.

**Table G2. Regression results: lagged (in lieu of initial) misallocation**

Dependent variable: Change in dispersion	MRPK		MRPL	
	(1)	(2)	(3)	(4)
Changes in average real turnover (t/t-1)	0.110*** 0.04	0.114*** 0.04	0.079*** 0.03	0.086*** 0.03
Demand uncertainty (t-1)	0.198** 0.09	0.204** 0.09	0.08 0.06	
Changes in the cost of credit (t/t-1)	0.336** 0.15	0.348** 0.15	0.142 0.11	
Changes in PMR (t/t-1)	0.196** 0.1	0.194** 0.1	0.192*** 0.06	0.177*** 0.06
Changes in EPL (t/t-1)	-0.105 0.07		0.126** 0.05	0.119** 0.05
crisis	0.012 0.01	0.011 0.01	-0.020*** 0.01	-0.025*** 0.01
Changes in EPL (t/t-1)*Changes in PMR (t/t-1)			3.418*** 1.08	3.453*** 1.06
Dispersion in lag MRPK (ln)	-0.306*** 0.06	-0.303*** 0.06		
Dispersion in lag MRPL (ln)			-0.380*** 0.06	-0.306*** 0.05
constant	-0.085* 0.05	-0.088* 0.05	0.014 0.03	0.047*** 0.01
r2_a	0.238	0.236	0.282	0.249
N	283	283	283	351

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01

Country and sector fixed effects included but not reported

Notes: Estimates are obtained via OLS with White's correction for heteroskedasticity (standard errors are reported in small font). See footnotes 11 and 12 concerning the number of observations in our dataset; moreover, the number of observations drops when demand uncertainty is included, since this variable is missing in the initial years for some countries.

**Table G3. Regression results: replacing country fixed effects  
with time-variant country variables**

	<b>MRPK</b>	<b>MRPL</b>	
Changes in average real turnover (t/t-1)	0.120*** 0.04	0.091*** 0.03	0.094*** 0.04
Demand uncertainty (t-1)	0.167* 0.09	0.065 0.06	0.045 0.06
Changes in the cost of credit (t/t-1)	0.377** 0.16	0.092 0.13	0.08 0.13
Changes in PMR (t/t-1)	0.148 0.1	0.197*** 0.08	0.209*** 0.08
Changes in EPL (t/t-1)		0.065 0.07	0.129 0.08
Changes in EPL (t/t-1)*Changes in PMR (t/t-1)		2.732** 1.26	3.518*** 1.33
crisis	-0.006 0.01	-0.034*** 0.01	-0.035*** 0.01
Cost of credit	0 0.01	-0.009** 0	-0.010** 0
PMR	0.068 0.05	-0.006 0.03	0.127 0.08
EPL		-0.003 0	0.087 0.05
EPL*PMR			-0.060* 0.04
Ln MRPK 2002	-0.134** 0.06		
Ln MRPL 2002		-0.130* 0.07	-0.125* 0.07
constant	-0.192** 0.08	0.052 0.05	-0.125 0.12
r2_a	0.106	0.148	0.153
N	283	283	283
* p<0.10, ** p<0.05, *** p<0.01			

Notes: Estimates are obtained via OLS with White's correction for heteroskedasticity (standard errors are reported in brackets).

