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High Growth Firms and Productivity – Evidence from the United Kingdom

Jun Du
Yundan Gong
Yama Temouri

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Jun Du
Economics and Strategy Group, Aston Business School, Aston University

Yundan Gong
Economics and Strategy Group, Aston Business School, Aston University

Yama Temouri
Economics and Strategy Group, Aston Business School, Aston University

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Abstract

The concept of high growth firms (HGFs) has attracted considerable attention by governments and policy makers on the back of evidence that HGFs contribute significantly to employment and economic growth. However, the literature shows limited evidence on the link between HGFs and firm productivity. In this paper we investigate the empirical link between total factor productivity (TFP) growth and high growth phenomena (defined by turnover growth) in the United Kingdom over the period 2001-2010, by examining two related research questions. Firstly, does higher productivity growth lead to high growth incidence? Secondly, does high growth experience help firms to achieve faster TFP growth? Our two-part analysis reveals that firms are more likely to become HGFs in revenue when they exhibit higher TFP growth, and that firms which have had high growth experience tend to enjoy faster TFP growth afterwards. By contrast, we find that higher productivity, measured in levels, is negatively associated with HGF incidence, while high growth experience leads to higher productivity levels. These results are robust to several model specifications and controlling for a number of sources of firm heterogeneity and regional economic conditions. Marked differences are identified in the determination and the implication of high growth phenomena between the manufacturing and the services sector.

JEL Classification: D24 L11 L25

Keywords: productivity, firm growth, high growth firms

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1. Introduction

The concept of high growth firms (HGFs) has attracted significant interest by governments and policy makers around the world. This has developed from the evidence offered by the fast growing literature on small business economics and entrepreneurship. A small percentage of fast growing firms play a disproportionately large role in the economy in both recessionary periods and economic booms (NESTA, 2011). Policy makers are thus very keen on supporting these firms with various initiatives in order to sustain and expand this important potential driver of job creation, innovation and wealth creation (Acs et al., 2008; BERR, 2008; OECD, 1998, 2000, 2002). In understanding the nature and characteristics of such exceptional firms, the literature has identified a number of "stylized" facts which HGFs appear to have in common (see review by Henrekson and Johannsson, 2010a). However, there is evidence that suggests firms may grow in terms of employment without much efficiency improvements, or the reverse in case of capital investments for future efficiency gains (Daunfeldt et al., 2010; BERR, 2008)). Thus, we do not know if there is any association between high growth phenomena and productivity growth, which is widely considered the driver of long run economic growth.

So far the common characteristics shared by HGFs still remain uncertain and some important firm characteristics are not well understood or not explored in any great detail (Delmar et al., 2003). In particular, any review of the literature shows a clear absence of studies that offer a thorough treatment of the relationship between productivity and the incidence of high-growth. The economics and business management literature asserts that firm level productivity, alongside other firm-specific capabilities, such as innovativeness, technological and managerial know-how, has the potential to be translated into firm employment and output growth (Dunning and Cantwell, 1991; Horstmann and Markusen, 1989; Mason et al., 2009; Kirca et al., 2011). In particular, Total Factor Productivity (TFP) is now recognized as an important determinant of both long run economic growth and short run growth fluctuations.

There are several reasons that we might expect a positive relationship between productivity and HGFs. Theoretical and empirical evidence shows that the levers that firm managers can use to improve business performance and productivity include managerial practice and talent, employee quality or input quality, information technology and R&D, product innovation, organization structure and learning by doing (Syverson, 2011). Several of

these factors may relate to what drives the high growth phenomenon, even though few have been tested. For example, HGFs outperform their rivals with their ability to exploit their previous investments in successful innovation. Mason et al. (2009) find that innovative UK firms grow twice as fast compared with other firms that do not. Mason and Brown (2010) find that being knowledge-based and innovative is identified to characterize most HGFs in Scotland, which is also the key driver of the spectacular growth resurgence in the United States (Jorgenson, Ho and Stiroh, 2005; Oliner, Sichel and Stiroh, 2008[1]), and the gap between European and the superior US productivity experience over the last few decades (Bart van Ark, O'Mahony and Timmer, 2008). Another example is that firm's core competences for high quality output and their employees' knowledge of the markets and customers seems to be associated with the high growth phenomenon (Mason and Brown, 2010). This also confirms recent work that links human capital in determining productivity heterogeneity (see Abowd et al, 2005; Ilmakunnas et al, 2004; and Fox and Smeets, 2011).

From the internationalization and trade perspectives, many HGFs are globally oriented and sell overseas, which is consistent with what has been found in the economics and international business literature where firms self-select into global markets due to superior productive efficiency (see a review by Greenaway and Kneller, 2007). Therefore it is reasonable to expect that productivity may not only describe a key firm characteristic but potentially explains the nature, driver or even consequences of high growth phenomena alongside various other determinants that have already emerged from the HGF literature.

However, one could also argue that the relationship between HGFs and productivity can be absent or negative. For instance, one important determinant of high productivity is the process improvement due to experience accumulation, commonly known also as learning by doing. This is often what incumbents would take years of business experience to acquire, not something HGFs could achieve easily, especially those that are younger or start-ups. For instance, the study by Daunfeldt et al. (2010) for Sweden uses productivity and value added in addition to turnover and employment to define HGFs and tests whether various definitions contribute differently to aggregate economic growth and employment. They find that HGFs defined by employment in the period 1997-2005 have a small or negative effect on productivity growth, while HGFs defined by productivity have an insignificant or even negative effect on employment and sales growth. This they argue suggests that there is at least a short-term trade-off between employment and productivity in how they affect each

[1] These studies document that IT-related productivity increases in the IT-producing and IT-using industries in the US in the past decades.

other. In other words, a firm may grow in terms of employment without much efficiency improvements, or the reverse is true in case of capital investments for future efficiency gains. This is echoed by a recent BERR report (2008) which notes that HGF status in itself may not necessarily imply high productivity.

Thus the potential economic significance of the causal link between productivity and HGFs and the potential policy relevance warrants a thorough examination of the relationship. This paper fills this gap by exploring the relationship between firm productivity growth and the high growth phenomenon measured by turnover in both the manufacturing and services sector in the UK using a large firm level data over the period 2001-2010. More specifically, we ask two questions. Firstly, does higher productivity growth lead to HGF status? Secondly, do HGFs achieve higher productivity growth? Thus, our analysis contains two parts, where the first part investigates the role of productivity growth in determining the probability of a firm becoming a high growth performer, and the second part examines the productivity growth consequence of high growth experience following the high growth period.

By employing an array of measures of TFP and estimation approaches, our estimates on the link between HGFs and productivity growth overall show that a) firms which exhibit higher productivity growth are more likely to become HGFs in turnover and b) that HGF experience enhances the prospects of higher productivity growth in the future through a number of firm level and regional economic channels. These results are found for both the manufacturing and services sector, and interesting differences are uncovered between these two sectors.

Furthermore, we test if the same link can be found between the level of productivity and HGFs. We find contrasting results such that higher productivity, measured in levels, is negatively associated with HGF incidence, while high growth experience leads to higher productivity levels.

The rest of the paper is structured as follows. Section 2 gives an overview of the main strands of literature on HGFs and productivity. Section 3 describes the data and measurement issues. Section 4 discusses the estimation strategy and the regression results for our two main research questions. Section 5 extends this discussion by using productivity level as opposed to productivity growth as the key variable. Section 6 concludes.

2. Literature Review

2.1 HGF literature

The literature on HGFs that has been developed since the work of Birch (1987), and studies by the US- Small Business Administration on the identification of HGFs, and more recent studies that attempt to explain the nature, cause and implications of the high growth phenomenon. Based on a synthesis of 19 studies, Henrekson and Johansson (2010a) note that there is no general agreement on the definition of HGFs.[2] Definitions vary in terms of the following: choice of growth indicator (e.g. employment, sales, profits); measurement of growth; length of time-period over which growth is measured; and whether growth through acquisition is included or just organic growth (Delmar et al., 2003). The consensus of opinion favors the OECD definition – the main reason why it is being adopted here – which seeks to achieve some consistency in defining HGFs as those with an average employment growth rate exceeding 20 per cent per annum over a three-year period and with 10 or more employees at the start of the period (EUROSTAT-OECD, 2007).

A number of findings emerge from the literature review despite differences in country choice, methodology, time-periods and HGF definitions. First, they confirm the existence of HGFs; a few rapidly growing firms that generate a large share of all net new jobs, irrespective of the population studied, which is particularly marked in recessionary periods when HGFs continue to grow (Anyadike-Danes et al., 2009). There is less consistency between studies in terms of whether HGFs make a disproportionate contribution to total job growth. The evidence is positive for the USA but not for some other countries, such as Sweden (Davidsson and Delmar, 2006).

Second, HGFs can be of all sizes. Whereas small firms are over-represented in the population of HGFs, large firms can also be important creators of jobs, particularly a sub-group of so-called 'super-gazelles' which in some other studies have been called 'gorillas', and which are in essence firms that are larger in size (BERR, 2008). Third, evidence for the UK and other countries shows that young firms are more likely to be high-growth, but the

[2] Birch (1987) defined HGFs as establishments which have achieved a minimum of 20 per cent sales growth each year over the interval, starting from a base-year revenue of at least $100,000. This definition, therefore, includes three criteria: (i) growth rate, (ii) sales as the measure of growth; and (iii) minimum start-size (avoiding problems associated with growth from a very small base). An alternative approach is to define HGFs as a subset of the fastest growing (new) firms. For example, Acs et al. (2008) have produced an important study of HGFs in the United States from 1994-2006. They refer to HGFs as "high-impact firms" which they define as enterprises whose sales have at least doubled over a four year period and which have an employment growth quantifier (the relationship between its absolute and percentage change) of two or more over the period.

majority of high-growth firms are over 5 years old (Anyadike-Danes et al., 2009, Bravo-Biosca, 2011). Fourth, younger HGFs are more likely to grow organically; hence they make a greater contribution to net employment growth. Larger and older HGFs are more likely to grow through acquisition. In addition, between firm size and age, being young is a more important factor than small size in explaining HGF incidence. Finally, HGFs are found in all industries (Bravo-Biosca, 2011). They are not over-represented in high tech industries. If anything, they are over-represented in services.

Acs et al. (2008) findings deviate considerably from Henrekson and Johansson's (2010a) synthesis, mainly due to the focus being on high impact firms which are enterprises whose sales have at least doubled over a four year period and which have an employment growth quantifier (the relationship between its absolute and percentage change) of two or more over the period. They find that the average age of a US high impact firm is 25 years old with the minority of them being start-ups. They observe that high impact firms come in all sizes, but about half of the jobs are created by small firms (less than 500 employees). They also find that high impact firms exist in all industries and are not specific to high technology industries. They also exist in almost all US regions, states, metropolitan areas and counties. They also find that large firms (500+ employees) are able to double their sales in more than one time-period and expand their employment over eight years or more. These contrasting findings can perhaps be due to the way HGFs are defined, the time-period of analysis and data availability.

However, Acs et al. (2008) is one of the few studies that attempts to link rapidly growing firms and productivity and find that high impact firms in the US have a larger impact on productivity. Although relying on labour productivity (revenue per employee) and only statistical mean comparison between high impact firms and low impact firms, they generally find that high impact firms are more associated with higher labour productivity than low-impact firms. They also find that the difference in labour productivity between high and low-impact firms is widening in the US over time. They argue that productivity is an important channel through which HGFs contribute to the aggregate economy, despite being difficult to measure, but this is not directly tested. Bravo-Biosca (2013) also attempts to analyse the relationship between a dynamic growth distribution and productivity growth and find that there is a positive correlation between the two, and the relationship become stronger as countries converge to the global technology frontier.

