University of Kent
School of Economics

MSc Dissertation

UK Productivity Dispersion during the Great Recession

Carlos Córdova

Supervisor: Miguel León-Ledesma

Submitted in partial satisfaction of the requirements for the qualification of Master of Sciences in Economics & Econometrics.

September 2015
Abstract

Using as a testbed the period of the Great Recession of 2008/09, this study demonstrates that the dispersion of Total Factor Productivity levels in the UK is procyclical. This implies that productivity dispersion is lower in recessions, reflecting a higher influence of Schumpeterian models of creative destruction along the business cycle. The present research confirms that the latest recession had cleansing effects for unproductive businesses and sullying effects for the most efficient ones, implying a less prominent role for the uncertainty shocks developed by Bloom (2009) as a source of business cycles. Using the same methodology as in Faggio, et al. (2010), I also confirm these results for the manufacturing sector where, in contrast to Kehrig (2015), productive and unproductive firms seem to have suffered similar sullying effects during the credit crunch. Finally, similar to the findings of Oulton (1998) and Haskel & Martin (2002), I show that, though small in levels, these relative changes in dispersion reflect a higher sensitivity of the manufacturing sector toward the business cycle.

Acknowledgments: I am very grateful to my supervisor Miguel León-Ledesma for his helpful comments, advice and support throughout the period of this research. I would like to express my gratitude to the Ecuadorian government that gave me the financial support to complete my MSc degree in the United Kingdom. Finally, I am deeply thankful to my family, who with their unconditional support and advice, have helped me to fulfil this dream. All errors are my own.
Contents

1. Introduction .................................................................................................................... 3
   Structure of the dissertation ......................................................................................... 3

2. Literature Review ......................................................................................................... 4
   2.1. What are we measuring? ......................................................................................... 4
   2.2. Methodologies used ............................................................................................... 4
   2.3. What about the data? ............................................................................................ 5
   2.4. Previous Results .................................................................................................... 6
   2.5. Theoretical Framework: Why does productivity dispersion change? ................. 7
   2.6. Research for the UK .............................................................................................. 8

3. The empirics of productivity dispersion ................................................................. 9
   3.1. The database ........................................................................................................... 9
   3.2. Structure of the enterprise and aggregation of the data ......................................... 9
   3.3. Testing accounts’ composition .............................................................................. 10
   3.4. Additional cleaning ............................................................................................... 10
   3.5. Deflating the series ............................................................................................... 11
   3.6. Productivity Calculation ...................................................................................... 11
   3.7. Measuring dispersion ............................................................................................ 12

4. Results .......................................................................................................................... 12
   4.1. Result 1: Productivity dispersion is procyclical .................................................... 12
   4.2. Result 2: Manufacturing sector is less dispersed and more procyclical ............... 15

5. Conclusions ................................................................................................................. 18

References ....................................................................................................................... 19

Appendix 1 ....................................................................................................................... 21
1. Introduction

What is the cyclicality of productivity dispersion in the UK? More specifically, is productivity dispersion procyclical (with low dispersion coinciding with recessions) or countercyclical (low dispersion coinciding with booms)? This is a fundamental question, as it confronts the Schumpeterian views of creative destruction along the business cycle with the uncertainty shocks developed by Bloom (2009), which are considered to have a prominent role in explaining the latest recession (Kehrig, 2015). The main contribution of this dissertation is to shed more light into this discussion, by characterising the cyclicality of productivity dispersion during the period of the Great Recession in the United Kingdom.

In essence, Schumpeterian models predict that productivity dispersion should be positively correlated with output, since unproductive firms should exit the market when demand for goods is low i.e. cleansing effect, making these models to consider recessions as beneficial (Christopoulos & Leon-Ledesma, 2014). On the other hand, Bloom’s uncertainty shocks proposes that given the higher uncertainty associated with recessions, the gap between productive and less productive firms becomes wider. This makes firms reluctant to invest and hire, freezing the role of reallocation across units (Bloom, 2009). This approach is commonly called the ‘wait and see’ effect, and relies on the assumption that productivity dispersion follows a countercyclical pattern (Tian, 2012). However, empirical evidence backing this reasoning has been limited in recent years, and at best has been focused on firms from the US manufacturing sector only. Likewise, with few exceptions, most empirical work has covered just periods prior the Great Recession, making the formation of sound conclusions on this topic harder.

This research tries to overcome these problems by using the methodology found in Faggio, et al. (2010), which uses firm-level data from the UK manufacturing and non-manufacturing sector, along the period of the Great Recession. Considering the lack of empirical evidence for the UK, this research is innovative in that it attempts to extend the research frontier on the topic. Under this context, the present research does not intend to determine the causes of the changes in productivity dispersion; rather it intends to determine some stylised facts which can contribute to further research in the field.

Structure of the dissertation

The dissertation is divided into three different parts: a literature review, the empirical strategy, and results with conclusions. The literature review offers a critical account of what has been written regarding productivity dispersion. It relates the empirical strategies used in previous studies to those in the present research. In that sense, it evaluates in detail previous methodologies with their corresponding results, and briefly explains the theories backing the cyclicality of productivity dispersion, focusing in particular on past studies in the UK.

In the second part of this dissertation I focus attention on the empirics of productivity dispersion. Essentially I am replicating the methodology used in (Faggio, et al., 2010), with some modifications which reflect my differing aim. This section makes a brief description of the database, its geographical coverage, the industries contained, and describes the difficulties I found during construction of the samples. These are related to the cleaning and deflating process of the data, the treatment given to missing or negative values, the classification of industries, and to the structure of the data (consolidated or unconsolidated nature). Finally, the second section explains the maths behind the calculations of TFP, labour productivity, and the measures of dispersion.

The last section of the dissertation shows the different results obtained for the UK, divided into the manufacturing and non-manufacturing sector. This section includes robustness checks, and contains the final conclusion of the research.
2. Literature Review

2.1. What are we measuring?

Conceptually speaking, there is no debate in the literature over the definition of productivity. In its simplest form, productivity is the degree of efficiency by which inputs are turned into outputs (Syverson, 2011). The most common measure of productivity is based on a single factor: labour. However, this measure is indirectly affected by prices and the allocation of other inputs such as capital. That is why, at least in the literature, it is generally preferred to use a broad and uniform measure of productivity that does not depend on a single input and its allocation. This is where Total Factor Productivity (TFP), also commonly referred to as ‘multifactor productivity’, comes in. Theoretically speaking, changes in TFP represent a shift in the isoquants of the production function (Syverson, 2011). This means that changes in output, given the same level of input, will depend exclusively on changes in TFP. Therefore, higher levels of TFP represent greater amounts of output. Consequently, TFP captures changes in productivity that are not explained by changes in inputs. This is why it is important for the present research.