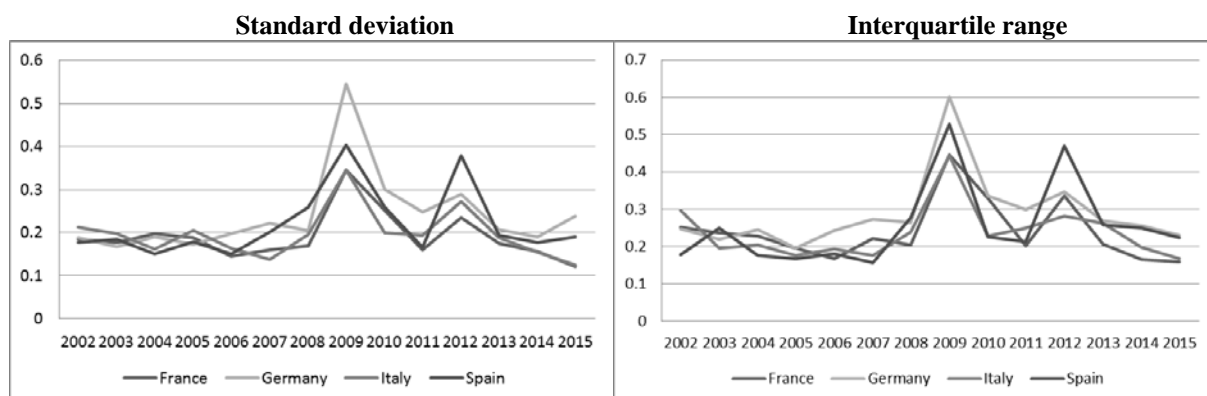


**Table G4. Regression results: OP gap as dependent variables**

<b>OP Gap</b>	<b>eq 1</b>	<b>eq2</b>
Changes in average real turnover (t/t-1)	-0.013 0.05	-0.006 0.05
Changes in the cost of credit (t/t-1)	-0.062 0.13	-0.019 0.13
Demand uncertainty (t-1)	-0.298*** 0.08	-0.292*** 0.08
Changes in PMR (t/t-1)	-0.075 0.12	-0.112 0.12
Changes in EPL (t/t-1)	-0.035 0.09	-0.134 0.11
crisis	0.005 0.01	0.008 0.01
Changes in EPL (t/t-1)*Changes in PMR (t/t-1)		-3.683 2.71
constant	0.341*** 0.05	0.335*** 0.05
r2_a	0.618	0.618
N	290	290
* p<0.10, ** p<0.05, *** p<0.01		
Country and sector fixed effects included but not reported		

Notes: Estimates are obtained via OLS with White's correction for heteroskedasticity (standard errors are reported in small font). See footnotes 13 and 14 concerning the number of observations in our dataset.

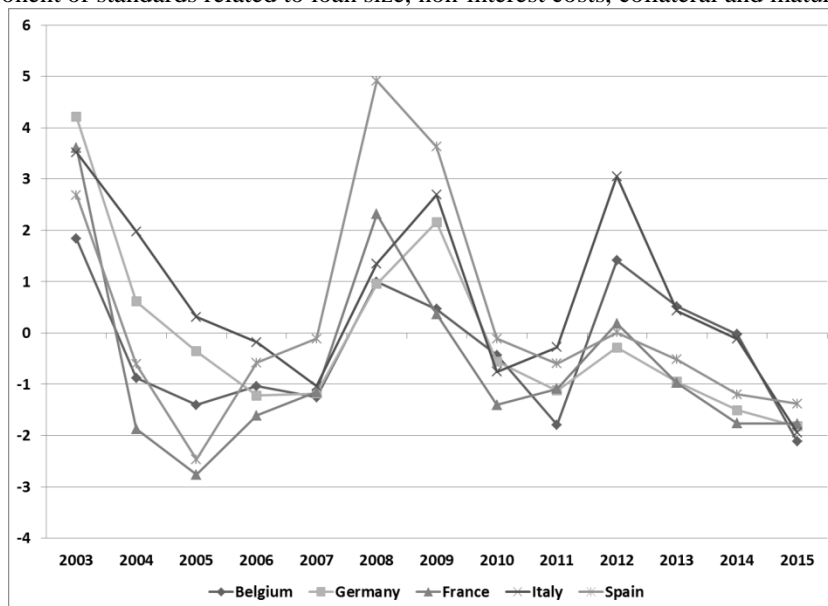
**Figure G1. Uncertainty proxied by disagreement across GDP forecasts**



Source: Authors' calculations on Consensus Economics data.