Besides the studies that either look at simple labour productivity characterising HGFs by comparing figures across firm types, there is limited evidence on the causes and

consequences of productivity growth on HGF incidence and contribution to overall economic growth. An exception is Mason et al. (2012) who for UK firms present static and dynamic decomposition estimates of labour productivity growth changes over the period 1998-2007. They find HGFs to be on average more productive, but with limited contribution to overall industry productivity growth. A related cross-country study was undertaken by the OECD (2003) using firm data for 10 advanced countries which reveals that new firms rather than existing ones contribute more to TFP, as they enter with innovative combinations of factors of production and new technologies.

2.2 The Wider Literature

The economic literature is extensive with respect to firm growth. Indeed, the literature on productivity is, in its own right, extensive and has stimulated many areas in economics, including macroeconomics, industrial organization and international trade (Bartelsman and Doms, 2000; Syverson, 2011). For example, productivity comparisons have been undertaken across firms according to different levels of engagement in international markets (Helpman et al., 2004; Melitz, 2003; Wagner, 2007), across various industries (Harris and Robinson, 2003) and country of foreign ownership (Criscuolo and Martin, 2007). They essentially show that productivity differences are a key determinant of firm heterogeneity and if firm productivity is one of the main channels for aggregate economic growth, then policy makers are advised to take this into account when formulating certain initiatives. The entry of multinational firms and export activities have been shown to have an impact on domestic firms' output, employment and efficiency through enhanced competition, technology diffusion, export market access and training of workers. There is a large body of empirical evidence that points to a robust correlation between multi-nationality, exporting and firm performance (for example, Bernard and Jensen, 1999; Girma et al., 2004; Harris and Li, 2007) and most of the work has shown that exporters and foreign-owned firms generally have a higher performance.

The international business and entrepreneurship literature also offers a plethora of evidence on the performance effects of internationalization (Driffield et al., 2010), R&D and innovation (Roper et al., 2008). A recent study by Ganotakis and Love (2013) use survey responses of UK technology firms to investigate how the characteristics and experience of the entrepreneurial founding team affects the export orientation and subsequent performance of the businesses they establish, while allowing for the mutually reinforcing relationship between exporting and productivity. They find that the set of management skills (i.e.

commercial experience) needed to enter foreign markets via exports is different from the skills required in succeeding in export markets (i.e. education). They also confirm that the more productive firms self-select into export markets and that exporting leads to further firm productivity improvements. Therefore, it may not be surprising to find that multinational firms as well as exporters are more likely to be associated with high growth firm performance.

Recently there is a growing interest in understanding intangible assets and the potential role in driving firm growth. A recent attempt to link intangible assets to productivity growth in the UK (for example Riley and Robinson, 2011; Dal Borgo et al., 2012), and they find that intangible assets have a significant, positive, association with productivity, and that firms with a higher proportion of intangible assets are more likely to be highly productive. Thus, it presents another measurement unit to complement our understanding of the sources of firm growth beyond the known tangible factors of production. However, intangible assets include a wide range of contents and are more difficult to measure than R&D expenditure or innovation capabilities of firms. The various elements of intangible assets are also found to contribute to productivity in different ways (Riley and Robinson, 2011).

In addition to the above, the literature suggests that firm growth rates may be also be affected by a range of other factors including the reliance on internal finance (Oliveira and Fortunato, 2006) or leverage (Lang et al., 1996; Huynh and Petrunia, 2010), R&D expenditure (Coad and Rao, 2010) and innovative activity (Mason et al., 2009). Organic growth of the firm or growth through merger and acquisition activity can also be a source of productivity growth (Deschryvere, 2008; Lockett et al., forthcoming).

Finally, another perspective in explaining firm growth comes from regional science and institutional economics literature, where local and institutional factors may either induce or hinder firm growth. A recent World Bank report (2008) on Central and Eastern Europe examines both firm level as well as institutional indicators in explaining productivity growth. Hart and McGuinness (2003) show a similar analysis for UK manufacturing and services where differences across a wide set of regional factors or the external business environment can explain small firm growth. A recent study by Henrekson and Johansson (2010b) makes the case for how a number of complementary policies can create a framework which can improve the conditions for HGFs to flourish. In this regard it is advised that policymakers do not pick winners or even industries but to adopt a broad approach and implement a wide array of complementary institutional reforms in order to improve conditions for HGFs. Bravo-Boisca, Criscuolo and Menon (2012) investigate the impact of several institutional

drivers such as labour regulation, bankruptcy laws, financial market institutions and R&D support policies on the distribution of firm growth using an aggregated micro data based on ten countries.

2.3 Manufacturing versus Services Productivity

The UK service sector accounts for more than three quarters of total gross domestic product (ONS, 2012). In terms of total turnover in the period 2008-2012, the manufacturing sector has achieved £400 billion worth of orders and production which is a recovery and in 2012 is on par with the pre-crisis level of turnover. However for the service sector has recovered more rapidly, from £1,570 billion in 2008 to £1,697 billion in 2012. However, although the service sector has been growing quickly as a share of total output, the sector's aggregate productivity growth has been lower than that of the manufacturing sector in some leading industrial countries, such as the US, Canada, Japan and the UK (Triplett and Bosworth, 2004). Over the period 1998-2010, labour productivity of the UK manufacturing sector rose by an average 3.7 per cent while labour productivity of the service sector only increased by an average of 2.1 per cent (ONS, 2011). Hughes and Saleheen (2012) estimate average annual productivity growth of 4.3 per cent in the manufacturing sector and 2.3 per cent for the pre-crisis period of 1998-2004, whereas the productivity growth of 2.9 per cent and 0.4 are reported for the 2009-2011 period for the manufacturing and service sector, respectively.

A commonly cited explanation for the disparity in productivity between product and service activity is the Baumol effect (Baumol, 1967). The theory behind the Baumol effect is that productivity improvements in services are harder to achieve than in goods producing industries due to its relative labour intensity. With the shift in developed countries from manufacturing to services there was a concern that this might lead to slower aggregate growth rates in the long-run as resources are reallocated towards industries with slow or zero growth.

Many scholars however argue that the Baumol effect view is too simple (Triplett and Bosworth, 2000; Woelfl, 2003) and since the 1980s strong productivity growth in ICT-related industries in countries such as the US and Australia have challenged Baumol's theory. These authors argue that substantial productivity disparities exist among different sectors, especially within the service sectors (Lewis et al, 1992). For example, one would expect that the potential for productivity growth of ICT-related/ICT-using industries such as telecommunications, banking and the financial sector are very different from the productivity in sectors like hotels and restaurants. Triplett and Bosworth (2002) found that ICT equipment

contributed to between 30- 37 per cent to labour productivity growth in business service, wholesale trade and transportation services in the US over the 1995-2000 periods. Moreover, they also find that TFP growth rates vary in different industries. Between 1987-1995 and 1995-2000 TFP growth rates in wholesale trade accelerated from 1.1% annually to 2.4%, in retail trade from 0.4% annually to 3.0%, and in securities from 2.9% to 11.2%.

Given the significant role that the services sector plays in the UK economy and recent evidence that over half of all HGFs are operating in the UK service sector (NESTA, 2009), we include the manufacturing as well as the service sector to see if there are interesting differences in productivity growth and the channels through which growth can be attained.

3. Data and Methodology

3.1 Data source and panel structure

The data for our analysis is drawn from *FAME*, which is a commercially available dataset compiled by Jordans and distributed by Bureau van Dijk, which source their information from Companies House. The dataset provides information on company profiles, profit and loss accounts, balance sheets, ownership, industry affiliation etc. The Fame dataset is collection of business records on UK firms rather than a comprehensive and coherent business register. Although the most basic company information (e.g. name, location, industry affiliation) are available for millions of firms in the UK, the size of the database shrinks considerably if one isolates firms which report detailed figures for a set of key variables, such as the ones used in this paper. There are a number of reasons for this. For example, many small sized firms are exempt from reporting full annual accounts. Some firms enter the market and as such new companies have almost two years to submit their first annual accounts and thus will not show figures immediately (BERR, 2009). Fame also shows firms which have become inactive or exit the market and thus will not show accounts, other firms can have duplicate entries, depending upon the type of business record considered (consolidated or unconsolidated economic accounts) or possible unit duplications. Finally, as we only include firms which operate in the manufacturing and services sector, and a large number of firms operating outside these two sectors are not included in our analysis.

There are advantages as well as weaknesses in using *Fame*. The collection of annual accounts is more current than officially available datasets, so that one can analyse firms up to the year 2010 which may give interesting insights on firm reactions to the recent financial crisis, while relying on the Annual Respondents Database (ARD) provides data with a time

lag that makes it hard for a timely analysis (i.e. including more recent years) that can feed into decision making in the policy arena (Mason, et. al., 2012). Regarding productivity analysis, *FAME* unlike other datasets offers the opportunity to measure TFP due to the availability of tangible fixed assets which is commonly used to proxy capital in the production function. However, one of the main weaknesses is the poor coverage of smaller firms which may not need to report full sets of accounts. Therefore the datasets is biased towards larger firms, but this bias has become smaller as the dataset has been extended over the last few years to include more SMEs that do report balance sheet figures (Ribeiro et al. 2010). Finally, *FAME* allows the construction of longitudinal panels as it collects firm-level information over a period of ten years. Also, many firms are observed for a shorter period of time, making the panel unbalanced and exits of firms cannot be attributed to non-reporting. For a detailed review of the *FAME* dataset see BERR (2009) and Ribeiro et al. (2010) who assess in detail the many advantages and shortcomings of dataset with the characteristics of official statistical databases. They also investigate the level of representativeness of data samples sourced from datasets available by Bureau van Dijk. Another study that assesses representativeness is Geishecker et al. (2009), who have assessed the Amadeus dataset with respect to their representativeness, which includes FAME. For this, they use the 60-industry database of the Groningen Growth and Development Centre and the OEC Business by Size Class (BSC) dataset. They conclude that the data for the UK is biased towards larger firms compared with the BSC dataset. Average employment coverage for the UK is around 48 per cent compared to aggregate manufacturing figures. They also find that the coverage of firms in sectors which are more concentrated in terms of fewer number of firms is over-represented compared with more dispersed industries This is shown for the Euro area as a whole.

In addition to firm specific variables, we follow the existing literature that emphasizes a number of regional indicators which may explain the different environments in which firms operate (Hart and McGuiness, 2003). We include GDP growth, unemployment levels, infrastructure (we use the volume of Air traffic as proxy), and the number of patents registered at the NUTS2 regional levels, to capture the environmental factors that shape HGF incidence. This data is drawn from Eurostat and is available annually. In order to merge firms with regional data, we use the postcode of every firm to locate the UK NUTS-2 region in which they are located before merging the regional indicators to the firm level dataset.

Table 1a shows the panel structure of our sample across time. After isolating firms which report information on the key variables used in our analysis, we end up with 183,024 firm-year observations, for 26,313 firms, covering the time period 2001-2010. It is important

to note that the panel of firms is unbalanced and most firms are not observed for the entire 10 year period. We also have only included firms for which we have unconsolidated accounts. As this is an unbalanced panel, the number of observations differs across years and ranges from 12,000 to 20,000. However, for each year between the period 2001 and 2009 the number of observations is around 9-11 percent of the total. The year 2010 captures fewer firms, namely 6.7 percent of the total observations, which can be due to firm exits, late reporting of accounts and fewer firms reporting key variables used in this analysis. However, this is a common characteristic with commercially available datasets which update their datasets with a lag. Table 1b shows the industry distribution of our sample of firms. Certain industries are larger than others, such as food and beverages, publishing and printing, chemicals, fabricated metals and furniture.

Unlike many previous studies that use consumer price indices to deflate the industrial outputs and other monetary variables, we deflate our data using 4-digit producer prices indices (PPI) for manufacturing sectors (Nace-codes 15-37) and service indices (SPPI) for service industries (Nace-codes 50-74 and 80-93) sourced from the ONS and EconStats (for more details see the Appendix 1). This approach helps us to get a more accurate account of the production elements for productivity estimation purposes.