2.2. Methodologies used

As noted by Bartelsman & Doms (2000), TFP calculation methods are vast, and their use depends both on the research question posed and the amount of data available. In general, measuring productivity is conducted via the use of production functions, and can be divided by the different assumptions these make. For example, most of the researches such as Haskel & Martin (2002), Kehrig (2015), and others use a Cobb-Douglas (CD) form, for this has a feasible assumption of perfect competition, which ensures that factor expenditure can be used as a proxy for factor quantities making simpler the calculation of TFP. This simplicity makes the use of this type of production functions attractive and the present research is no exception. However, one of the main weaknesses of this type of calculation is the self-selection and simultaneity bias as indicated by Haskel & Martin (2002). On that respect there are other, more robust, methods for calculating productivity, such as the one used in Bartelsman & Doms (2000). This was developed by Olley & Pakes (1996) using an estimation algorithm which removes this problems and is therefore suggested as a useful tool for calculating TFP. In fact, Kehrig (2015) uses the Olley & Pakes (1996) approach to reduce this endogeneity and selection bias problems. This particular sophistication is however beyond the scope of this dissertation.

When determining the elasticities of inputs Syverson (2011) explains that when assuming a setting of perfect competition and constant returns to scale, as the Cobb-Douglas function does, it is enough to calculate this elasticities as the share of revenues paid to each input. This assumption, however, implies that the elasticity of substitution between capital and labour is equal to 1, which has been rejected by a large body of research (León-Ledesma & Satchi, 2011). Nevertheless, research such as Kehrig (2015), Faggio, et al. (2010), and Levinsohn & Petrin (2003), follow the Cobb-Douglas approach, since the calculations are less complex than the (CES) method. For that reason, the Cobb-Douglas (CD) approach is also followed in the present study.

At the same time, in terms of capital share, there are small differences in terms of how capital stock is generally tracked. For instance, studies such as Oulton (1998) and Baily, et al. (1992) calculated capital stock as a firm’s fixed assets on its book value. On the other hand, Haskel & Martin (2002), and Bloom (2009) built capital using the perpetual inventory method. In Haskel & Martin (2002), data is interpolated to rule out the effect of missing capital stock values. In the present study it is preferred to avoid that process, since interpolating values would hide the real effect that the Great Recession had on some businesses and industries, as any break in the trend would be omitted.

---

1 As per Bartelsman and Doms (2000), the difference between TFP and labour productivity is that the latter can be affected by capital intensity in the production process without changes in the underlying technology.
Equally, in terms of measuring labour, depending on the availability of data, the literature seem to have an agreement in using labour as headcount measure, except where the number of hours worked is available, especially for the manufacturing sector (Kehrig, 2015). There is some research, such as Oulton (1998), which strongly recommends counting part-time employees as half of the head count. Yet this ideal treatment of this variable depends ultimately on the availability of data in order to separate full from part-time employees.

On the other hand, there is a long-standing debate over the use of sales or value added in the calculations, as Oulton (1998) points out. That is why, in part, research such as Faggio, et al. (2010) uses both measures. Yet most research in the literature follows the value added approach, calculated as the sum of the wage bill plus any form of payments to capital (i.e. interests and rent). Likewise, most of the literature uses revenue as a source of output. More specifically, it uses deflated revenue, since this a condensed measure of the different outputs that businesses produce (Syverson, 2011). However, one of the problems associated with this kind of measure, as this author emphasises, is that this measure reflects not only the level of output, but also the market power of producers2.

Finally, the methodology for measuring dispersion is more straightforward in the literature. Almost all of the research that measures dispersion—such as Kehrig (2015), Haskel & Martin (2002), Faggio, et al. (2010), and Ito & Lechevalier (2009) among others—uses either the standard deviation or the difference between the 90th and 10th percentile of the distribution after transforming the data to logarithmic scale. To ensure comparability of results, I replicate these measures in the present research. It is important to note, that these measures can show different pictures of the same data. For example, the distance between percentiles tell us to some extent the gap between certain groups of the population, not considering values close to the mean which could bias the results. On the other hand, the standard deviation considers all values of the distribution and hence gives an unbiased estimate of dispersion for the whole sample, as it assigns the same relative weight to each observation (Mittelhammer, 2013).

2.3. What about the data?

There is a wide range of data sources for analysing productivity found in the literature. Most previous research has used panel census samples collected by annual surveys from government agencies. In the US case, research including Kehrig (2015) and Bloom (2009) use surveys such as the Annual Survey of Manufactures (ASM), the Longitudinal Business Data Base (LBD), and Compustat, which compile information from more than 20 years especially for the manufacturing sector. For the UK there is also vast use of different surveys for calculating productivity. Past studies such as Haskel & Martin (2002) and Martin (2008) have used mainly the Annual Respondents Database (ARD), which contains a considerable amount of information from the manufacturing sector beginning in the early 70s. Since these surveys are based on a census population, their main contribution is the representability regarding the whole population of firms. Nevertheless, studies such as Oulton (1998) and Faggio, et al. (2010) use different sources in order to expand the scope of sectors in the sample. Indeed, the present study, similar to Faggio, et al. (2010), uses the Financial Analysis Made Easy (FAME) database, which includes information from the non-manufacturing sector. To some extent, the inclusion of this sector in the analysis becomes a source of innovation as most of the previous empirical works have been concentrated on the manufacturing sector.

For the treatment of data, most previous studies have focused their attention on evaluating the manufacturing sector. There are just a few exceptions especially for the UK, such as Haskel & Martin (2002) and Faggio, et al. (2010). Yet there seems to be an agreement in terms of the sectors to be removed from the sample when conducting the analysis. Basically all of the studies such as Oulton & Sebastiá-Barriel (2013), Ito & Lechevalier (2009), Faggio, et al. (2010) and others exclude the financial sector. The reason as per Crespi, et al. (2006) is that in

2 Another problem is that improvements in the quality of goods are not necessarily reflected, hiding a downward bias in productivity. This is more relevant for firms without an unique product in the service sector. See Bartelsman & Doms (2000) for more detail.
the financial sector accounts conventions and predefined adjustments make the data difficult to interpret. Ruling out the financial sector, however, would hide the effects that the Great Recession had on these institutions. Therefore this sector is not omitted in the present research. Additionally, in previous studies, sectors such as agriculture, mining, construction, and utilities have been segregated on the basis of government intervention. This argument is valid considering the 80s or 90s decades, but since the present research evaluates the past ten years where government intervention has substantially decreased, these sectors are also included in the analysis. Further, most of the studies— including Kehrig (2015), Bloom (2009), Haskel & Martin (2002), Ito & Lechevalier (2009) and others—cut the 1% or 0.5% tails of the distribution to rule out extreme values, to make more solid conclusions and test the sensitivity of their results. This strength in the treatment of data is replicated in the present research.

2.4. Previous results

Since there is a shortage of supply in studies focused on the cyclicality of productivity dispersion, results in the literature can be classified by those that measure dispersion and those that include its cyclicality. For the former group, which has a long tradition, most results agree that the amount of dispersion among firms is substantially large. In other words, some firms are considerably more productive than others. For example, albeit just for the US manufacturing sector, seminal studies such as Dhrymes & Bartelsman (1992) and later Syverson (2004) found that when comparing the average distance between the 90th and 10th percentile within the same industry, at the SIC 4 digits level, the difference was almost twofold. This meant that very productive firms produce almost twice what low productive firms normally do. This confirmed previous results by James, et al. (1989), which were focused on the car industry, and Bartelsman & Doms (2000), who found that efficient and less efficient firms tend to remain at the same levels of efficiency after some years. Though the latter authors suggest a relative constant spread between developing and developed countries, studies such as Hsieh and Klenow (2009) suggest a wider dispersion for China and India. More recent research by Ito & Lechevalier (2009) regarding the Japanese case has also confirmed that there was an increase in productivity dispersion in the last decade. All these findings suggest a high degree of heterogeneity among firms in terms of productivity.