### Figure G2. Evolution of the stringency in credit standards

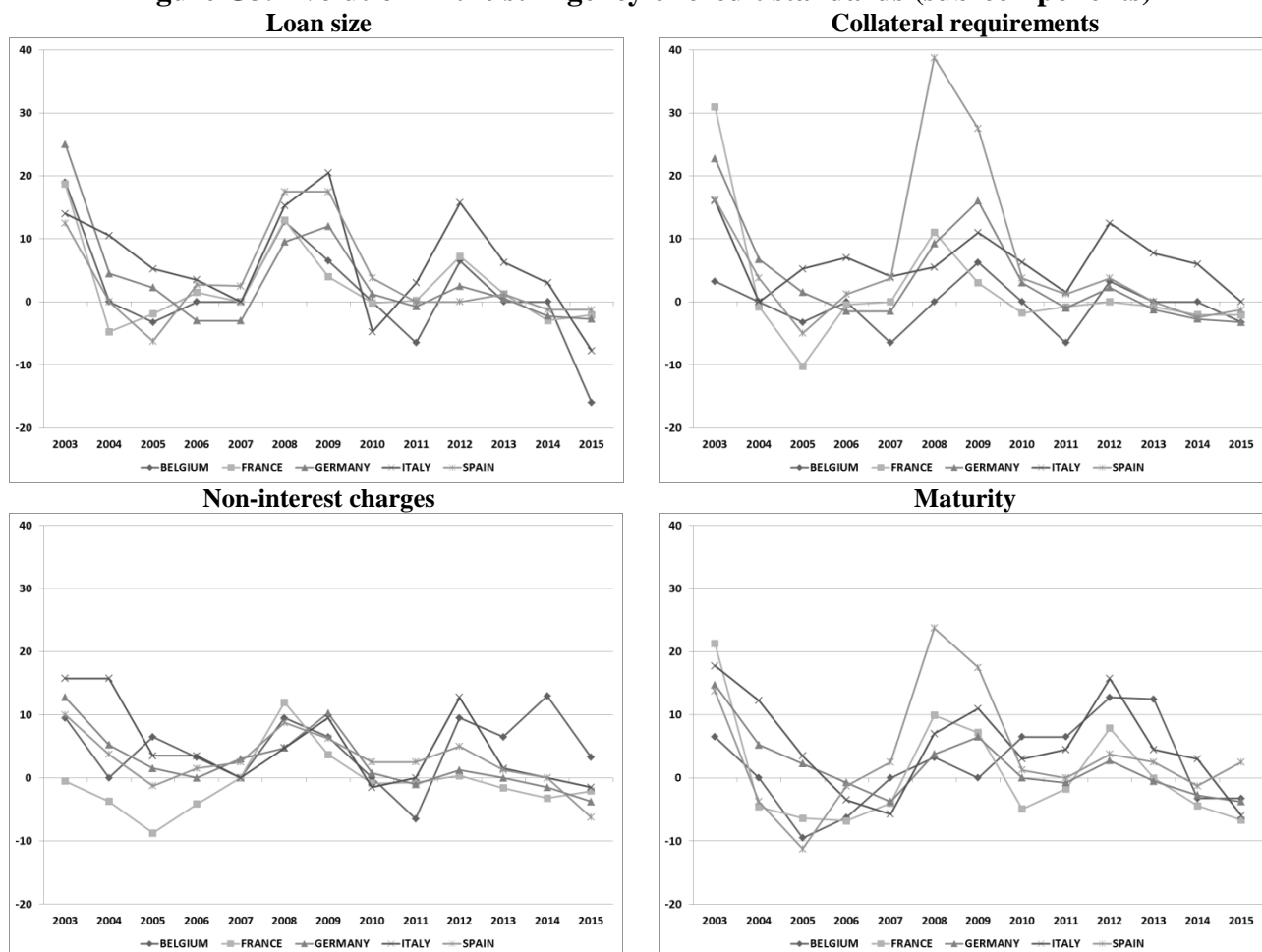
(principal component of standards related to loan size, non-interest costs, collateral and maturity requirements)



Source: Authors' calculations based on Bank Lending Survey data.

Notes: The lines are the first component of a principal component analysis conducted on four questions of the Bank Lending Survey. A rise in the series indicates a tightening of credit standards. See text for further details.

**Figure G3. Evolution in the stringency of credit standards (sub-components)**



Source: Authors' calculations based on Bank Lending Survey data.