[INSERT Table 1a]

[INSERT Table 1b]

3.2 High growth definition and summary statistics

In this paper, we rely on firm turnover growth to define high growth incidence, in the context of the high growth literature that tend to adopt either employment or value growth as high growth criterion. Employment adjustment is usually slower during productivity shocks and hence may not reflect contemporary firm performance change. From the theoretical point of view, the links between employment growth adjustment and total factor productivity seem much more debatable in the current literature. There are reasons to believe that employment growth and size patterns have more to do with industrial characteristics than firm performance variations. Adopting the compounding annual growth calculation consistent with the OECD definition, Table 2 shows the distribution of the incidence of HGFs across the manufacturing 2-digit industries using two different indicators for capturing high firm growth. The first indicator (HGF^a) defines a HGF incidence as a firm growing at an average

annual growth in *turnover* of at least 20% over a three-year period and employs 10 or more employees at the start of the growth period. The second indicator (HGF^b) uses the same calculation but is based on *employment* is also provided for comparison purposes.

As shown in Table 2, HGF^a gives an estimate of the HGF incidence for all sectors of around 11.64% based on turnover growth rate and 4.6% based on employment growth[3]. Compared with the well-known HGF figures around 6% based on employment for the UK (Anyadike-Danes et al., 2009), these figures are slightly lower, which could be due to the sample bias towards large firms. The industry differences of the HGF incidences are evident. Some sectors show above average HGF incidence over the last decade, such as Office Machinery, Communication Equipment and Recycling for Manufacturing and Post and Telecommunications, Financial Intermediation, Real Estate Activity, Research and Development, and Computer and Related Activities. Interestingly, the HGF incidence is much higher in service industries (13%) than the manufacturing industries (8.89%), which is contrary to the historically held view of higher productivity growth in manufacturing (Baumol, 1967). According to our calculation, 60% of the observations of high growth firms by turnover are also high growth by employment, while only 24% of employment-defined high growth are also high growth in turnover.

There is currently an active discussion about the low level of economic productivity growth since the start of the recession in the UK (Dale, 2011). We have therefore, compared high-growth firms before and during the recession. Table 2 shows the number of HGF incidences in various sectors overall, before the recession in 2006 and during the recession in 2009. Overall, a clear drop in the number of high-growth firms can be observed. Whereas 18% of firms experience high growth at the end of 2006, only 7.6 per cent fell into this category in 2009 – a drop of 62.5 per cent. If we compare industries more closely, then apart from the Wood Product industry (NACE 20) that has maintained more or less the same level of HGF incidence, other sectors seem to have experienced a reduction in HGF incidence. For example, the Wearing apparel (NACE 18) and Activities of membership organization (Nace 91) have been affected more than others, such as Water transport (NACE 61) and Activities auxiliary to financial intermediation (NACE 67). These results are largely in line with what has been found in the recent studies, for example Anyadike-Danes and Hart (2012), which show a decline in both new firms formation and HGF incidence that during the crisis period.

[3] Conventionally, the estimates of HGF incidence using turnover tends to be much higher than those based on employment figures.

[INSERT Table 2]

Table 3a provides descriptive statistics of the variables used in our subsequent analysis. Based on turnover growth as our HGF definition (HGF[a]), the data shows a clear pattern that HGFs are smaller and younger firms with extraordinary turnover growth and employment growth, in both the manufacturing and service sectors. They tend to have slightly higher level of intangible assets, pay higher wage on average, slightly more experienced in internationalization, and quite more productive than their peers. At the same time, large standard errors indicate that there are great heterogeneities in each group, which in turn suggests that large as well as older firms can be HGFs as well; consistent with the evidence shown in the literature (Henrekson and Johannsson, 2010a, Acs et al., 2008).

Table 3b shows four regional economic indicators as averages over the period 2001-2010 across the NUTS-2 regions. Each of the four indicator show significant differences in magnitude across the regions. For example, the average number of patent applications per million of inhabitants ranges from 15.6 in North Eastern Scotland to 202.6 in Berkshire, Buckinghamshire and Oxfordshire. Air traffic also varies considerably from 0.5 people in West Wales and the Valleys to 32220.45 in Surrey, East and West Sussex. However, there is much less variation within regions during the time period 2001-2010.

[INSERT Table 3a]

[INSERT Table 3b]

3.3 TFP estimation and sensitivity

Since Solow's seminal paper (1957), productivity has become one of the most important concepts in economics. Given what we know, TFP is both the source of long term economic growth, and closely tied with innovation and internationalization, it is important to consider TFP both as cause and effect, when viewed in combination with employment growth, export status, and technology adoption (Van Biesebroeck, 2003), as well as with industrial competition (Martin, 2008)[4].

Conceptually, productivity captures what makes differences in output production after

[4] There is a large literature, spanning in the area of Industrial Organization, International Trade, International Business, and Innovation, both theoretical and empirical, to examine the two-way relationship between TFP and its growth with economic growth, export behaviour, technology adoption, and industrial market structure.

controlling for differences in inputs. However, the measurement of productivity has not been a straightforward task, as problems often arise with measurement errors in inputs and simultaneity in production functions. As a result, the debate on the most appropriate method is extensive and ongoing (cf., Bartelsman and Dhrymes, 1992; and Griliches and Mairesse, 1995; Olley and Pakes 1996; Levinsohnn and Petrin, 2003; Van Biesebroeck 2003; Wooldridge 2009; Petrin and Levinsohn, 2011).

We employ four widely used methodologies of estimating TFP in this investigation, which fall into three statistical strands: parametric, semi-parametric and a GMM framework. We do not consider non-parametric approaches, such as index number, mainly because they tend to be more sensitive to measurement error. In what follows, we start with estimating productivity using a Cobb-Douglas production function, by least squares and corrected for firm individual heteroskedasticity. To relax the assumption of constant returns to scale and allow a more flexible functional form, a translog production function is estimated as an alternative. We then introduce the Levinsohn and Petrin (2003) and Wooldridge- Levinsohn-Petrin (2009) estimators to control for endogenous inputs and measurement error. All estimations are conducted in each of the NACE 2-digit industrial sectors separately.

The Cobb-Douglas production function approach (LS)

Following the mainstream literature, TFP can be estimated through a standard Cobb-Douglas production function for firm i at time t:

$$y_{it} = b_0 + b_l l_{it} + b_k k_{it} + w_{it} + e_{it},$$

where y is log of total output or value added, l is the log of labour input and k is the log of capital input. ω_{it} represents a productivity difference known to the firm, but unobservable to the econometrician. ε_{it} is the residual term that captures other sources of *i.i.d.* error. The consistency of the parameter estimates relies on the assumption of the classic linear regression assumptions, including homoskedasticity and endogeneity in the model. Once consistent estimates of the input elasticities are derived, the log of productivity can be obtained as $\hat{w}_{it} = \hat{y}_{it} - b_0 - \hat{b}_l l_{it} - \hat{b}_k k_{it}$. We call this approach LS for short as it is estimated using OLS.

The Cobb-Douglas functional form of a production function is limited by its assumptions of trade-off inputs and constant returns to scale, which motivates using more flexible production functional forms such as the translog production function.

The translog production function approach (TL)

A translog production function takes the following form:

$$y_{it} = b_0 + b_l l_{it} + b_k k_{it} + b_{ll} \times 0.5 \times l_{it} l_{it} + b_{kk} \times 0.5 \times k_{it} k_{it} + b_{lk} l_{it} k_{it} + w_{it} + e_{it},$$

where the notations and factors remain the same as in the Cobb-Douglas functional approach above, and hence how the log of productivity is derived. It is worth mentioning that both Cobb-Douglas and the translog production function can be estimated using fixed effects panel estimators, which specify a firm specific fixed effect that is potentially correlated with the inputs.

The dissatisfaction of the above two approaches of production function estimation stems from the potential simultaneity and endogeneity in the model, when inputs and outputs may be simultaneously determined by production shocks that is unobservable to the econometrician and captured by the residual term. We introduce a widely used technique named after Levinsohn and Petrin (2003) and the recently proposed Wooldridge- Levinsohn-Petrin (2009) that is a modified version of the former.

Levinsohn and Petrin (2003) approach (LP)

Based on Olley and Pakes (1996) (OP) who propose a two-step estimation procedure that proxies unobserved and time-varying productivity with investment, Levinsohn and Petrin (2003) advance the approach by addressing the lumpy investment problem with using an alternative variable, namely intermediate inputs (e.g. raw materials or electricity).

Following the Cobb-Douglas production function specified above,

$$\begin{aligned} y_{it} &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it} \\ &\equiv \beta_l l_{it} + \phi_t(k_{it}, m_{it}) + \varepsilon_{it} \end{aligned}$$

where $\phi_t \equiv \phi_t(k_{it}, \omega_{it}) = \beta_0 + \beta_k k_{it} + \omega_{it}(k_{it}, m_{it})$ is an unknown function of capital and intermediate inputs. ϕ_t is strictly increasing in the productivity shock ω_t, so that it can be inverted and one can write $\omega_{it} = \omega_t(m_{it}, k_{it})$ for some function ω_t. Levinsohn and Petrin (2003) approximate $\phi_t(k_{it}, m_{it})$ by a third order polynomial in k and m, $\sum_{j=0}^{3}\sum_{s}^{3} \delta_{js} k_{it}^{j} m_{it}^{s}$ and obtain and estimate of β_l and ϕ_t (up to the intercept) via OLS. This constitutes the first stage

of the estimation procedure. At the second stage the elasticity of[5] capital β_k is defined as the solution to $\min_{\beta_k^*} \sum_i \sum_t \left(y_{it} - \hat{\beta}_l l_{it} - \beta_k^* k_{it} - \varpi_{it} \right)^2$, where ϖ_{it} is a nonparametric approximation $E[\omega_{it} \mid \omega_{it-1}]$. Since the estimators involve two stages, the calculations of the covariance matrix of the parameters must allow for the variation due to all of the estimators in the two stages, and hence standard errors are estimated by the bootstrapping procedure. Based on consistent estimates, the log of productivity can be obtained as $\hat{\omega}_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it}$.

The advantage of the LP approach lies in controlling for the simultaneity between firm's choice of input levels and unobserved productivity shocks. The downside on the other hand is that the complicated two-step setup of the methodology restricts the ways that the unknown function is approximated, and in some cases variable inputs are unidentified in the first stage of the estimation, as argued by Ackerberg et al. (2008) and Wooldridge (2009).

Wooldridge-Levinsohn-Petrin methodology (2010) (WLP)

The Wooldrige modification of the canonical LP technique is popularly referred to as the Wooldridge-Levinsohn-Petrin methodology (Petrin, et al. 2011). WLP proposes to implement the moment conditions used by LP in a general method of moments (GMM) framework. The modification allows both identifying variable inputs in the first stage of the estimation, and obtaining robust standard errors in a more straightforward fashion (see Wooldridge (2009) for the details).

Both LP and WLP can be applied both for an "output" approach where TFP is the residual of output after adjusting for shares of capital, labour or materials, and a "value-added" approach, where value-added is used as output adjusted for cost of material inputs and then denote TFP as residual share of value added after adjusting for share of capital and labour. While both approaches have been applied in literature (Javorcik (2004) and Javorcik and Spatareanu (2011) uses the "output approach and Petrin, et al.(2011) have used the "value-added" approach), we follow the suggestions of Ackerberg et al. (2008) and Petrin, et al.(2011) and apply the WLP methodology to the NACE 2-digit industry-specific "value-added" production functions.

[5] Olley and Pakes (1996) provide an observable expression for productivity by inverting the investment function nonparametrically and propose a two-step estimation procedure to allow controlling for the potential simultaneity bias.