In terms of the second group, the literature is relatively limited and is once again focused mainly on the US manufacturing sector. For example, Tian (2012) found a lagged countercyclical pattern in productivity dispersion using firms’ profit levels as the main variable rather than TFP. Similarly, Bloom (2009), when studying the uncertainty shocks found a countercyclical pattern in firms’ profit growth that suggested a countercyclical pattern in the underlying productivity.

It is only with Kehrig (2015) that a recent, broad, and serious analysis of the cyclicality of productivity dispersion under the framework of business cycles was finally conducted. In his work Kehrig (2015) used more than 20 years’ plant-level data from manufacturing businesses covered mainly by the Annual Survey of Manufactures (ASM) and the Longitudinal Business Data Base (LBD). Following the approach of Olley & Pakes (1996) he found a countercyclical pattern for productivity dispersion which is more pronounced for the durables sector. In other words, this author showed that the dispersion of TFP levels is higher in recessions and lower in booms, and therefore concludes that Schumpeterian models and its corresponding cleansing effects do not fit the empirical data, at least for the manufacturing sector in the US. Another interesting aspect of his findings is that this countercyclical pattern is more closely followed by bottom quantiles of the distribution as opposed to their counterparts at the top.

One of the main contributions of Kehrig (2015) to the present research is in comparability of results, since this author also tested their results using the classic Solow residual method. Using this Solow approach, Kehrig (2015) confirmed a countercyclical pattern. One of the weaknesses, however, is that it only covers the manufacturing sector, which in the case of the UK has a small share of total income or total gross value added. In that sense, there is not a comparable study for the non-manufacturing sector.
Since Kehrig (2015) is the most complete source that has a long horizon and a comparable cyclicality pattern, Figure 1 presents his results, split into durables and non-durables sectors.

![Figure 1: Cyclicality of productivity dispersion](image)

Source: (Kehrig, 2015)

2.5. Theoretical framework: why does productivity dispersion change?

Although the main goal of the present research is not related to determining the causes of productivity dispersion, it is necessary to understand the mechanics behind this behaviour when considering the results from my empirical work. Basically the causes for changes in dispersion can be classified by its nature. For example, there is the view suggested in Faggio, et al. (2010), Ito & Lechevalier (2009) and Tian (2012) in which productivity dispersion is driven by the rate of technology adoption or the amount of utilisation of information technology (ITC), which at the same time is ultimately dependent on the capital invested in these new technologies. Although the direction of dispersion is not constant, for these authors the role of technology adoption is important in determining firm heterogeneity.

There is also the view explained in Syverson (2011) in which productivity dispersion is driven by external factors such as regulation, competition, and trade liberalisation. This view proposes a Darwinian selection approach during downturns. The idea is simple: external factors not controlled by companies make the productivity level insufficient for achieving a profit and hence those firms ought to exit the market (Syverson, 2011). In terms of the trade liberalisation channel Melitz (2003) explains that trade exposure makes productive firms more competitive, forcing less efficient firms to exit. Ito & Lechevalier (2009) use as an example the liberalisation process in Japan during the 80s and 90s, which made companies more heterogeneous.

At the same time Syverson (2011) also offers a demand-based explanation for the evolution of productivity dispersion. The idea behind this approach is related to Schumpeterian models of business survival across the business cycle. In essence this approach establishes that in downturns occasioned by a demand contraction, only those firms that are efficient will remain in the market making the dispersion of productivity low.

All the causes mentioned above can explain to some extent the change in productivity dispersion, but they do not seem to completely match the empirical facts. In that respect the works of Bloom (2009) through the uncertainty shocks and Melitz (2003) through the input cost channel become a useful tool in understanding the evolution of dispersion. In his novel research, Bloom (2009) mainly focused on the relation between uncertainty and business cycles using a model with a time varying second moment at the firm level. In essence, these uncertainty shocks produce a sharp and quick drop and rebound in output. In this context productivity growth also falls due to a freeze in the input reallocation channel, as referred by Chen & Zha (2011).
Intuitively this means that productivity dispersion across firms jumps, since the distance between productive and less productive firms is wider in this economic setting (Kehrig, 2015). This means that uncertainty shocks expand the gap between good and bad firms making volatility to coincide with downturns. This approach is commonly called the ‘wait and see’ effect (Tian, 2012). The other approach developed in Melitz (2003) basically states that the increase in the cost of inputs during boom times will leave unproductive firms out of the market, making firms less heterogeneous. In that sense, these views imply a countercyclical pattern of productivity dispersion along the business cycle.

These theoretical constructs oppose the Schumpeterian models which express economic growth as a process of creative destruction, implying a procyclical pattern along the business cycle. As commented in Christopoulos & Leon-Ledesma (2014), under this Schumpeterian perspective, recessions tend to have cleansing effects, i.e. removing unproductive firms from the economy during economic downturns and therefore reducing productivity dispersion. In other words, as Kehrig (2015) emphasises, the bottom quantiles of the distribution (less efficient firms), should lift up its productivity in a recession. This cleansing effect and its real dimension, however, depends ultimately on the cost of entry for new businesses which at the same time could force the exit of unproductive businesses (Christopoulos & Leon-Ledesma, 2014).

2.6. Research for the UK

For the UK there is not a field in which the cyclicality of productivity dispersion has been analysed as for the US. In that sense and at least to my knowledge there is not a research that have depicted the cyclicality of productivity dispersion for the UK, which limits any contribution toward the present research. Nonetheless, there are two main categories into which past studies can be divided. The first, which has longer tradition, is mainly focused on the spread of productivity in a static framework. For example, in his seminal work Oulton (1998), through a sector analysis of manufacturing and services companies, found that manufacturing firms face a higher degree of foreign competition making them more efficient and therefore with a lower productivity dispersion than non-manufacturing counterparts. He also found that one of the sources of the productivity gap is associated with the type of ownership: either locally- or foreign owned. Foreign owned companies, the argument follows, have more intensive use of capital and more skilled labour than their local counterparts, making them more efficient.

The other category of studies found in the literature, besides measuring the spread of productivity, focus attention on its evolution. For instance, Haskel & Martin (2002), contrary to Oulton, use TFP as productivity measure and the (ARD) database in order to test whether there is a relationship between productivity growth and its spread. In other words, they tried to find an interdependence between the first and second moments of productivity. Interestingly, they found that the spread is not necessarily harmful for productivity growth, but might matter for productivity levels. Similar to later studies such as Martin (2008) they also found that, at least in the manufacturing sector, more competition tends to reduce the spread of the distribution.