In a last robustness check we have also considered the possibility that using U.S. sectorial weights does not allow the correct measurement of the technological characteristics that determine the industry-specific degree of exposure to regulation or the need for external finance. Ciccone and Papaioannou (2010) indeed caution against using a benchmark country to derive exposure indices, in that if there is an idiosyncratic component that differentiates the benchmark country's exposure to the frictionless exposure, then regressions including the interacted variables may lead to biased results (both an attenuation and an amplification bias are possible). The authors therefore suggest running auxiliary regressions on actual country-specific sectorial exposure rates to derive the frictionless exposure. Owing to data availability, we were able to construct sectorial exposure indicators only to gauge the impact of credit standards. In particular, a sector with a higher capital-to-labour ratio presumably requires more funding, and therefore, external finance than a more labour-intensive sector. This sector is also more intensely affected by credit constraints as a result. We were able to build sectorial capital-intensity measures, on the basis of Eurostat data, for all countries except Spain. Following Ciccone and Papaioannou (2010) and the applications in Barone and Cingano (2011) and Haltiwanger, Scarpetta and Schweiger (2014), first we regressed the country-industry capital intensities on country dummies, industry dummies and industry dummies interacted with the country-level credit standards to estimate the marginal effect of credit standards on industry dependence:

$$(G1) \text{ kintensity}_{j,c} = \mu_j + \mu_c + \delta_j X_c + \varepsilon_{j,c}$$

In this regression the country with the loosest credit standards (France, as seen in Figure G2) is excluded from the sample. Second we estimated the benchmark sectorial capital intensities as the fitted values of  $\text{kintensity}_{j,c}$  when country dummies are set to zero and when credit standards are those recorded in France. These benchmark capital intensities are thus purged of the impact of

credit constraints and of country specificities. Third, we used the interaction between the benchmark capital intensities and credit standards as an instrument for the similar variable based on the U.S. capital intensity in a two-stage least squares estimation procedure. The first-stage of the regressions confirms the significant positive relationship between the two sectorialized credit standards variable. Our baseline results of tighter credit conditions increasing capital misallocation are again confirmed, although the variable is not significant at the 10 per cent level, also due to the low number of observations in this exercise.<sup>44</sup>

<sup>44</sup> These results are available upon request.

## References

- Adalet McGowan, A., Andrews, D., Criscuolo, C. and Nicoletti, G. (2015), *The Future of Productivity*, OECD, Paris.
- Andrews, D. and Cingano, F. (2014), “Public policy and resource allocation: evidence from firms in OECD countries”, *Economic Policy* 29(78), pp. 253-296.
- Andrews, D., Criscuolo, C. and Menon, C. (2014), “Do resources flow to patenting firms? Cross-country evidence from firm-level data”, *OECD Working Papers* 23.
- Asker, J., Collard-Wexler, A. and De Loecker, J. (2014), “Dynamic Inputs and Resource (Mis)Allocation”, *Journal of Political Economy* 122(5), pp. 1013-1063.
- Aw, B., Chen, X. and Roberts, M. (1997), “Firm-level evidence on productivity differentials and turnover in Taiwanese manufacturing”, *Journal of Development Economics* 66(2001), pp. 51-83.
- Bachmann, R., Elstner, S., and Sims, E.R. (2014), “Uncertainty and economic activity: evidence from business survey data”, *American Economic Journal: Macroeconomics* 5(2), pp. 217–249.
- Baily, M., Hulten, C. and Campbell, D. (1992), “Productivity dynamics in manufacturing plants”, *Brooking Papers on Economic Activity, Microeconomics*, pp. 187-267.
- Banerjee, A.V., and Moll, B. (2010), "Why does misallocation persist?", *American Economic Journal: Macroeconomics* 2(1), pp. 189-206.
- Barone, G. and Cingano, F. (2011), “Service regulation and growth: evidence from OECD countries”, *The Economic Journal* 121(555), pp. 931-957.
- Barro, R.J. and Sala-i-Martin, X. (2004), “Economic Growth”, Second Edition, The MIT Press: Cambridge, MA.
- Bartelsman, E. J., Gautier, P. A. and de Wind, J. (2011), "Employment protection, technology choice, and worker allocation", *De Nederlandsche Bank Working Paper* 295.
- Bartelsman, E., Haltiwanger, J. and S. Scarpetta (2013): “Cross-Country Differences in Productivity: The Role of Allocation and Selection,” *American Economic Review* 103(1), pp. 305-34.
- Bartelsman, Lopez-Garcia and Presidente (2016): “Assessing the labour reallocation process in Europe: Productivity-enhancing or not?”, ECB mimeo.
- Bassanini, A., Nunziata, L. and Venn, D. (2009), “Job protection legislation and productivity growth in OECD countries”, *Economic Policy* 24(58), pp. 349-402.
- Basu, S. and Fernald, J. (1997), “Returns to Scale in U.S. Production: Estimates and Implications”, *Journal of Political Economy* 105(2), pp. 249-283.
- Bena, J. and Ondko, P. (2012), “Financial development and the allocation of external finance”, *Journal of Empirical Finance* 19(1), pp. 1-25.
- Berthou, A., Dhyne, E. and the CompNet trade module taskforce (2015), “Assessing European firms’ exports and productivity distributions: the CompNet trade module”, *ECB Working Paper* 1788.
- Blanchard, O. and Giavazzi, F. (2003), “Macroeconomic Effects of Regulation and Deregulation in Goods and Labor Markets”, *The Quarterly Journal of Economics*, August, pp. 879-907.
- Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten I., and Terry, S.J. (2014) “Really Uncertain Business Cycles”, Stanford University mimeo.
- Bloom, N., Kose, M.A. and Terrones, M.E. (2013), “Held back by uncertainty”, *Finance and Development* 50(1).
- Borio, C., Kharroubi, E., Upper, C. and Zampolli, F. (2015), “Labour reallocation and productivity dynamics: financial causes, real consequences”, *BIS Working Paper* 534.
- Broadberry, S.N., Giordano, C. and Zollino, F. (2013), “Productivity”, *The Oxford Handbook of the Italian Economy since Unification*, New York: Oxford University Press.