Comparing Estimates

Before we report the estimates of TFP using different methodologies, it is useful to obtain an overview of the set of estimates and discuss the similarity and discrepancy between them. There are certainly no clear-cut rules that can easily provide the optimal estimator in any given situation, as it depends on the sample, the assumptions about the production process, and the specific data characteristics. The productivity literature suggests that the existing estimation methods provide close estimates of TFP (which is the residual of the production function). The choice of specific method becomes critical when one derives an observed part of the production process to analyse the input elasticity of output (Van Biesebroeck 2008). However, since our main purpose is to measure the unobserved part of the production process, the choice of TFP estimators is unlikely to make a significant difference.

Nevertheless, we employ an informal "test" used by researchers to gauge the appropriateness of the TFP estimates within our data set, and test for the sensitivity of using alternative measures (for example Girma and Gong, 2008). To this end, the Spearman rank correlation coefficients between labour productivity and each of the TFP estimates are calculated. Labour productivity is defined as log of total revenue per employee or value added per employee, whichever is applied accordingly with production function specification when TFP is measured. Our working assumption is that a good measure of TFP should exhibit a reasonably high correlation with labour productivity. This was done for each two-digit industry, and the results of the rank correlation coefficients between labour productivity and TFP estimates (based on value-added) are summarized in Table 4. It appears that estimates obtained by LS, TR and LP are positively and highly correlated with labour productivity and statistically significant at 1% level. The rank correlation between labour productivity and WLP estimates are relatively lower but it still stays reasonable. Given these findings, we prefer the LP estimates due to its statistical properties discussed above, although we do not expect the differences between them to be significant.

[INSERT Table 4]

4. Linking productivity growth and HGFs

4.1 Does higher productivity growth lead to high growth incidence?

Estimation strategy

To examine the determinants of HGF incidence, we specify a probability function of a firm entering a 3-year high growth period, and test the role of firm productivity growth. Our baseline model takes the following form:

$$HGF^*_{it} = a + b' gtfp_{it-1} + c' Z_{it-1} + k' R_{kt-1} + n_t + n_j + e_{it} \quad (1)$$

where HGF^*_{it} is a latent variable, linking to a binary variable HGF, which takes value 1 if firm *i* is in a high growth period at time t, and takes value 0 otherwise. Our main interest is how TFP growth in the previous year, $gtfp_{t-1}$, affects the probability of HGF-incidence. The vector Z_{it-1} captures a set of control variables that have been found in the literature to be important in explaining HGF-incidence or firm growth in general. These variables include firm age, size, cash holdings, intangible assets ratio, average wage and international activities.

Firm size is measured by the log of total employment. Cash holdings and intangible assets are both normalised by firm's total fixed assets. In the empirical literature intangible assets are often used as an input indicator of innovation and as an alternative to R&D spending or innovation success (Riley and Robinson, 2011; Dal Borgo et al., 2012). It includes goodwill, intellectual property rights, patents, trademarks, R&D investment, website domain names and typically long-term investment which may relate to a firm's innovative efforts. Some argue that intangible assets as a variable has the advantage of being continuous and derived from administrative data sources rather than from surveys (Bartoloni, 2010), but we do not know the exact composition of this variable because of the discretion of what firms decide to report as intangible assets.

The finance literature argues that large cash holdings can be seen to negatively affect a firm, especially when interests and incentives of managers and shareholders are in conflict over the optimal size of the firm and the payment of dividends to shareholders. In other words, large cash holdings may be a sign of managers not being able to spot profitable investment opportunities and at the same time not distributing these to shareholders either (Jensen, 1987). In the current uncertain economic climate, companies also tend to hold large amounts of cash as an insurance policy against a sudden catastrophic event like a collapse of the Euro currency.

Average wage is measured by dividing the total wage bill by the number of workers employed by the firm. Due to the lack of detailed information on employee qualifications in

FAME, we use average wages as a proxy for the average level of human capital in the firm, which is common in the firm level literature (Wagner, 2012).

A firm's international activities are captured by export and outward FDI activities. We generate a state variable to indicate a multinational firm, *MNE*. It takes a value of 1 if a firm has any outward FDI at any time during the observation period, which means that this variable is time invariant. It is well known that the records of export volume are sparse over time in FAME, which is unfortunate. To remedy this, we construct a dummy variable, export experience, *expexpr*, takes a value of 1 if a firm is observed to export in any previous period. The gain of having a stable measure of export activities has the trade-off of losing the magnitude of export activities.

The vector R_{k-1} is a vector of regional characteristics, lagged one period. The existing literature emphasises a number of regional indicators which may explain the different environments in which firms operate (Hart and McGuiness, 2003). We include GDP growth, unemployment levels, infrastructure (we use the volume of air traffic as a proxy), and the number of patents registered at the NUTS2 regional levels, to capture the environmental factors that shape HGF-incidence, and controls for the differences in effects they may have for firms in manufacturing and service sectors. Finally, the error term is made up of a time-specific component (v_t), a 2-digit industry-specific component (v_j), and an idiosyncratic error term $\boldsymbol{\varepsilon_i}$.

As a baseline investigation, we estimate pooled static Probit models in which all explanatory variables, except *MNE*, are lagged by one year to diminish potential endogeneity and correct heteroskedastic standard errors by clustering at the individual firm level. The regressions are estimated separately for the manufacturing and service sector. We also separately look at new firms and incumbents, as the impediments to firm growth at various stages may be quite different.

Empirical findings on the link between productivity growth and HGFs

Table 5a and 5b report the marginal effects of the determinants of HGF incidence in the manufacturing and service sectors over the examined period, 2001-2010. Two sets of static model estimation results are discussed below, namely a standard Probit model, and a random effects panel Probit model. They give us broadly consistent results of the key variables. The split-by-age sample estimates are also reported for new firms (no older than 5 years) and incumbents (older than 5 years).

The first thing to note is that across model specifications, we find highly statistically significant estimates of the coefficients on TFP growth for both sectors, and for both new firms and incumbents. This is strong evidence that, controlling for other factors, firm TFP growth increases the probability for a firm to enter a high growth period. The magnitudes of the TFP growth coefficients yield interesting insights. For manufacturing, after specifying individual unobserved heterogeneity by the random effects panel estimator, the TFP growth coefficient is larger for incumbent firms than for new firms, suggesting that incumbents are more likely to reach HGF status with productivity improvements. The opposite is true for the service sector, although the marginal effects between new firms and incumbents are quantitatively small. This implies that the learning curve for manufacturing firms is likely to be relatively steeper for *incumbent* firms whereas it is steeper for *young* service firms, and it may take longer to accumulate knowledge, experience and the capability to identify productivity improvements (Syverson, 2011).

We control for a number of variables which draw from the literature and they confirm the qualitative results found therein. Firm age has unanimously negative signs in all specifications, including those for new and incumbent firms. This suggests that firms are more likely to experience high growth at the earlier stage of their lives. Whereas size has a significantly negative impact on HGF incidence in manufacturing industries, the coefficients are mostly positive but marginally significant for the service sector. This suggests that HGFs are on average smaller in the manufacturing sector, but not in the service sectors. This trend is more obvious for newly established firms than for incumbents, consistent with the existing evidence (Anyadike-Danes et al., 2009, Bravo-Biosca, 2011). Our results also support the findings by Bravo-Biosca (2011) that when comparing the impact of firm size and age, being young is the more important factor in explaining HGF incidence. This is the case for both the service and manufacturing sectors.

Firms with more intangible assets on average have a higher probability of becoming HGFs, for both manufacturing and service industries, which is broadly in line with research on HGFs and innovation and other intangible asset expenditure (Mason et al., 2009). Moreover, analysing firms of different age, we find the intangible assets effects are mainly statistical significant among incumbents, not among new firms. This may suggest that it takes time to acquire intangible assets, especially when it involves aspects such as research and development, brand development and other expenses with a long term effect. Therefore, the accumulation of several key components of intangible assets may require substantial investment in the early stages of a firm, which may also hold up firm growth potential.

More interestingly, the effect of intangible assets is negative and significant for young firms while incumbents enjoy positive effects in the service industry. On one hand, this suggests that the accumulation of the key components of intangible assets, such as R&D, brand development and goodwill, take time to establish, especially in the service sector where customers would in general trust the service provided by a firm with a longer history and better reputation (Li and Prescott, 2009). On the other hand, once a company manages to survive in the market for more than five years, a further investment in intangible assets helps to boost the company's growth and this impact is much stronger in the service than in the manufacturing sector.

Average wage appears to be associated with a higher probability of becoming a HGF. Assuming average wage indicates labour quality in a competitive labour market, this result then suggests that labour quality improves firm growth perspectives. Further, we find average wage to be an important factor for service sector overall and more so for new service firms than incumbents. In contrast, it is important mainly for manufacturing incumbents, and not for new firms. This is consistent with the current understanding that service sector firms, although labour intensive, rely heavily on the quality of the service offered to consumers, particularly at the beginning of the life cycle when firms are in the process of establishing reputation.

We find negative and statistically significant coefficients for cash holding for both sectors, but these are very small in magnitudes. The level of cash held by firms seems to decrease the probability of achieving HGF status mainly among incumbents for both manufacturing and service sectors. A large amount of cash holding may indicate a lack of investment opportunities or capabilities, which may be detrimental for business growth (Jensen, 1987), as idle cash is accumulated and is not easily invested into the production process.

Being an exporter and/or being a multinational are often regarded as indicators of internationalisation. In the manufacturing sector, export is a significant driving force of becoming a HGF, but only for firms that are over five years old, which is due to the experience effect that takes time to build up, consistent with the evidence that younger firms first focus on their home market, before starting to export to other countries (Girma and Kneller, 2005). It is interesting to note the striking contrast between the impact of internationalisation on HGF incidence between the manufacturing and the service sector. Being a multinational in the service sector makes a firm highly likely to become a HGF, regardless of age group. This is likely driven by successful service firms replicating a

successful business model in other countries as well as its management practice (Battisti and Lona, 2009), showing that the high-growth service sector is not just focused on the UK economy. However, it does not have a significant effect in the manufacturing sector.

Regional economic indicators deliver some quite interesting results. First of all, the baseline estimation shows little evidence to suggest that the regional economic condition, infrastructure, and patent stock as included in our model are key determinants of HGF incidence for manufacturing firms. Considering that UK regional markets are well integrated, these findings do not come as a surprise. The quality of regional infrastructure, proxied by the volume of the air traffic, is not found to be a significant explanatory variable for HGF-incidence. However, this does not mean that infrastructural development is not important for firm growth, and it may well indicate that the already sound infrastructure development in the UK does not display many regional differences.

In contrast, regional economic conditions matter slightly more for service firms. We find the unemployment rate is negatively associated with HGF-incidence, particularly for incumbent firms. From our data, we are unable to distinguish different types of unemployment (structural or cyclical) in the regional statistics. However, high unemployment rate on the one hand may be associated with a labour force that is lacking appropriate education and training needed by firms, while on the other hand can signify lower purchasing power by consumers, which may explain the negative impact.

Consistent with the prediction on the unemployment rate, GDP growth is a driver of the HGF-incidence among service firms, suggesting that service sector is more likely to thrive in good economic periods. This is particularly the case for incumbent firms, showing that over the long period, macroeconomic conditions do matter for superior growth performance. We do not find regional economic conditions affecting the HGF perspective for new firms, which echoes the finding that HGFs exist even during financial crisis periods (NESTA, 2009).

[INSERT Table 5a]

[INSERT Table 5b]

Robustness check: Dynamic panel estimation

A potential drawback of the static model of high growth determinants is that it fails to take into account a firm's past HGF experience. If a firm is ever a high growth performer, it is likely that it possesses firm specificity that associates with the drivers of high growth, and hence may help the firm to become a HGF again. A static model such as our baseline model does not incorporate the dynamic nature of the HGF incidence. To deal with path dependence, we therefore adopt two approaches to address the dynamics in the HGF determination.