In recent years Faggio, et al. (2010) have also studied the evolution of productivity dispersion. Mainly focused on wage dispersion, these authors also make an analysis of the dispersion of productivity at the firm level, including both the manufacturing and non-manufacturing sectors, using the (FAME) panel database. Following a Cobb-Douglas (CD) approach, Faggio, et al. (2010) found that the driver in wage dispersion is the rate of adoption of information technologies or (ITCs). One of the key findings of their research is that this rise in productivity dispersion is mainly driven by the service sector, which explains the underestimation of previous researches which focused only on the manufacturing sector. Yet when Ito & Lechevalier (2009) used the same methodology as Faggio, et al. (2010) for the Japanese case, they obtained the opposite result. Nevertheless, the main contribution of Faggio, et al. (2010) to my research comes from its empirical part since I use the same database and methodology.
3. The empirics of productivity dispersion

3.1. The database

Like Faggio, et al. (2010) I use the FAME database to obtain the observations necessary for my analysis. This source, part of the databases available at the University, is a UK company-level dataset with information available from the period beginning 1982. Though I only had access to data from 2005 up to 2014, this still allowed me to cover the years of the Great Recession and even some years before the crunch. Unlike most of the databases in the US, the FAME database include firms from the non-manufacturing sector representing almost 99 industries, and as in Kehrig (2015), includes not only publicly-traded but also privately owned firms.

More in detail the database includes information related to employment, fixed assets, turnover, gross profits, and wage bill, which are variables that I use in the analysis. Likewise, the geographical coverage of the data includes all parts of the UK: England, Wales, Scotland, Northern Ireland, and even some other British Crown dependencies, and Ireland. Yet the observations considered are only from firms registered in the UK. Though the data is not based in a census population of firms and rather it is formed by reporting units, the total coverage of the database reaches up to six million companies in the UK from 2005. This number, however, does not consider the different screening procedures necessary to refining the sample. One of the advantages is the merging procedure of the database. Haskel & Martin (2002) noted that when merging different databases, there can be embedded information, and the aggregation level might be different. This makes the matching process vulnerable to error.

In the FAME database the sample is less numerous and follows a more orderly structure since is synthesised in one single database.

3.2. Structure of the enterprise and aggregation of the data.

I start by analysing reporting units. In the FAME database, the reporting units are enterprises which have a unique registered number irrespective of the number of local units they might represent. This is important since the level of aggregation may differ. For example, local units are determined by their address, and therefore there might be 100 enterprises with more than 100 local units. This becomes critical depending on whether we want to know employment levels or productivity measures. As mentioned by Haskel & Martin (2002), when dealing with employment it is preferable to deal with local units’ information. However, when productivity aspects are relevant to the analysis, company-level information is more useful. This is because the production function links inputs to outputs with technologies that the local units share as being part of a company. Therefore, according to these authors, working with company-level data is preferable for TFP calculations. Hence I consider data at the company level.

Another potential source of error comes from the structure of the data—or more specifically, from the treatment given to consolidated and unconsolidated accounts. Theoretically speaking, a firm’s unconsolidated accounts do not register the results of its subsidiaries. Consolidated accounts on the other hand include transactions and correspondent adjustments between subsidiaries that form part of a corporate group (Tiffin, 2007). In that sense, companies with unconsolidated accounts might duplicate information contained within the consolidated accounts of the parent company. Therefore, if I do not separate the observations with consolidated accounts from observations with unconsolidated accounts, I would be overcounting the data. That is why in Faggio, et al. (2010), only firms with consolidated accounts are part of the final sample. This issue becomes even messier under panel data where both type of accounts (consolidated and unconsolidated) have been reported for the same company in different years. This means that if uncorrected, I would be comparing information between consolidated and unconsolidated accounts within the same company. As a result this comparison would be technically wrong and misleading. I therefore rule out observations with these characteristics and use only those with consolidated accounts for the whole sample period.
After performing these adjustments, the decrease in the number of observations is substantial, with almost 75% of observations lost. For this reason I also use a cross-sectional sample that allows me on the one hand to increase substantially the number of observations for each year, and on the other to account for firms’ compositional changes (i.e. firm exit and entry). Appendix I contains the characteristics and details of each of these samples.

3.3. Testing accounts’ composition

An important process when dealing with this type of information is testing the composition of each of the accounts to validate the formation of total values in each variable. I start with total fixed assets (FA), which tracks capital stock in the production process of each enterprise. This account is composed of tangible (TA) and intangible assets (IA), which remain fixed in the production process, and the amount of investments (I) allocated to increase the capital stock. At the same time tangible assets are composed of assets such as land (L), buildings (B), plants (P) and vehicles (V). Thus,

\[
FA = TA + IA + I, \quad \text{where} \quad TA = L + B + P + V.
\]

I also take into account all the data related to employee expenses in order to establish whether the final amount reflects all expenses related to labour utilisation in the firm’s production process, and in any event include some data that might be suppressed and is important for the analysis. Taking this into account, the wage bill (WB) is composed of: wages or salaries (W), social security (SS) and pension costs (PC). Thus,

\[
WB = W + SS + PC.
\]

In terms of turnover (T), this variable is basically formed by the turnover generated both locally (LT) and due to exports (FT). The composition of Gross Profit (GP) is based on the difference between turnover (T) and the cost of sales (CS)\(^4\). Hence the formulas for these two variables:

\[
T = LT + FT, \\
GP = T – CS.
\]

3.4. Additional cleaning

First, following Faggio, et al. (2010), I only consider those companies with at least ten employees, since these companies are obliged to report detailed information in relation to employee remuneration. Second, since some companies have different SIC codes (4 digits level), I consider the code that represents the major sector of activity. I also suppress observations with no SIC code assigned, since otherwise some companies would be assigned to a non-existent industry. At this point I also classify each company by its industry but at the 2 digit level creating two main groups: manufacturing and non-manufacturing. For the cross-sectional sample this procedure is replicated each year, and for the panel data it is only replicated the first year. Third, I suppress those companies which are not registered as active. The main goal of this adjustment is to compare dispersion within active companies, since non-active companies might skew the results. Hence I also discard the observations of companies which are registered as active but are in the process of disintegration (i.e. ‘active in liquidation’ and ‘active in default’). In terms of geographical location I consider businesses that are registered and located in the United Kingdom, meaning England, Scotland, Wales and Northern Ireland. British dependencies and Overseas Territories such as the Cayman Islands are not considered since these are not part of the United Kingdom (Foreign and Commonwealth Office, 2008).

---

3 I exclude CEO remuneration since this might introduce bias into the data, as these are not aligned with the labour productivity of the rest of employees (Faggio, et al., 2010). If I were tracking just wages, CEO salaries would be important as they substantially alter tails in distribution and thus dispersion.

4 To testing the validity of this consolidation process, I also contrast the information with the formulas contained in the FAME user’s guide.
3.5. Deflating the series

Like Faggio, et al. (2010) and Kehrig (2015) I deflate nominal values in order to obtain real quantities and render my results comparable. In that sense I use SPPI and PPI, which are industry deflators for the service and manufacturing sectors respectively\(^6\). In theory these deflators could offer a more accurate picture, since firms tend to face different price levels for their inputs and outputs depending on the industry to which they belong (Office for National Statistics, 2014). However, these price differentials are replicated within each industry, which suggests that even using industry deflators, relative prices between firms would remain unchanged. This would make the deflation process pointless (Foster, et al., 2001). Consequently, I opt for calculating the series on a deflated and non-deflated basis, as otherwise I could not compare my result with previous works which have used price deflators.