- Bulligan, G. and Emiliozzi, S. (2013), “Uncertainty and economic activity in Italy”, Banca d’Italia mimeo.
- Buseti, F., Giordano, C. and Zevi, G. (2016), “Drivers of Italy’s Investment Slump During the Double Recession”, *Italian Economic Journal*, doi 10.1007/s40797-016-0028-9.
- Caballero, R. and M. Hammour (1994), “The cleansing effect of recessions”, *American Economic Review* 84(5), pp. 1350-68.
- Calligaris, S. (2015), “Misallocation and Total Factor Productivity in Italy: Evidence from Firm-Level Data”, *Labour* 29(4), pp. 367–393.
- Christopoulou, R. and Vermeulen, P. (2012), “Markups in the Euro area and the U.S. over the period 1981-2004: a comparison of 50 sectors”, *Empirical Economics* 42(1), pp. 53-77.
- Ciccone, A. and Papaioannou, E. (2010), “Estimating cross-industry cross-country models using benchmark industry characteristics”, *CEPR Discussion Paper* 8056.
- Comin, D. and Hobijn, B. (2010), “An exploration of technological diffusion”, *American Economic Review* 100 (December), pp. 2031-2059.
- Comin, D. and Mestieri, M. (2014), "Technology Diffusion: Measurement, Causes, and Consequences" *Handbook of Economic Growth* 2(2), pp. 565-622, Elsevier: Amsterdam.
- Davis, S.J. and Haltiwanger, J. (1990), “Gross job creation and destruction: Microeconomic evidence and macroeconomic implications”, *NBER Macroeconomics Annual 1990*, ed. O. Blanchard and S. Fischer. MIT Press.
- Davis, S.J. and Haltiwanger, J. (1991), “Wage dispersion between and within U.S. manufacturing plants 1963-86”, *Brookings Papers on Economic Activity: Microeconomics* 1991, pp. 115-200.
- Davis, S.J., Haltiwanger, J. and Schuh, S. (1996), “Small Business and Job Creation: Dissecting the Myth and Reassessing the Facts”, *Small Business Economics* 8(4), pp. 297-315.
- De Loecker, J. and Konings, J. (2006), “Job reallocation and productivity growth in a post-socialist economy: Evidence from Slovenia”, *European Journal of Political Economy* 22(2), pp. 88-408.
- Dias, D., Robalo Marques, C. and Richmond, C. (2014), “Misallocation and productivity in the lead up to the Eurozone crisis”, *Bank of Portugal Working Paper* 201411.
- Ferrando, A., Iudice, M., Altomonte, C., Blank, S., Felt, M.H., Meinen, P., Neugebauer, K. and Siedschlag, I. (2015), “Assessing the financial and financing conditions of firms in Europe: the financial module in CompNet”, *ECB Working Paper* 1836.
- Fiori, G., Nicoletti, G., Scarpetta, S and F. Schiantarelli (2012), “Employment effects of product and labour market reforms: are there synergies?”, *The Economic Journal* 122, pp. 79-104.
- Fontagné, L. and Santoni, G. (2015), “Firm Level Allocative Inefficiency: Evidence from France”, *CEPII Working Paper*.
- Fontagné, L., Santoni, G. and Tomasi, C. (2016), “Resource misallocation and aggregate outcomes: towards a better assessment of competitiveness”, in Altomonte, C. and Békés, G. (eds.), *Measuring competitiveness in Europe: resource allocation, granularity and trade, Bruegel Blueprint Series* XXIV.
- Foster, L., Grim, C. and Haltiwanger, J. (2014), “Reallocation in the Great Recession: cleansing or not?” *NBER Working Paper* 20427.
- Foster, L., Haltiwanger, J. and Krizan, C.J. (2001), “Aggregate productivity growth: lessons from microeconomic evidence” in Hulten, C.R., Dean, E.R. and Harper, M.J. (2007), *New Developments in Productivity Analysis*, Chicago and London, University of Chicago Press, pp. 303-363.
- Foster, L., Haltiwanger, J. and Krizan, C.J. (2006), “Market selection, reallocation, and restructuring in the U.S. retail trade sector in the 1990s”, *Review of Economics and Statistics* 88(4), pp. 748-58.
- Fuss, C. and Vermeulen, P. (2008), “Firms’ investment decisions in response to demand and price uncertainty”, *Applied Economics* 40(18), pp. 2337–2351.
- Gamberoni, E., Gartner, C., Giordano, C. and Lopez-Garcia, P. (2016), “Is corruption efficiency-enhancing? A case study of nine Central and Eastern European countries”, *ECB Working Paper* 1950.