Technically, the past HGF experience can be captured by a lagged HGF experience dummy in the model, which is estimated by a random effect Panel Probit estimator with a dynamic term. The interpretation of the coefficients is slightly different and perhaps more desirable: controlling for the past HGF experience, the probability of HGF incidence is determined by:

$$HGF_{it}^{*} = a + d' HGF_{it-1} + b' gtfp_{it-1} + c' Z_{it-1} + k' R_{kt-1} + n_t + n_j + e_{it} \qquad (2)$$

Furthermore, the consistency of the dynamic Panel estimator relies on the assumption of the exogeneity of the initial status of the dynamic term, which in our case is HGF_{i1}. Put differently, this requires that a firm which is born a HGF has little to do with the unobserved firm characteristics. If this assumption is violated, as it is likely to be the case, then we have the well-known initial condition problem. This motivates the application of the second dynamic approach, the so-called dynamic Probit estimator proposed by Wooldridge (2005) which is based on the following the model:

$$HGF_{it}^{*} = \alpha + \delta' HGF_{it-1} + \beta' gtfp_{it-1} + \chi' Z_{it-1} + \kappa' R_{kt-1} + \phi' HGF_{i1} + \vartheta' \overline{Z_i} + \varpi' \overline{R_k} + \nu_t + \nu_j + \varepsilon_{it} \qquad (3)$$

where the initial status of HGF, and the firm specific time average of the covariates are included in the model; the model is estimated by a random effects panel estimator. Wooldridge (2005) shows that consistent estimates can be obtained even the initial condition problem is present.

Robustness check: findings

Next we discuss the estimation results of the dynamic Probit models. As explained in the methodology section, dynamic Probit models take into consideration the path dependence of HGF-incidence that is not considered in the static modelling. The dynamic Probit model proposed by Woodridge (2005) further resolves the initial condition problem that a standard random effects panel Probit model cannot. Notice that the highly significant lagged HGF dummy in all model specification verifies the dynamic specification. The results are reported in Table 6a and 6b for the manufacturing and service sectors respectively.

The important finding here is that TFP growth remains a highly significant determinant of HGF incidence for most model specifications, which lends robustness to our previous results. Higher TFP growth on average increases the likelihood of a firm entering a high growth period, for both manufacturing and service sectors. The results consistently hold for incumbents for both sectors, and also new service firms. Once controlling for path dependence and firm unobserved heterogeneity, TFP growth loses its statistical significance in affecting the HGF-incidence among new firms in the manufacturing sector, which reflects the heterogeneous nature of new firms' high productivity that has been found in the literature (Henrekson and Johansson, 2010a).

Although several control variables are no longer statistically significant in the dynamic model estimations, such as intangible assets, average wage and export, their firm specific time averages tend to be significant and have expected signs. Overall, for both sectors the results are qualitatively similar. It is also worth noting that in the dynamic model estimations, we find that GDP growth has positive impact on HGF incidence, while the unemployment rate has negative impact among new manufacturing firms, which has not been the case in the static models.

In summary, we find consistent and robust evidence that previous productivity growth increases the probability of HGF-incidence. This is robust to sector differences and different model specifications. Broadly, the findings of the control variables are in line with the literature, and many differences are found between manufacturing and service industries, and between new firms and incumbents. Several regional economic indicators are found to affect service firms HGF-incidence, but to a lesser extent for manufacturing firms.

[INSERT Table 6a]

[INSERT Table 6b]

4.2 Do HGFs achieve higher productivity growth?

Estimation strategy

In this section we investigate the productivity implication of the high growth phenomenon. Does high growth experience enhance productivity following the high turnover growth period? If it does, then what are the possible channels of this effect?

To associate high turnover growth experience with productivity growth, we first adopt a quantile regression approach to investigate the role of HGF experience in enhancing productivity growth along the TFP growth distribution. The motivation of adopting a quantile regression approach is that distinguishing a HGF from other firms using a threshold, such as at least 20% growth rate over the last three-year period, can be rather artificial. What is more important to know is the mechanism that encourages firms to grow in general along the whole TFP growth distribution, no matter which quantile a firm may be located in the distribution. A natural way of analysing the differential effects of turnover high growth experience across the firm TFP growth distribution is by deploying quantile regression technique (Koenker and Bassett, 1978). Thus, assuming the population regression takes on the following form:

$$gtfp_{it} = \alpha + \beta' HGF\_EXP_i + \chi' Z_{it-1} + \kappa' R_{kt-1} + \nu_t + \nu_j + \varepsilon_{it} \tag{4}$$

where the variables are defined in the same way as in equation (1). The quantile regression model can be written as

$$\begin{aligned} &gtfp_{it} = \alpha + \beta' HGF\_EXP_i + \chi' Z_{it-1} + \kappa' R_{kt-1} + \nu_t + \nu_j + \varepsilon_{it}; \\ &Quant_\theta(gtfp_{it} \mid HGF\_EXP_i, Z_{it-1}, R_{kt-1}, \nu_t, \nu_j) = \alpha_\theta + \beta_\theta^{'} HGF\_EXP_i + \chi_\theta^{'} Z_{it-1} + \kappa_\theta^{'} R_{kt-1} + \nu_t + \nu_j \end{aligned} \tag{5}$$

where $Quant_\theta(gtfp_{it} \mid HGF\_EXP_i, Z_{it-1})$ denotes the conditional quantile of *gtfp*. The distribution of the error term ε_θ is left unspecified, so the estimation method is semiparametric.

Thus by increasing θ from 0 to 1, we can trace the effects of high turnover growth experience on the entire distribution of TFP growth, conditional on the set of control variables. In addition, we can focus our attention on specific parts of the TFP growth distribution, and identify where in this distribution HGF experience exerts the greatest or the least significant impact.

One of the main difficulties in understanding the implication of high growth is that we know very little about the nature of high growth and how to quantify it. High growth is not a property, nor a characteristic, but rather an experience. Therefore, we specify a dichotomous HGF experience variable, HGF_EXP_i, to capture what high growth experience may do to a firm once it happens. Testing if this dummy is statistically significant in affecting TFP growth will show us evidence for the existence of a high growth experience, controlling for other factors and firm unobserved heterogeneity. This approach is equal to allowing for *intercept heterogeneity***.** We correct heteroskedastic standard errors first by clustering at the individual firm level in the baseline least squares estimation, and then by using fixed effects panel estimator as a robustness check.

Conditional on the productivity growth effects of HGF experience, we further search for potential channels through which HGF experience may shape TFP improvements. To this end, we modify model (4) by allowing *parameter heterogeneity* in HGF experience:

$$gtfp_{it} = \alpha + \beta' HGF\_EXP_i + \chi' Z_{it-1} \times HGF\_EXP + \kappa' R_{kt-1} \times HGF\_EXP + \nu_t + \nu_j + \varepsilon_{it} \quad (6)$$

By interacting HGF_EXP_i with firm characteristics and regional environment, we examine the average TFP growth effects due to HGF experience indirectly through various firm characteristics and regional environmental differences.

Empirical findings on the link between HGFs and productivity growth

After establishing that productivity growth is a significant driver of the HGF phenomenon, we turn our attention to the productivity implications of high growth. Tables 7a and 7b show quantile regression results for the prospect of enhanced productivity once a firm has achieved high growth status. We find that HGF experience helps improve TFP growth and this finding holds along the entire TFP growth distribution for both the manufacturing and service sector. If a firm has had a fast growth experience, then it is more likely to display higher TFP growth later on. In particular, the coefficients increase steadily along the quantiles of TFP growth, and peak towards the top quantile of TFP growth. This means that HGF experience generates even better results for already fast-growing firms, and this is particularly the case for the manufacturing sectors.

Both age and size show similar associations with TFP growth for both sectors. Before the median level of TFP growth, they appear to have a positive impact, and afterwards turn

negative. This suggests that incumbents and bigger firms are more likely to improve the productivity growth rate at the lower end of the distribution. At the higher end of the TFP growth distribution, younger and smaller firms are able to achieve faster growth (Evans, 1987; Geroski 1995; Caves 1998; Cabral and Mata, 2003; Du and Girma, 2012).

It is interesting to observe that intangible assets have a different impact on manufacturing and service firms. For manufacturing firms, the positive and significant impact only exists at and above the 50 per cent quantile of TFP growth. For the service sector, intangible assets are positive and significant across the entire TFP growth distribution. One of the reasons could be that IT departments in service industries have a more direct role in strategy development than is the case in the manufacturing industries (Sohal et al., 2001). Sohal et al. (2001) also finds that service industries employ IT to enhance the value of products and services to a greater extent than manufacturing, which can then lead to a higher TFP growth.

Average wage is differently related to a firm's TFP growth in the manufacturing and in the service sector. For manufacturing, higher wage could be an indicator for a higher number of skilled workers, which would then translate into a higher TFP growth rate. If a service firm pays more for its labour, which typically is the most important cost factor of the firm, then this is likely to lower the TFP growth of the company. However, while we have not tested this formally in our model, this relationship is likely to be different for sectors such as banking or consultancy where wage increases are likely to be at least partially correlated with productivity increases (Griffith et al., 2003).

For manufacturing firms, cash holding has a negative impact on TFP growth across the entire TFP growth distributions. However, while for service firms at the upper end of the TFP growth distribution this is also the case, at the lower end of the TFP growth distribution holding more cash boosts TFP growth. Exporting is only positively associated with TFP growth at the higher end of the TFP growth distribution in the manufacturing sector, while it has a positive (but not always significant) impact across the entire distribution in the service sector. If a manufacturing firm has a high growth rate, then being an exporter could boost TFP growth, but this effect does not occur for those manufacturing firms with a lower growth rate. In the service sector, firms are often either multinationals, such as most banks or insurance companies, or companies with a very confined local market, like real estate or education, such that being a multinational and being involved in the global market clearly could improve both manufacturing and service firms' TFP growth. The results are in line with Girma and Kneller (2005) for the UK service sector, Girma and Görg (2007) for UK

manufacturing plants and Hijzen et al. (2007) for Japan firms covering mining, manufacturing and wholesale/retail trade sectors.

Regional characteristics have a very similar impact on firm's TFP growth on both manufacturing and service sector. As expected, firms located in higher GDP growth regions have a higher TFP growth rate, regardless of whether they are manufacturing or service firms. A higher unemployment rate has a negative impact on TFP growth, but the impact turns positive for firms with a higher TFP growth rate and for firms in the service sector. This might be caused by fast growing firms which are less negatively affected by the low employment rates in a region, but rather benefiting from a higher number of skilled professionals that are available for lower remuneration (Dale, 2011). The local infrastructure and patents do not appear to have a significant impact on TFP growth for most quantiles across manufacturing and services.

[INSERT Table 7a]

[INSERT Table 7b]

Robustness check and the channels of TFP growth

Having shown quantile regression estimates which gives consistent evidence that high growth experience boosts firm TFP growth, we move on to the following two tasks. The first task is to further check the robustness of our findings, by estimating the TFP growth equation using the fixed effects panel estimator, which mitigates the unobserved heterogeneity and measurement error, and to some extent deals with potential endogeneity in the growth model. We also test if the assumption of correlation between fixed effects and residuals holds to justify the fixed effect panel estimator against random effect estimators.

Our second task is to seek an understanding of possible growth channels through which a previous high growth experience may help firms grow faster. We do this by interacting the HGF experience dummy and key firm and regional characteristics. Table 8a and 8b report the estimation results for the manufacturing sector and service sector.

When comparing columns (3) and (4) in both tables, we tend to rely more on the fixed effects estimates which account for firm unobserved heterogeneity. In particular, we find some significant results in the OLS estimation which become insignificant in the panel estimator. When interpreting the estimates, we look for statistical significant coefficients of the interaction terms, which indicate potential growth channels.