3.6. Productivity calculation

Following Faggio, et al. (2010) I consider TFP as a residual of output from weighted inputs. In that sense TFP is the ‘equation residual’ from a standard logarithmic Cobb-Douglas production function. The weight parameter for labour is the ratio of the wage bill over value added. Yet some restrictions in weights are imposed in order to test for possible changes in the results, i.e., using industry weights or firm weights. In the case of measurement errors, as Faggio, et al. (2010) emphasises, given I am not measuring physical units (pointless deflation), productivity should be considered as ‘revenue productivity’. Therefore, TFP for firm j at time t is:

$$\text{TFP}_jt = \ln Y_{jt} - \alpha_l \ln L_{jt} - (1-\alpha_l) \ln K_{jt},$$

where \(\alpha_l\) is the share of labour costs in output, \(L_{jt}\) is labour, and \(K_{jt}\) refers to capital stock. Normally, production functions use the number of hours as an input for labour, especially when dealing with manufacturing firms. Under this type of data, however, I use the number of employees as an input for labour, and fixed assets as a measure for the stock of capital. Further, as stated above, \(\alpha_l\) is computed as an industry specific ratio of total wage bill over value added. Once TFP is estimated, I select the 10th, 50th and 90th percentiles of TFP distribution and normalise them at the base year (2005).

Value Added

Following Faggio, et al. (2010) I calculate value added as the sum of gross profits before tax plus staff expenses. I consider gross and not operational profit, as the former includes interest expenditure which, with rent, forms part of the payments made to capital. In that sense I am considering the retribution of capital either as interest payments to lenders or as rents to investors. Hence:

$$VA_{jt} = WB_{jt} + GP_{jt},$$

---

5 For example, either the numerator or the denominator could be zero in the case of the labour productivity, and since the logarithm of a negative number is undefined (Varian, 1992), TFP would not have any economic intuition.

6 SPPI coverage includes 14 of the 20 available major sectors according to the SIC industry classification codes, i.e. those I use to classify each company. The sectors that do not belong to either PPI or SPPI are deflated using the GDP deflator. This latter adjustment is negligible, since these sectors represent less than 10% of gross value added for the UK (Office for National Statistics, 2014). The base year is the same that the ONS uses regularly for deflating GDP, that is, 2009.
where $VA_f$ reflects the value added for firm $f$ at time $t$, $WB_f$ refers to the wage bill for firm $f$ at time $t$, and $GP_f$ is the gross profit for firm $f$ at time $t$.

**Labour productivity**

Estimation of labour productivity follows the standard value added per worker calculation. To that end, the measure for labour productivity is the ratio of value added over the number of workers within a firm. As with TFP, the 10th, 50th and 90th percentiles of the labour productivity distribution are normalised at the base year (2005). That said, labour productivity is defined as:

$$\ln MPL_f = \ln VA_f / N_f,$$

where $\ln MPL_f$ is the natural logarithm of labour productivity of firm $f$ at time $t$, $\ln VA_f$ refers to the natural logarithm of value added for firm $f$ at time $t$, and $N_f$ is the number of workers for the firm $f$ at time $t$.

**3.7. Measuring dispersion**

Similar to Kehrig (2015), Oulton (1998) and Haskel & Martin (2002), I calculate the standard deviation to track dispersion. However, I focus not only on its absolute value but also consider its change along the business cycle. This strategy allowed me to make a reasonable comparison with past studies that have tracked exclusively the changes in the standard deviations towards GDP growth. Hence I indexed and normalised this measure at the base year 2005.

**4. Results**

**4.1. Result 1: Productivity dispersion is procyclical**

Panel data is probably the best view for disentangling the cyclicality of productivity dispersion since it considers surviving firms—i.e. the same companies along the period analysed. After the cleaning process the sample is formed of more than one thousand observations. As depicted in Figure 2, productivity dispersion—or more specifically the standard deviation of TFP—follows a procyclical pattern during the business cycle.

![Figure 2: Cyclicality of TFP](chart.png)

*Source: FAME Database & Macrobond. Elaboration: Carlos Cordova.*
A clearer picture of this procyclical relation, especially for the years of the Great Recession can be seen in Figure 3, where annual changes are considered for both GDP and the standard deviation\(^7\).

**Figure 3**

*Figure 3: Cyclicality of TFP*

Although the validation and testing of the ultimate causes for this type of cyclicality are beyond the scope of this dissertation and are not the goal of this research, this strong procyclical relation offers various interpretations in the context of the theoretical frameworks considered in Section 2 (Literature Review). For example, considering the uncertainty shocks developed by Bloom (2009), who found a countercyclical pattern, the above results contradict the view in which due to high uncertainty during recessions the distance between productive and less productive firms becomes wider. This distance, according to my results, actually contracts when output plunges, suggesting a process of convergence rather than dispersion across firms. As such my result implies that volatility does not necessarily coincide with downturns as suggested by Bloom (2009) and therefore to some extent this would reduce the role of risk or uncertainty as a driver of business cycles.

On the other hand, this procyclicality is more aligned with the insights found in Faggio, et al. (2010) and Syverson (2011), offering additional evidence in favour of Schumpeterian models across the business cycle. Starting with Faggio, et al. (2010) these results suggest that due to a decrease in investment during the crisis, the rate of adoption of new technologies, which are the main drivers of dispersion under this perspective, stagnated reducing productivity dispersion across firms. In the case of Syverson (2011), who proposed a demand explanation for productivity dispersion, these results could explain to some extent the role in which the contraction of demand forced unproductive firms to exit the market during the Great Recession. In that sense, this implies a clear influence of the Schumpeterian models on firm survival, i.e. cleansing and sullying effects behind this type of cyclicality.

To dig a little deeper into these conclusions, I use the cross-sectional sample to track the pattern that productive and less productive firms followed during the Great Recession and therefore determine the different effects across these firms. In principle under the cross-sectional sample I am allowing for firm exit and entry, which as a result changes the composition of observations for each year. This means that the companies at the top or the bottom of the distribution are not necessarily the same each year, and are sometimes formed by either new or old enterprises in the market. This becomes especially important when considering the rates of productivity of entrants compared to incumbents. As seen in Figure 4, before and after the crisis the gap in TFP increased, mainly due the entrance of less productive units (indicated by the dotted line). However, once the recession started and until its peak in 2009, this gap tended to diminish.

\(^7\) At this point is important to recall that, as per Kehrig (2015) and Oulton (1998), I am measuring the dispersion of TFP levels. Other measures such as the dispersion of the growth of TFP entail different concepts that would eventually lead to different results.
This convergence in productivity is caused mainly by two simultaneous and opposite effects. On the one hand, as explained by Christopoulos & Leon-Ledesma (2014), less productive firms exit the market (liquidation process) and/or become more efficient; on the other, for the companies at the top of the distribution—i.e. the most efficient ones—productivity levels are reduced. In that sense, aligned with the ‘on-the-job’ view of Barlevy (2002), the data shows both mechanisms taking effect during the Great Recession, but with the sullying effect dominating due to a fall in the aggregate level of productivity. This therefore imply that during the credit crunch, firms were affected differently depending on their efficiency levels, as predicted by Schumpeterian models.