- Garcia-Santana, M., Moral-Benito, E., Pijoan-Mas, J. and Ramos, R. (2015), “Growing like Spain: 1995-2007”, mimeo.
- Gilchrist, S., Sim, J.W and Zakrajsek, E. (2015), “Misallocation and financial market frictions: some direct evidence from the dispersion in borrowing costs”, *Review of Economic Dynamics* 16(1), pp. 159-176.
- Giordano, C. and Zollino, F. (2016), “Macroeconomic estimates of Italy's mark-ups in the long-run, 1861-2012”, *Bank of Italy Economic History Working Paper*, forthcoming.
- Gopinath G., Kalemli-Ozcan S., Karabarbounis L. and Villegas-Sanchez, C. (2015), “Capital allocation and productivity in South Europe”, *NBER Working Paper* 21453.
- Guglielminetti, E. (2016), “The Labor Market Channel of Macroeconomic Uncertainty”, forthcoming *Banca d'Italia Working Paper*.
- Haltiwanger, J. (1997), “Measuring and analyzing aggregate fluctuations: the importance of building from microeconomic evidence”, *Federal Reserve Bank of St. Louis Review*, May, pp. 55-78.
- Haltiwanger, J., Scarpetta, S. and Schweiger, H. (2014), “Cross country differences in job reallocation: the role of industry, firm size and regulations”, *Labour Economics* 26, pp. 11–25.
- Hopenhayn, H.A. (2014), “Firms, Misallocation, and Aggregate Productivity: A Review”, *Annual Review of Economics* 6, pp. 735-770.
- Howitt, P. (2000), “Endogeneous growth and cross-country income differences”, *American Economic Review* 90(4), pp. 829-846.
- Hsieh, C.-T., and Klenow, P. (2009), “Misallocation and manufacturing TFP in China and India”, *Quarterly Journal of Economics* 124(4), pp. 1403-1448.
- Jones, C. I. (2013), “Misallocation, economic growth and input-output economics”, in Acemoglu, D. Arellano, M. and Dekel, E. (eds.), *Advances in Economics and Econometrics, Tenth World Congress, Applied Economics*, Vol. II, Cambridge University Press, pp. 419-456.
- Levine, R. (2005), “Finance and growth: theory and evidence”, in Aghion, P. and Durlauf, S. (Eds.), *Handbook of Economic Growth* 1, pp. 865-934.
- Lopez-Garcia, P., di Mauro, F. and the CompNet Task Force, (2014), “Assessing European Competitiveness: the new CompNet micro-based database”, *ECB Working Paper* 1764.
- Melitz, M. J. (2003), "The impact of trade on intra-industry reallocations and aggregate industry productivity", *Econometrica* 71(6), pp. 1695-1725.
- Melitz, M. and Polanec, S. (2015), “Dynamic Olley-Pakes productivity decomposition with entry and exit”, *The RAND Journal of Economics* 46(2), pp. 362-375.
- Midrigan, V. and Xu, D.Y. (2014), “Finance and Misallocation: Evidence from Plant-Level Data”, *American Economic Review* 104(2), pp. 422-458.
- Mortensen, D. and Pissarides, C. (1994), “Job creation and job destruction and the theory of unemployment”, *Review of Economic Studies* 9(3), pp. 397-415.
- OECD (2003), *The Sources of Economic Growth in the OECD Countries*, OECD: Paris.
- Olley, G.S. and Pakes, A. (1996), “The dynamics of productivity in the telecommunications equipment industry”, *Econometrica* 64(6), pp. 1263-1297.
- Pellegrino, G. and Zingales, L. (2014), “Diagnosing the Italian Disease” (forthcoming), *Chicago Booth Working Paper*.
- Peters, M. (2013), “Heterogeneous mark-ups, growth and endogenous misallocation”, *LSE Working Paper*.
- Petrin, A. and Sivadasan, J. (2013), “Estimating Lost Output from Allocative Inefficiency, with an Application to Chile and Firing Costs”, *The Review of Economics and Statistics* 95(1), pp. 286-301.
- Petrin, A., White, K. and Reiter, J. (2011), “The Impact of Plant-level Resource Reallocations and Technical Progress on U.S. Macroeconomic Growth”, *Review of Economic Dynamics* 14(1), pp. 3-26.