While age shows a significant positive coefficient in the fixed effect panel estimation in Table 8a, we do not find a significant interaction term of age and HGF experience among manufacturing firms. It is quite the opposite for service firms, for which age has negative sign, and the interaction term with HGF experience is also negative and significant. This seems to suggest that for the manufacturing firms, the benefit from HGF experience is not tangential to age, but for service firms, the earlier stage at which a firm experiences high growth, the higher growth in productivity it would experience subsequently. We do not find similar results for size.

The finding on cash holding confirms our previous results. For both sectors, the amount of cash holding plays negative role in TFP growth, and the interaction term with HGF experience is statistically insignificant in manufacturing sectors and negatively significant in service sectors. Again cash holding that may indicate insufficient investment opportunities or capabilities, and hence may hinder business growth (Jensen, 1987). This appears particular pertinent for service firms, which is in line with the conventional understanding that it is more difficult for service firms to identify good investment opportunities to the production process.

Intangible assets play a positive role in promoting productivity growth according to the quantile regressions. However, these effects lose statistical significance in the panel estimator, implying that intangible assets accumulation may be closely linked with some unobserved firm characteristics. According to the interaction term estimates, we do not have the evidence that intangible assets are a potential channel through which high growth experience translates to high TFP growth for both manufacturing and services firms.

Our internationalisation variables appear to be driving growth through HGF experience. For example, in Table 8a, although higher export intensity does not lead to significant TFP growth differences, firms with previous high growth experience do show higher productivity growth following the increased export intensity. We do not find statistically significant results on multinationality for manufacturing firms. However, services firms appear to benefit from multinationality if they had a high growth experience and the relationship is highly significant in the fixed effect panel estimation. Griffith et al. (2004) support this view with UK service firms, where they find that multinationals play an important role in the service sectors, and that British multinationals have lower levels of labour productivity than foreign multinationals, but the difference is less stark in the service sector than in the manufacturing sector. Regional environmental variables reveal further informing results. The unemployment rate is found to be a significant constraint on growth.

All else being equal, firms which locate in regions with higher unemployment rate tend to grow less, for both manufacturing and service sectors. In addition, even firms that had previous HGF experience tend to grow less than otherwise equal firms with HGF experience, if located in regions with higher unemployment rates. These results show strong detrimental impact of the sluggish macroeconomic environment and possible structural asymmetry between labour demand and supply (Hart and McGuinness, 2003). Hence, the evidence lends some support to the government's endeavour to promote employment and learning schemes to encourage young entrepreneurial talent. Indeed, many advanced countries including the UK maintain entrepreneurship training in schools, which at university level is especially advanced in the US which has close ties with the private sector (OECD, 2005). We use the number of patent application at the regional level to control for the level of technology and innovation in UK regions. We find that firms with HGF experience in regions with high levels of patent activity grow faster in terms of productivity which can be attributed to the increased potential for imitation and exploitation of advances in technology (Archibugi and Michie, 1995; Hart and McGuinness, 2003).

In summary, we find consistent and robust evidence that previous high growth experience helps firm enhance productivity. While this is the case for both manufacturing and service firms, there are differences in the effects for firms that locate at different points of the growth distribution. Fast growing firms seem to benefit more from high growth experience ("Success breeds success"). And finally, we find evidence that the TFP growth due to previous high turnover growth experience may relate to firm age, size, finance, human resource, internationalization, and regional economic conditions.

[INSERT Table 8a]

[INSERT Table 8b]

5. Linking productivity level and HGFs

In this section, we take a different angle and extend our previous analysis from focusing on TFP growth to TFP level. The motivation is the following. Firms that have fastest productivity growth are not necessarily those that have highest productivity levels. It is very likely that these two types of firms locate in different stages of development, hence may exhibit varied characteristics and drivers of high growth. Considering that a negative

association between level and growth is usually expected[6], our expectation on testing the link between TFP level and HGFs is that the results may deviate from what we have found in the previous section. We first replicate the estimation for our two research questions, and then discuss the main findings, as well as highlight the key differences in the results between the level and growth estimations.

5.1 Does a higher productivity level lead to HGF status?

To examine the role of TFP level in determining HGF-incidence, we slightly modify equation (1) and substitute productivity level for productivity growth. All other variables remain the same as described in Section 4. Table 9a and 9b report the static model estimation results. The robustness analysis using a dynamic probit models deliver highly consistent results with the static models, as reported in Table 9c and 9d.

[INSERT Table 9a]

[INSERT Table 9b]

[INSERT Table 9c]

[INSERT Table 9d]

The results of both static and dynamic models show that across all specifications, previous TFP levels are significantly and negatively associated with the probability of a firm entering a high growth period. It is not surprising that a firm with higher level of productivity might not achieve high growth rates, compared with a firm with low productivity levels, as it is easier to catch up and consequently enter a high growth period if a firm starts from a lower level. It also could be that only after achieving a certain level of productivity, firms are able to put more emphasis on strategic development and expanding capacity to grow the company in the longer term, which may be at the expense of high growth in revenue or employment in the short term. This is particularly the case for new firms, compared to incumbents, shown by the magnitudes of the TFP coefficients which are lower for new manufacturing firms compared with incumbent firms. A good real example is the case of new manufacturing businesses that may in fact be lower growth and high productivity spin-offs of existing firms

[6] It is often observed in macroeconomic literature, for example Barro (1991).

(see for example Samsung's spin-off of its LCD unit (Yang, 2012)). A similar effect is found in the service sector, although in the static Probit model the difference in marginal effects between new firms and incumbents is quantitatively larger than the difference between marginal effects in the manufacturing sector. This reflects the fact that the accumulation of knowledge, experience, capacity, and hence credibility and brand name in the market place in the service sector may only have a longer-term impact on improving a firm's performance, whereas firms in the manufacturing sector can improve the productivity level more quickly by investing in skilled work or more advanced machines (Syverson, 2011).

Next we briefly report the estimation results of the control variables, which deliver similar results to the TFP growth equations. Our interpretations of these results remain the same as in the Section 4 unless otherwise stated. Controlling for other factors, younger firms are more likely to become HGFs. The marginal effects for newly established firms are smaller than for incumbents for both manufacturing and service sectors, reinforcing the age effect. Firm size is a less important determinant compared to age for both sectors, consistent with the previous findings (for example Bravo-Biosca, 2011). Intangible assets on average have a significant and positive impact on a firm's probability of becoming a HGF for both manufacturing and service sectors, but the effects are different for firms in different age groups. The growth-driving effects of intangible assets are only significant among incumbents, while for young service firms the effects seem discouraging.

Firms with higher average wages are more likely to become a HGF, and the impact is similar across different age groups in the service industry, but in manufacturing the positive association between average wages and HGF-incidence only exists for incumbents. Again, cash flow shows little impact on a firm's probability to become a HGF; indeed all cash flow coefficients are insignificant in the manufacturing sector. In the service sector, although the estimated coefficients for new firms are positive, the magnitudes are very small. The results on export and being multinational highlight the differences between manufacturing and service sectors. While being an exporter helps manufacturing firms achieve high growth, multinational activities seem to only promote high growth for service firms. A weak association is identified between regional economic conditions and HGF-incidence, with evidence that regional GDP growth, regional knowledge stock (in terms of total patents) are positive and significantly linked to HGF-incidence for service firms.

In summary, the results show that productivity level, in addition to productivity growth, is an important determinant of HGF-incidence. However, these two effects may work in opposite directions. Whereas productivity growth is positively associated with the

likelihood of HGF-incidence, the level of productivity appears to be negatively associated with the probability of HGF-incidence. Taken together, the evidence suggests that firms that show faster productivity growth but still at a lower productivity level are the most promising HGF achievers.

5.2 Do HGFs achieve a higher productivity level?

We now turn to the analysis of the productivity consequence of high growth experience, by replicating the estimation of the equation (5) and (6) by replacing TFP growth with TFP level. The quantile regression results are reported in Table 10a and 10b for the manufacturing and service sector firms, while Table 11a and 11b show the results of the potential channels to increase TFP level.

[INSERT Table 10a]

[INSERT Table 10b]

[INSERT Table 11a]

[INSERT Table 11b]

These results confirm that past high growth experience have very similar stimulating effects as with TFP growth, and it is reassuring to see that similar strong and positive effects exist for both manufacturing and service sectors. This effect holds for service firms over the entire TFP level distribution and for manufacturing firms with a higher than median productivity level. For both manufacturing and service sectors the magnitude of the estimated HGF indicator coefficients reaches the highest point at the top quantile TFP level. This suggests that high growth experience can help firms to achieve a higher TFP level, especially for those firms that have higher than average TFP levels.

Most of the other variables in manufacturing and services have similar impacts to the ones discussed in the previous section, such as age, intangible assets, average wages, export and all regional characteristics. Both age and size show an increasing and positive impact along the TFP level distribution for both manufacturing and services, suggesting that incumbents and larger firms are more likely to achieve higher productivity levels. This result is in line with the literature which finds positive size- and age-productivity relationships (Leung, et al. 2008; Van Biesebroeck, 2005, Rao and Tang, 2000).

The intangible asset coefficients – our proxy for innovation - are positive and significant across the entire TFP distribution with little changes across the different quantile

points. The high magnitudes strongly suggest a positive relationship between intangible assets and the productivity level, which has been also found in a recent BIS report using different innovation modes of UK data (Lambert and Frenz, 2008)[7]. Hall (2011) concludes that there are substantial positive impacts of product innovation on productivity, but the impact of process innovation is more ambiguous, which might explain our less significant results from the service sector, in which most innovations are process related.

Average wage and cash holdings both have a significant impact on the TFP level and the coefficients increase steadily along the TFP level quintiles. As we mentioned above, higher wages could be an indicator for a higher number of skilled workers, which would be associated with higher TFP levels. Consistent with the previous findings (Carpenter and Guariglia, 2008) more cash could also release restrictions on hiring more skilled labour and develop more innovation and hence leading to higher productivity. These positive impacts hold for both manufacturing and service sectors.

Being an exporter does not help a firm to increase its productivity, and the negative effect is more significant for service firms in general. However, being a multinational firm increases the likelihood to achieve a higher productivity level. One reason might be that, as the well-known Melitz (2003) model suggests, only "better" firms, i.e. those that are more efficient or productive, are able to overcome the entry barriers to enter foreign markets and to be competitive in the host markets. They in general have higher productivity levels than domestic firms.

It is interesting to see that regional characteristics have very different impacts on productivity levels for manufacturing and service firms. A higher unemployment rate has a significantly negative impact on TFP level, but the effects are diminishing when the TFP level moves to the high end of the distribution. For service firms, the unemployment rate does not show a strong association with the level of TFP. The estimated results show limited evidence on the relationship between local infrastructure and the manufacturing firm's TFP level, but the impact of the local infrastructure is more significant for service firms. One reason might be due to our measurement of the local infrastructure in this paper, which is measured as the air transport of passengers. The infrastructure capability is very important for service firms, especially for financial and professional services firms.

[7] Lambert and Frenz (2008) use a variety of innovation measures such as UK in-house/IPR innovation and wide innovations as well as traditional innovations (product and process innovations) which lends some support to the use of intangible assets as an innovation proxy.

Manufacturing firms with patents are less likely to have a high productivity level, but patent is one of the driving forces to help service firms to achieve a high level of productivity and the impact is across the whole quantile of the distribution. Finally, regional macroeconomic conditions have a significant and positive impact on both manufacturing and service firms' TFP level.

Turning to the channels of achieving a higher TFP level, we note that the potential channels through which firms may learn from the past high growth experience differ among manufacturing firms and service firms. For the manufacturing firms, it is evident that labour quality measured by average wage could be the potential channel through which high growth experience translates to high TFP level. This is in addition to the direct productivity-driving effect of skilled labour. Firms with higher skilled labour tend to benefit more from their high growth experience by being more likely to achieve higher TFP. In the service sector, the potential positive impacts take place through a number of channels including age, cash holding and being multinational activities. For example, older firms that had high growth experience in the past are more likely to exhibit higher TFP level than younger firms, all else being equal. This may be the experience accumulation effect as argued in the empirical productivity literature (Svyverson, 2011).