Figure 4
TFP Evolution by Percentiles (in Logs; base year 2005=1)

Robustness checks

In order to consolidate and contrast my results, I run robustness checks using a variety of approaches. First I use firm weights as coefficients of the production function, similar to Faggio, et al. (2010). As illustrated by Figure 5, under these weights there is an even stronger procyclical relation towards the business cycle.

Figure 5
Cyclicality of TFP (under firm weights)

Second, instead of using TFP I take into account an alternative measure to track efficiency: labour productivity. Figure 6 shows that the pattern for this variable remains the same as found in previous results. This would eventually mean that, as with TFP, the output produced per employee tends to converge across firms during recessions and correspondingly tends to be more widely dispersed during boom times.

---

8 This pattern does not hold for 2014. This is caused by companies that have not yet reported their financial information, or where the reported data is not definitive. Hence in 2014 there is a drop in the gap without any unusual change in GDP growth.
This seems reasonable under the demand-based explanations of Syverson (2011) considering that, as mentioned in Section 3, we are measuring strictly revenue productivity. Finally, I conduct additional tests\(^9\), obtaining similar results, making this procyclical pattern the new stylised fact of this research (see Appendix 1 for the additional tests).

**Figure 6**
Cyclicality of Labour productivity

![Graph showing cyclicality of labour productivity.](source: FAME Database & Macrobond. Elaboration: Carlos Cordova.)

To formalise and resume these findings I correlate the standard deviation and the 90\(^{th}\)-10\(^{th}\) percentiles distance against GDP under different samples (panel and cross-sectional), using different accounts (consolidated and unconsolidated), cutting and non-cutting the 1% tails in the distribution, and with industry and firm weights in the production function. As illustrated in Table 1, there are 32 result combinations, most of them establishing a procyclical relation.

**Table 1**
Correlation Coefficients TFP vs. GDP

<table>
<thead>
<tr>
<th>Sample</th>
<th>Accounts</th>
<th>Tails</th>
<th>Standard Deviation</th>
<th>90th-10th distance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Industry Weights</td>
<td>Firm Weights</td>
</tr>
<tr>
<td>Panel Data</td>
<td>Consolidated</td>
<td>Cut</td>
<td>0.58</td>
<td>0.85</td>
</tr>
<tr>
<td>Panel Data</td>
<td>Consolidated</td>
<td>Non-Cut</td>
<td>0.53</td>
<td>0.66</td>
</tr>
<tr>
<td>Panel Data</td>
<td>Unconsolidated</td>
<td>Cut</td>
<td>0.69</td>
<td>0.73</td>
</tr>
<tr>
<td>Panel Data</td>
<td>Unconsolidated</td>
<td>Non-Cut</td>
<td>0.69</td>
<td>0.71</td>
</tr>
<tr>
<td>Cross-section</td>
<td>Consolidated</td>
<td>Cut</td>
<td>0.16</td>
<td>-0.27</td>
</tr>
<tr>
<td>Cross-section</td>
<td>Consolidated</td>
<td>Non-Cut</td>
<td>0.15</td>
<td>-0.34</td>
</tr>
<tr>
<td>Cross-section</td>
<td>Unconsolidated</td>
<td>Cut</td>
<td>0.53</td>
<td>0.03</td>
</tr>
<tr>
<td>Cross-section</td>
<td>Unconsolidated</td>
<td>Non-Cut</td>
<td>0.72</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Source: FAME Database & Macrobond
Elaboration: Carlos Cordova.

4.2. Result 2: Manufacturing sector is less dispersed and more procyclical

In contrast to the results exposed in Kehrig (2015)\(^10\), which tracked only the US manufacturing sector, my results show a procyclical relation of TFP along the business cycle. Figure 7 shows that, as with the rest of the economy, lower dispersion coincides with downturns. This pattern therefore could be explained by the same causes used for the whole economy such as the influence of Schumpeterian models on the business cycle (i.e. cleansing and sullying effects).

---

\(^9\) These tests include: using firms with unconsolidated accounts, using growth rates for GDP and standard deviation, not cutting the 1% tails, using the 90th-10th difference, using a cross-sectional sample in order to increase the number of observations, and using non-deflated series.

\(^10\) Refer to Section 2 for more detail.
To confirm this influence I once again use the cross-sectional sample to track the path followed by productive and unproductive firms in the manufacturing sector, while allowing for compositional changes (i.e. firm entry and exit), for the analysed period.

**Figure 7**
Cyclicality of TFP: Manufacturing Sector

![Graph showing cyclicality of TFP in the manufacturing sector](image)

Source: FAME Database & Macrobond.
Elaboration: Carlos Cordova.

As seen in Figure 8, firms in the manufacturing sector were subject to different effects that their counterparts in the non-manufacturing sector during the Great Recession. More specifically, as previously mentioned, the 2009 drop in dispersion of the whole economy can be explained by a cleansing effect on the less efficient firms and a sullying effect for the most efficient ones. For the manufacturing sector, however, the data shows that the drop in dispersion coincides with a sullying effect for both productive and unproductive firms. As Figure 8 illustrates, in 2009, when GDP falls, the productivity levels of companies at the top and at the bottom of the distribution both tumble. This therefore could reinforce the insulating effects explained in Christopoulos & Leon-Ledesma (2014), in which a fall in firm’ entry rate makes incumbents less likely to face the full blast of falling demand, reducing the impact of recessions on exits (destruction). These results however cannot be taken as definitive, given they are sensitive to the coefficients used for the production function as shown in Appendix 1.

**Figure 8**
TFP by Percentiles Manufacturing Sector (in Logs; base year 2005=1)

![Graph showing TFP by percentiles in manufacturing sector](image)

Source: FAME Database.
Elaboration: Carlos Cordova.

**Dispersion between manufacturing and non-manufacturing sectors**

Another interesting picture in the results comes from the difference between the levels of dispersion across sectors. As seen in Figure 9, the level of dispersion in the manufacturing sector is considerably lower (almost half) to the one obtained in the non-manufacturing sector (which incorporates the service sector).
This therefore implies a more homogeneous level of efficiency between firms in the manufacturing sector, as also found in Martin (2008), Oulton (1998), and Haskel & Martin (2002), which were likewise focused on the UK.

**Figure 9**
Dispersion levels

![Figure 9: Dispersion levels](image)

This could be explained in part by the nature of the manufacturing sector where, according to Oulton (1998) and Melitz (2003), there is a higher degree of foreign competition and exposure to exports, making them more efficient and therefore less heterogeneous than their counterparts in other sectors. However, when tracking relative changes in dispersion, Figure 10 shows that these are more stable for the non-manufacturing sector. This implies that, though small, the dispersion of the manufacturing sector is relatively more sensitive to the business cycle. In fact, the correlation of GDP with the standard deviation is higher in the manufacturing sector, meaning that the latter is more procyclical than the non-manufacturing sector.

**Figure 10**
Change in dispersion towards the Business Cycle

![Figure 10: Change in dispersion towards the Business Cycle](image)

**Robustness checks**

Similar to the whole economy, I use firm weights for the production function and labour productivity as alternative measures to confirm the procyclicality of the manufacturing sector. As seen in Appendix 1 this and other tests show that the procyclicality of this sector remains unaltered. I also test whether the manufacturing sector is more procyclical than the non-manufacturing sector.