- Quah, D., (1993), “Galton's Fallacy and Tests of the Convergence Hypothesis”, *Scandinavian Journal of Economics* 95(4), pp. 427-443.
- Rajan, R. G., and Zingales, L. (1998), “Financial Dependence and Growth”, *American Economic Review* 88(3), pp. 559-586.
- Riley, R., Rosazza-Bondibene, C. and G. Young (2015), “The UK productivity puzzle 2008–13: evidence from British businesses”, *Bank of England Staff Working Paper* 531.
- Restuccia, D. and Rogerson, R. (2013), “Misallocation and productivity”, *Review of Economic Dynamics* 16(1), pp. 1-10.
- Schaal, E. (2015), “Uncertainty and Unemployment”, New York University mimeo.
- Schiantarelli, F. (2008), “Product Market Regulation and Macroeconomic Performance: A Review of Cross-Country Evidence”, *Boston College Working Paper in Economics* 623.
- Schivardi, F., Sette, E. and Tabellini, G. (2016), “Misallocation of credit during the financial crisis”, Banca d'Italia mimeo.
- Schmitz, J.A. (2005), “What determines productivity? Lessons from the dramatic recovery of the U.S. and Canadian iron ore Industries following their early 1980s Crisis”, *Journal of Political Economy* 113(3), pp. 582-625.
- Syverson, C. (2011), “What determines productivity?”, *Journal of Economic Literature* 49(2), pp. 326-365.
- Zeugner, S. (2013), “Tradable vs. non-tradable: an empirical approach to the classification of sectors”, European Commission mimeo.



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