Regional characteristics are found to play active roles in facilitating firms assimilating high growth experience. Again there are clear sector differences. Manufacturing firms seem to thrive in the regions that have better infrastructure and high GDP growth, which may indicate the benefits of smooth investment channels, developed logistic services and hence lower transportation cost, and generally higher economic prosperity. Service firms that locate in the regions with better knowledge stock (captured by patents) tend to have higher productivity, which may be due to selection and clustering effects. Moreover, the productivity-driving effects for the firms with high growth experience in these regions tend to be weakened, which may capture some competition effect (Aghion et al., 2005). While not surprising, in both sectors firms suffer from higher unemployment rates.

Overall, the implication of HGF experience is positive on both productivity growth and level. The reason for this is likely that a firm with HGF experience might be an indication of a "better" firm (i.e. with international activities, having more R&D activities, with better institutional settings, being more entrepreneurial and having a vision for more growth opportunities). All of these factors have been found to be conducive of both higher productivity levels and higher productivity growth (Bhaumik et al, 2011; Teruel and Wit, 2011; Henrekson and Johansson, 2009; Hölzl, 2009). For both manufacturing and service

sectors, the estimated coefficients increase steadily along the quintiles and peak at the high end of productivity growth/productivity level.

It is also interesting to see that estimated results of other variables from the TFP level model are different from the TFP growth estimates. The main differences are that both age and size have an increasingly positive impact along the TFP level distribution, but show an inverted-U shaped relationship with TFP growth. Secondly, in contrast to the small or even negative effects of intangible assets on TFP growth, the intangible asset coefficients are positive and significant across the entire TFP distribution with little changes across the different quantile points. Thirdly, average wage and cash flow are positively associated with TFP level, but either have a limited wage or negative cash flow impact on TFP growth. Last but not least, channels of improving productivity growth and productivity level through HGF experience are largely similar. A small number of channels have been identified: in the growth estimations, export and patents are potential channels, while in the levels estimations, only average wage shows a positive and significant sign.

6. Conclusion

In light of the on-going debate about the average productivity lag of the UK compared to for example the US and France, policy-makers are hopeful that one of the channels of alleviating this gap is to support and fund innovative and rapidly growing businesses (Bravo-Biosca, 2010). Identifying and supporting these HGFs is another opportunity for public policy to encourage productivity and economic growth in the UK economy.

The literature on HGFs wrestles with the unresolved debate, concerning whether policy-makers should assist new firms of better quality or whether the quantity of new firms is more important. In other words, is it better to have a large number of business start-ups or a few firms that grow rapidly? This report contributes to this debate and the literature of HGFs by showing for the first time strong and robust evidence of a causal relationship between TFP growth and HGF-incidence based on turnover high growth definition. Using a large UK firm level dataset spanning the period of 2001-2010, we demonstrate that total factor productivity (TFP) acts both as a determinant of HGFs, as well as a consequence of high growth experience. This report also contributes by analysing both the manufacturing and service sector separately and contrasting the differences in the characteristics and growth channels.

We differentiate TFP growth and TFP level when measuring TFP, and draw the following headline conclusions based on our study: (1) All else being equal, the firms that

have higher TFP growth but still at a lower TFP level are mostly likely to experience high growth; (2) Firms' past high turnover growth experience helps firm to achieve higher TFP level as well as TFP growth in the future; (3) There are marked differences in what determines HGF-incidence among firms at different development stages, namely for new firms or incumbents; (4) Differences in UK regional characteristics are not crucial in determining the average HGF-incidence, but they play an active role in shaping firms productivity profiles and their high turnover growth experience.

Therefore this suggests that value generated in new and rapidly growing firms is just as crucial for total value growth as their TFP growth which essentially is improvement in technology that allows firms to become HGFs in the first place. Moreover, it is becoming clear that rapidly growing firms are both rare, showing some general common characteristics vis-à-vis the rest of the firm population, but are also very much heterogeneous when compared to each other (OECD, 2000; Delmar et al., 2003). Understanding more about such exceptional firms is needed, not only for identifying their characteristics at a point in time, but for determining how firms grow and perform over a significant period of time and across industries, as the nature of economic growth is both complex and a multi-faceted phenomenon.

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Tables

Table 1a: Panel structure across time

Year	Firm-year observation	Percent	Number of additional firms in the data
2001	20,511	11.21	20,511
2002	20,703	11.31	1,253
2003	20,062	10.96	847
2004	18,343	10.02	686
2005	17,704	9.67	650
2006	17,662	9.65	647
2007	17,679	9.66	578
2008	17,707	9.67	484
2009	20,398	11.14	431
2010	12,255	6.7	226
Total	183,024	100	26,313

Note: The data structure presented in the table is based on the final data matrix included in the benchmark estimation of productivity by OLS.

Table 1b: Panel structure across industries (2001-2010)

NACE_2_digit	Frequency	Percent
Manufacturing sectors		
15. Food & Beverages	5,529	3.02
17. Textiles	1,556	0.85
18. Wearing apparel	923	0.50
19. Tanning and dressing leather	281	0.15
20. Wood products	1,311	0.72
21. Pulp and Paper products	1,745	0.95
22. Publishing and printing	5,945	3.25
23. Coke, Petroleum and Fuel	284	0.16
24. Chemicals	4,733	2.59
25. Rubber and plastics	3,455	1.89
26. Other non-metallic minerals	1,647	0.90
27. Basic metals	1,725	0.94
28. Fabricated metals	8,332	4.55
29. Machinery and equipment	4,755	2.60
30. Office machinery & computers	855	0.47
31. Electrical machinery	3,576	1.95
32. Communication equipment	1,799	0.98
33. Medical, optical & precision	2,603	1.42
34. Motor vehicles	1,600	0.87
35. Other transport equipment	1,329	0.73
36. Furniture	6,117	3.34
37. Recycling	487	0.27
Service sectors		
51. Wholesale trade and commission trade	29,496	16.12
52. Retail trade	10,677	5.83
55. Hotels and restaurants	7,789	4.26
60. Land transport	4,660	2.55
61. Water transport	803	0.44
62. Air transport	597	0.33
63. Supporting and auxiliary transport	4,916	2.69
64. Post and Telecommunications	2,187	1.19
65. Financial intermediation	1,675	0.92
66. Insurance and pension funding	458	0.25
67. Activities auxiliary to financial intermediation	329	0.18
70. Real estate activities	2,886	1.58
71. Renting of machinery and equipment	1,911	1.04
72. Computer and related activities	7,618	4.16
73. Research and development	765	0.42
74. Other business activities	26,403	14.43
80. Education	1,224	0.67
85. Health and social work	4,726	2.58
90 Sewage and refuse disposal	421	0.23
91. Activities of membership organizations	313	0.17
92. Recreational, Cultural and sporting actives	5,259	2.87
93. Other service actives	7,324	4.00
Total	183024	100

Note 1: The data structure presented in the table is based on the sample included in the benchmark estimation of productivity by OLS.

Note 2: Tobacco sector (16), Collection, purification and distribution of water sector (41) are dropped due to insufficient observations

Table 2: Frequency of HGF incidence (2001-2010)

NACE_2_digit	Overall			2006			2009			% change in HGF[a] 2006 to 2010
	N	% of HGF[a]	% of HGF[b]	N	% of HGF[a]	% of HGF[b]	N	% of HGF[a]	% of HGF[b]	
15. Food & Beverages	5529	9.0%	3.6%	523	10.9%	4.2%	668	4.2%	3.4%	-61.5%
17. Textiles	1556	4.9%	1.2%	142	6.3%	0.7%	160	3.8%	1.9%	-40.8%
18. Wearing apparel	923	8.6%	4.0%	78	14.1%	7.7%	88	2.3%	3.4%	-83.9%
19. Tanning and dressing leather	281	3.2%	1.4%	24	0.0%	0.0%	23	8.7%	0.0%	n.a
20. Wood products	1311	4.0%	1.0%	112	2.7%	1.8%	149	2.7%	2.0%	0.2%
21. Pulp and Paper products	1745	5.2%	2.1%	156	8.3%	1.3%	176	4.5%	1.7%	-45.5%
22. Publishing and printing	5945	7.7%	2.4%	546	9.9%	2.0%	515	5.0%	1.6%	-49.0%
23. Coke, Petroleum and Fuel	284	4.2%	1.8%	30	6.7%	3.3%	34	0.0%	0.0%	-100.0%
24. Chemicals	4733	8.9%	2.3%	470	10.9%	1.9%	524	6.7%	2.7%	-38.4%
25. Rubber and plastics	3455	8.0%	2.7%	326	9.2%	5.2%	355	4.2%	2.5%	-54.1%
26. Other non-metallic minerals	1647	6.6%	1.2%	154	11.0%	3.2%	184	1.6%	0.0%	-85.2%
27. Basic metals	1725	7.7%	1.4%	158	12.7%	1.9%	195	6.2%	0.5%	-51.4%
28. Fabricated metals	8332	7.5%	2.3%	762	15.0%	3.4%	938	2.2%	2.0%	-85.0%
29. Machinery and equipment	4755	10.8%	2.1%	454	16.1%	3.1%	528	5.5%	1.5%	-65.8%
30. Office machinery & computers	855	17.1%	2.1%	78	15.4%	5.1%	69	4.3%	0.0%	-71.7%
31. Electrical machinery	3576	11.4%	2.1%	338	16.0%	2.1%	371	3.8%	1.1%	-76.4%
32. Communication equipment	1799	17.7%	2.5%	172	23.3%	5.2%	177	9.6%	2.3%	-58.7%
33. Medical, optical & precision	2603	11.6%	2.8%	265	17.0%	3.8%	290	6.9%	3.4%	-59.4%
34. Motor vehicles	1600	12.6%	2.9%	158	15.2%	1.9%	173	4.6%	1.2%	-69.6%
35. Other transport equipment	1329	12.4%	3.0%	125	19.2%	4.8%	139	5.8%	2.2%	-70.0%
36. Furniture	6117	6.8%	2.0%	549	10.6%	2.6%	657	2.7%	1.4%	-74.1%
37. Recycling	487	15.2%	4.3%	40	27.5%	5.0%	92	4.3%	3.3%	-84.2%
Total Manufacturing	**60,587**	**8.89%**	**2.37%**	**5,660**	**12.8%**	**3.1%**	**6,505**	**4.35%**	**2.0%**	**-70.1%**
51. Wholesale trade and commission trade	29496	8.1%	3.4%	2707	11.6%	4.5%	3358	3.5%	2.6%	-69.5%
52. Retail trade	10677	9.7%	6.0%	988	13.3%	7.8%	1191	7.1%	6.6%	-46.2%
55. Hotels and restaurants	7789	9.5%	4.7%	743	12.2%	6.2%	929	4.7%	2.9%	-61.3%
60. Land transport	4660	6.4%	4.2%	422	9.7%	5.5%	550	2.5%	4.2%	-73.8%
61. Water transport	803	13.2%	2.9%	77	14.3%	2.6%	92	12.0%	2.2%	-16.3%
62. Air transport	597	16.9%	10.2%	61	21.3%	18.0%	57	3.5%	0.0%	-83.5%
63. Supporting and auxiliary transport	4916	12.0%	5.1%	478	16.3%	6.5%	548	6.9%	3.3%	-57.5%
64. Post and Telecommunications	2187	26.7%	10.0%	223	30.0%	15.7%	222	22.1%	8.6%	-26.5%
65. Financial intermediation	1675	24.2%	8.7%	204	32.4%	11.3%	165	15.2%	9.1%	-53.2%