---

**Notes:**

11 These tests include: using firms with unconsolidated accounts, using growth rates for GDP and standard deviation, not cutting the 1% tails, using the 90th-10th percentile difference, using a cross-sectional sample in order to increase the number of observations, and using non-deflated series.
For this task I use a test developed in Kehrig (2015) in which the correlation coefficients between standard deviation and GDP are compared across sectors. I conduct this test under different settings, i.e. using both TFP and labour productivity. Table 2 contains the results of this exercise. As seen in this table, the manufacturing sector contains higher coefficients, making it more procyclical.

### Table 2

<table>
<thead>
<tr>
<th>Variable</th>
<th>Weights</th>
<th>Sector</th>
<th>Panel Data Consolidated Accounts Correlation Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFP</td>
<td>Industry Weights</td>
<td>Manufacturing</td>
<td>0.75</td>
</tr>
<tr>
<td>TFP</td>
<td>Industry Weights</td>
<td>Non-Manufacturing</td>
<td>0.50</td>
</tr>
<tr>
<td>TFP</td>
<td>Firm Weights</td>
<td>Manufacturing</td>
<td>0.73</td>
</tr>
<tr>
<td>TFP</td>
<td>Firm Weights</td>
<td>Non-Manufacturing</td>
<td>0.70</td>
</tr>
<tr>
<td>Labour Productivity</td>
<td>NA</td>
<td>Manufacturing</td>
<td>0.48</td>
</tr>
<tr>
<td>Labour Productivity</td>
<td>NA</td>
<td>Non-Manufacturing</td>
<td>0.40</td>
</tr>
</tbody>
</table>

Source: FAME Database & Macrobond.
Elaboration: Carlos Cordova.

5. Conclusions

Answering the main question of the research: ‘what is the cyclicality of productivity dispersion in the United Kingdom?’ The present study, after different robustness checks, has determined that TFP dispersion in the UK is procyclical, using as a testbed the period of the Great Recession. This implies that the empirical evidence in the UK is aligned with the theoretical constructs of Schumpeterian models of creative destruction, in which cleansing and sullying effects ultimately shape the cyclicality of productivity. The present research has confirmed that the latest recession had cleansing effects for unproductive businesses and sullying effects for the most efficient ones.

In terms of the manufacturing sector, the present study has determined that TFP dispersion follows a procyclical pattern opposite to the results found in Kehrig (2015). This result could imply that volatility does not necessarily coincide with downturns, reducing the role of Bloom’s uncertainty shocks as a possible explanation for the latest recession, at least for the UK. This leaves more space to other theories such as the ones of Syverson (2011) focused in demand as possible explanations for the cyclicality of productivity dispersion in the UK. However, this and other potential explanations require further research and are beyond the scope of this study.

The present research has further determined that, as opposed to the non-manufacturing sector, the procyclicality of the manufacturing sector is shaped by a sullying effect in both productive and unproductive firms. These results reinforce the view of insulating effects during downturns as explained by Christopoulos & Leon-Ledesma (2014), and suggest that during the Great Recession fewer firms from the UK manufacturing sector exited the market.

Finally, similar to the findings of Martin (2008), Oulton (1998), and Haskel & Martin (2002) which were focused on the UK, the present research determines a lower level of dispersion for the manufacturing sector compared to the non-manufacturing sector. When tracking relative changes in dispersion, however, the manufacturing sector shows a more sensitive response to changes in output. This implies that, though small, the dispersion of the manufacturing sector is relatively more sensitive to the business cycle. This is backed up by correlation coefficients between standard deviation and GDP, which confirm a high degree of procyclicality of this sector.
References


Appendix 1

Panel Data

Initially, more than ten thousand panel data observations were obtained. After running the cleaning process, only 1200 observations were considered for analysis. The final observations do not have missing or negative values, belong to active companies, have an industry allocated, and are based only on consolidated accounts available for the whole sampling period. Table 3 contains the characteristics of these observations.

Table 3
Panel Data Composition

<table>
<thead>
<tr>
<th>Country</th>
<th>100 %</th>
<th>Industry</th>
<th>100 %</th>
</tr>
</thead>
<tbody>
<tr>
<td>England</td>
<td>91%</td>
<td>Agriculture, forestry and fishing</td>
<td>1%</td>
</tr>
<tr>
<td>Northern Ireland</td>
<td>2%</td>
<td>Mining and quarrying</td>
<td>1%</td>
</tr>
<tr>
<td>Scotland</td>
<td>5%</td>
<td>Manufacturing</td>
<td>22%</td>
</tr>
<tr>
<td>Wales</td>
<td>2%</td>
<td>Electricity, gas, steam and air conditioning supply</td>
<td>0%</td>
</tr>
</tbody>
</table>

Legal form 100 %

Guarantee 0.4% Construction 9.4%
Limited Liability 0.2% Wholesale and retail trade; repair of motor and motorcycles 19.0%
Private Limited 66.8% Transportation and storage 3.6%
Public AIM 9.1% Accommodation and food service activities 2.3%
Public Quoted OFEX 0.2% Information and communication 7.1%
Public, Not Quoted 9.6% Financial and insurance activities 5.7%
Public, Quoted 13.4% Real estate activities 3.1%
Unlimited 0.2% Professional, scientific and technical activities 11%

Listed/Unlisted/Delisted 100 %

Delisted 3% Public administration and defence; social security 0%
Listed 23% Education 1%
Unlisted 74% Human health and social work activities 1%

Main Sector 100 %

Manufacturing 22% Arts, entertainment and recreation 2%
Non-manufacturing 75% Other service activities 1%
Other 2% Activities of households as employers 0%
Services 5% Activities of extraterritorial organisations and bodies 0%

Source: FAME Database.
Elaboration: Carlos Cordova.

Cross-sectional sample

As with the panel data, all the observations do not have missing or negative values, represent consolidated accounts, and belong to active companies with an industry allocated. The main difference to panel data is that the cross-sectional sample allows for the entry and exit of new and old firms, changing the composition of firms in the sample, therefore increasing the number of observations. Tables 4 and 5 contain this and other characteristics of the sample.

Table 4
Cross-sectional sample composition

<table>
<thead>
<tr>
<th>Total number of firms</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
<th>2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>8,360</td>
<td>8,320</td>
<td>8,447</td>
<td>8,735</td>
<td>12,930</td>
<td>13,690</td>
<td>14,42</td>
<td>15,32</td>
<td>16,15</td>
<td>6,755</td>
</tr>
<tr>
<td>Manufacturing sector</td>
<td>1,505</td>
<td>1,498</td>
<td>1,521</td>
<td>1,583</td>
<td>2,461</td>
<td>2,603</td>
<td>2,740</td>
<td>2,911</td>
<td>2,908</td>
<td>1,284</td>
</tr>
<tr>
<td>Non-manufacturing</td>
<td>6,855</td>
<td>6,822</td>
<td>6,926</td>
<td>7,152</td>
<td>10,489</td>
<td>11,089</td>
<td>11,68</td>
<td>12,41</td>
<td>13,24</td>
<td>5,471</td>
</tr>
<tr>
<td>Country</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>England</td>
<td>91%</td>
<td>91%</td>
<td>91%</td>
<td>91%</td>
<td>89%</td>
<td>89%</td>
<td>89%</td>
<td>90%</td>
<td>89%</td>
<td>90%</td>
</tr>
<tr>
<td>Northern Ireland</td>
<td>1%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
</tr>
<tr>
<td>Scotland</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
</tr>
<tr>
<td>Wales</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>3%</td>
</tr>
<tr>
<td>Legal form</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Guarantee</td>
<td>Limited Liability</td>
<td>Not companies Act</td>
<td>Private Limited</td>
<td>Public AIM</td>
<td>Public Investment Trust</td>
<td>Public quoted OFEX</td>
<td>Public, Not quoted</td>
<td>Public, Quoted</td>
<td>Unlimited</td>
<td>Industrial/Provident</td>
</tr>
<tr>
<td>-----------</td>
<td>-------------------</td>
<td>------------------</td>
<td>----------------</td>
<td>-----------</td>
<td>------------------------</td>
<td>------------------</td>
<td>------------------</td>
<td>-------------</td>
<td>----------</td>
<td>---------------------</td>
</tr>
<tr>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Listed/Unlisted/Delisted</th>
<th>Delisted</th>
<th>Listed</th>
<th>Unlisted</th>
<th>Main Sector</th>
<th>Manufacturing</th>
<th>Services</th>
<th>Other sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>100 100 100 100 100 100 100 100 100 100 100 100 100</td>
<td>7% 6% 5% 3% 3% 2% 2% 1% 1%</td>
<td>8% 9% 6% 6% 6% 6% 5% 5% 9%</td>
<td>86% 85% 85% 91% 92% 92% 93% 93% 89%</td>
<td>100 100 100 100 100 100 100 100 100 100 100 100</td>
<td>18% 18% 18% 19% 19% 19% 19% 19% 18% 18% 19%</td>
<td>80% 80% 80% 79% 79% 79% 79% 79% 78%</td>
<td>2% 2% 2% 2% 2% 2% 2% 2% 2% 2% 3%</td>
</tr>
</tbody>
</table>

Table 5
Cross-sectional sample composition by Industry

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, forestry and fishing</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
</tr>
<tr>
<td>Mining and quarrying</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>18%</td>
<td>18%</td>
<td>18%</td>
<td>18%</td>
<td>19%</td>
<td>19%</td>
<td>19%</td>
<td>19%</td>
<td>18%</td>
<td>19%</td>
</tr>
<tr>
<td>Electricity, gas, steam and air conditioning supply</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Water supply; sewerage, waste management and remediation activities</td>
<td>0%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
</tr>
<tr>
<td>Construction</td>
<td>8%</td>
<td>8%</td>
<td>8%</td>
<td>8%</td>
<td>9%</td>
<td>9%</td>
<td>9%</td>
<td>8%</td>
<td>8%</td>
<td>9%</td>
</tr>
<tr>
<td>Wholesale and retail trade; repair of motor and motorcycles</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
<td>16%</td>
<td>17%</td>
<td>17%</td>
<td>17%</td>
<td>17%</td>
<td>16%</td>
<td>16%</td>
</tr>
<tr>
<td>Transportation and storage</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
<td>4%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>Accommodation and food</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
<td>4%</td>
<td>3%</td>
</tr>
<tr>
<td>Information and communication</td>
<td>8%</td>
<td>8%</td>
<td>8%</td>
<td>8%</td>
<td>7%</td>
<td>7%</td>
<td>7%</td>
<td>7%</td>
<td>7%</td>
<td>7%</td>
</tr>
<tr>
<td>Financial and insurance activities</td>
<td>7%</td>
<td>6%</td>
<td>7%</td>
<td>7%</td>
<td>6%</td>
<td>6%</td>
<td>7%</td>
<td>7%</td>
<td>7%</td>
<td>8%</td>
</tr>
<tr>
<td>Real estate activities</td>
<td>4%</td>
<td>4%</td>
<td>3%</td>
<td>3%</td>
<td>4%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>Professional, scientific and technical activities</td>
<td>20%</td>
<td>18%</td>
<td>17%</td>
<td>16%</td>
<td>13%</td>
<td>12%</td>
<td>11%</td>
<td>12%</td>
<td>12%</td>
<td>12%</td>
</tr>
<tr>
<td>Administrative and support</td>
<td>9%</td>
<td>9%</td>
<td>10%</td>
<td>10%</td>
<td>10%</td>
<td>11%</td>
<td>11%</td>
<td>11%</td>
<td>12%</td>
<td>12%</td>
</tr>
<tr>
<td>Public administration and defence; compulsory social security</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Education</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
</tr>
<tr>
<td>Human health and social work activities</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>Arts, entertainment, recreation</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
</tr>
<tr>
<td>Other service activities</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>1%</td>
</tr>
<tr>
<td>Activities of households as employers</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Activities of extraterritorial organisations and bodies</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
</tbody>
</table>

Source: FAME database.
Elaboration: Carlos Cordova.
Results 1: Additional tests

Figure 11
Cyclicality of TFP (using unconsolidated accounts, not cutting the 1% tails, and non-deflated series)

Source: FAME Database & Macrobond.
Elaboration: Carlos Cordova.

Figure 12
Cyclicality of TFP (90th - 10th Difference) (using unconsolidated accounts and not cutting the 1% tails)

Source: FAME Database & Macrobond.
Elaboration: Carlos Cordova.

Figure 13
Cyclicality of TFP (Cross-sectional sample) (using unconsolidated accounts and not cutting the 1% tails)

Source: FAME Database & Macrobond.
Elaboration: Carlos Cordova.
Result 2: Testing the cleansing and sullying effects in the manufacturing sector

**Figure 14**

TFP by Percentiles Manufacturing Sector (in Logs; base year 2005=1)

(using firm coefficients and cutting the 1% tails)

![TFP by Percentiles Manufacturing Sector](image)

Source: FAME Database.
Elaboration: Carlos Cordova.

Result 2: Robustness checks for the manufacturing sector.

**Figure 15**

Cyclicality of TFP (under firm weights)

![Cyclicality of TFP](image)

Source: FAME Database & Macrobond.
Elaboration: Carlos Cordova.

**Figure 16**

Cyclicality of Labour productivity

![Cyclicality of Labour productivity](image)

Source: FAME Database & Macrobond.
Elaboration: Carlos Cordova.
Additional tests for the manufacturing sector.

**Figure 17**
Cyclicality of TFP (using unconsolidated accounts, not cutting the 1% tails, and not-deflated series)

Source: FAME Database & Macrobond. Elaboration: Carlos Cordova.

**Figure 18**
Cyclicality of TFP (90th -10th Difference) (using unconsolidated accounts and not cutting the 1% tails)

Source: FAME Database & Macrobond. Elaboration: Carlos Cordova.

**Figure 19**
Cyclicality of TFP (Cross-sectional sample) (not cutting the 1% tails)

Source: FAME Database & Macrobond. Elaboration: Carlos Cordova.
Figure 20
Cyclicality of TFP using growth rates

Source: FAME Database & Macrobond.
Elaboration: Carlos Cordova.