66. Insurance and pension funding	458	22.5%	10.3%	46	17.4%	4.3%	46	10.9%	10.9%	-37.5%
67. Activities auxiliary to financial intermediation	329	31.9%	10.3%	33	33.3%	15.2%	37	29.7%	10.8%	-10.8%
70. Real estate activities	2886	21.1%	6.8%	303	31.4%	10.9%	278	10.8%	3.6%	-65.6%
71. Renting of machinery and equipment	1911	13.1%	6.6%	188	15.4%	8.5%	197	5.6%	2.5%	-63.8%
72. Computer and related activities	7618	18.0%	7.8%	813	24.1%	10.6%	748	12.3%	7.0%	-49.0%
73. Research and development	765	22.1%	8.5%	79	34.2%	16.5%	91	14.3%	3.3%	-58.2%
74. Other business activities	26403	17.2%	7.2%	2685	24.6%	10.7%	3190	11.3%	5.8%	-53.8%
80. Education	1224	13.6%	6.9%	115	15.7%	7.8%	152	8.6%	7.2%	-45.4%
85. Health and social work	4726	16.7%	6.5%	535	20.6%	9.3%	574	8.4%	6.4%	-59.3%
90 Sewage and refuse disposal	421	9.3%	3.1%	45	15.6%	4.4%	55	1.8%	3.6%	-88.3%
91. Activities of membership organizations	313	7.7%	2.9%	37	16.2%	5.4%	34	0.0%	2.9%	-100.0%
92. Recreational, Cultural and sporting actives	5259	13.7%	5.1%	508	14.6%	4.9%	540	8.0%	4.6%	-45.3%
93. Other service actives	7324	10.6%	5.3%	712	14.5%	5.6%	839	5.5%	5.0%	-62.1%
Total Services	**122,437**	**13%**	**5.7%**	**12,002**	**18.0%**	**7.8%**	**13,893**	**7.6%**	**4.7%**	**-62.5%**
Total	**183,024**	**11.64%**	**4.6%**	**17,662**	**16.3%**	**6.3%**	**20,398**	**6.59%**	**3.82%**	**-59.6%**

Note: HGF[a]: average annual growth rate in *turnover* equal or above 20% over the 3-year period;
HGF[b]: average annual growth rate in *employment* equal or above 20% over the 3-year period.

Table 3a: Summary statistics – at firm level (2001-2010)

Variables	Total		Manufacturing						Service					
			All		Non-HGFs		HGFs		All		Non-HGFs		HGFs	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Employees	203	552	201	447	206	460	154	285	204	597	212	619	151	421
Age	23	21	29	23	30	24	21	20	21	18	22	19	14	15
Turnover	27512.46	57395.01	27971.3	56270.8	28215.3	57133.5	25469.8	46441.9	27285.3	57942.1	27799.5	59516.0	23846.6	45906.0
Costs of Goods sold	16644.00	39356.80	16658.7	37342.0	16731.3	37710.4	15914.4	33323.8	16636.7	40316.7	16898.7	41149.3	14884.2	34180.9
Capital	4261.55	10832.94	4849.48	10920.6	4897.58	11014.1	4356.35	9898.11	3970.61	10777.4	4046.00	10906.7	3466.35	9854.90
Value added	10868.47	22716.57	11312.6	23246.2	11484.0	23635.1	9555.35	18711.7	10648.6	22446.6	10900.7	23138.8	8962.44	17016.3
Turnover growth	0.09	0.48	0.06	0.39	0.01	0.24	0.54	0.87	0.11	0.52	0.02	0.29	0.68	1.02
Employment growth	0.01	0.13	-0.01	0.11	-0.01	0.09	0.08	0.18	0.02	0.14	0.01	0.11	0.14	0.24
Intangible assets ratio	0.02	0.08	0.02	0.07	0.02	0.07	0.03	0.09	0.02	0.09	0.02	0.08	0.04	0.11
Average wage	30.14	23.60	28.22	14.30	28.06	14.30	29.88	14.17	31.10	27.00	30.33	25.09	36.23	36.94
Cash holding	1481.21	3297.52	1463.17	3259.13	1459.00	3270.30	1506.91	3139.68	1489.97	3315.98	1479.38	3329.82	1561.55	3220.07
Export experience	0.45	0.50	0.65	0.48	0.65	0.48	0.68	0.47	0.35	0.48	0.34	0.48	0.35	0.48
Multinational	0.05	0.21	0.06	0.23	0.05	0.23	0.06	0.24	0.05	0.21	0.04	0.20	0.06	0.23
tfp_ols, value added	1.22	0.90	1.19	0.79	1.17	0.77	1.33	1.02	1.23	0.94	1.21	0.91	1.36	1.09
tfp_ols, revenue based	1.09	0.53	1.06	0.44	1.06	0.43	1.11	0.51	1.10	0.56	1.09	0.56	1.13	0.61
tfp_translog, value	1.21	0.89	1.19	0.79	1.17	0.76	1.33	1.01	1.23	0.93	1.21	0.91	1.35	1.09
tfp_translog, revenue	1.06	0.37	1.04	0.31	1.04	0.30	1.05	0.37	1.06	0.39	1.06	0.39	1.07	0.44
tfp_lp, value added	5.09	0.89	4.56	0.77	4.55	0.76	4.66	0.87	5.35	0.83	5.34	0.82	5.41	0.90
tfp_lp, revenue based	5.67	1.68	5.04	1.84	5.06	1.81	4.84	2.16	5.98	1.49	5.98	1.49	5.97	1.54
tfp_wlp	1.08	0.51	0.97	0.40	0.97	0.41	1.01	0.39	1.15	0.56	1.14	0.55	1.23	0.59
N	183,024		60,587		55,203		5,384		122,437		106,512		15,925	

Note 1: Monetary values are reported in £ thousands, in case of turnover, material, capital and value added.

Note 2: The table reports the summary statistics of relevant variables based on cleaned data (1% trim and missing values).

Note 3: The HGFs classification is based on definition a (see the definitions in Section 4 and in Table 2).

Table 3b: Summary statistics – at firm level (2001-2010)

NUTS-2	Air traffic	Patent count	Unemployment	GDP growth
NORTH EAST (ENGLAND)				
Tees Valley and Durham	698.2222	56.24755	7.15	-0.6858
Northumberland and Tyne and Wear	4575.111	47.274	7.08	-0.67979
NORTH WEST (ENGLAND)				
Cumbria	n.a.	42.705	4.81	0.342257
Cheshire	1.966667	128.9116	4.43	-1.65943
Greater Manchester	20439.45	42.41245	6.28	-1.13088
Lancashire	311.7778	41.55789	5.07	-1.11353
Merseyside	4073.111	57.27478	7.44	-0.7542
YORKSHIRE AND THE HUMBER				
East Yorkshire and Northern Lincolnshire	463.8889	53.26389	6.62	-0.6043
North Yorkshire	n.a.	74.31067	3.74	-0.92607
South Yorkshire	629.4286	38.26355	6.79	-0.30041
West Yorkshire	2346	49.95211	6.13	-1.13468
EAST MIDLANDS (ENGLAND)				
Derbyshire and Nottinghamshire	n.a.	86.599	5.62	-0.67213
Leicestershire, Rutland and Northamptonshire	4312.556	76.15767	5.03	-0.07529
Lincolnshire	n.a.	45.021	4.96	-0.62244
WEST MIDLANDS (ENGLAND)				
Herefordshire, Worcestershire and Warwickshire	302.6667	111.1019	4.11	-0.79507
Shropshire and Staffordshire	n.a.	43.94411	4.94	-0.52709
West Midlands	8834.889	41.84566	8.56	-2.04579
EAST OF ENGLAND				
East Anglia	526.7778	198.0233	4.52	-0.12756
Bedfordshire and Hertfordshire	8341.777	139.287	4.42	-0.92734
Essex	20131.78	88.43144	4.78	-0.06795
LONDON				
Inner London	2189.222	82.34834	8.66	1.830524
Outer London	65493.22	40.09289	6.49	-0.64675
SOUTH EAST (ENGLAND)				
Berkshire, Buckinghamshire and Oxfordshire	0.333333	202.6167	4.07	-0.2265
Surrey, East and West Sussex	32220.45	147.9782	4.05	-0.84525
Hampshire and Isle of Wight	1538	141.8027	4.17	0.283964
Kent	42	67.66167	5.36	-0.1619
SOUTH WEST (ENGLAND)				
Gloucestershire, Wiltshire and Bristol/Bath area	4816.778	149.7638	3.82	-0.57039
Dorset and Somerset	713.6667	58.16533	3.93	-0.12706
Cornwall and Isles of Scilly	244.8571	33.02111	4.87	1.181244
Devon	691	35.74844	4.67	0.028769
WALES				
West Wales and The Valleys	0.5	27.76378	6.27	-0.629
East Wales	1795.667	52.64845	5.11	-1.20035
SCOTLAND				
Eastern Scotland	8114.778	81.82022	5.63	0.462586
South Western Scotland	10169.89	30.08089	6.92	-0.45763
North Eastern Scotland	2880	15.67778	3.69	0.858498
Highlands and Islands	1165.556	32.223	5.08	0.585117
NORTHERN IRELAND				
Northern Ireland	6812.556	28.292	5.35	-0.69102

Source: Eurostat

Table 4: Spearman rank correlation coefficients between labour productivity and TFP measures (value added based)

Sector	TFP_LS_va	TFP_TL_va	TFP_LP_va	TFP_WLP
15. Food & Beverages	0.889	0.866	0.744	0.816
17. Textiles	0.958	0.954	0.854	0.824
18. Wearing apparel	0.951	0.947	0.805	0.648
19. Tanning and dressing leather	0.937	0.883	0.801	0.718
20. Wood products	0.990	0.987	0.902	0.835
21. Pulp and Paper products	0.986	0.960	0.937	0.853
22. Publishing and printing	0.999	0.998	0.957	0.681
23. Coke, Petroleum and Fuel	0.841	0.825	0.740	0.894
24. Chemicals	0.990	0.972	0.910	0.872
25. Rubber and plastics	0.966	0.952	0.897	0.839
26. Other non-metallic minerals	0.933	0.925	0.880	0.831
27. Basic metals	0.911	0.898	0.870	0.825
28. Fabricated metals	0.981	0.980	0.918	0.789
29. Machinery and equipment	0.972	0.967	0.841	0.722
30. Office machinery & computers	0.994	0.991	0.940	0.766
31. Electrical machinery	0.987	0.986	0.923	0.791
32. Communication equipment	0.973	0.968	0.835	0.773
33. Medical, optical & precision	0.976	0.974	0.836	0.762
34. Motor vehicles	0.979	0.965	0.861	0.844
35. Other transport equipment	0.916	0.912	0.763	0.793
36. Furniture	0.970	0.970	0.886	0.758
37. Recycling	0.975	0.970	0.951	0.832
51. Wholesale trade and commission trade	0.949	0.947	0.814	0.750
52. Retail trade	0.880	0.876	0.551	0.772
55. Hotels and restaurants	0.911	0.908	0.821	0.712
60. Land transport	0.946	0.943	0.685	0.575
61. Water transport	0.829	0.831	0.689	0.778
62. Air transport	0.883	0.864	0.598	0.679
63. Supporting and auxiliary transport	0.925	0.925	0.769	0.604
64. Post and Telecommunications	0.881	0.874	0.770	0.726
65. Financial intermediation	0.909	0.886	0.840	0.664
66. Insurance and pension funding	0.981	0.974	0.827	0.580
67. Activities auxiliary to financial intermediation	0.855	0.773	0.731	0.737
70. Real estate activities	0.926	0.927	0.840	0.758
71. Renting of machinery and equipment	0.837	0.836	0.656	0.651
72. Computer and related activities	0.967	0.955	0.886	0.566
73. Research and development	0.993	0.988	0.961	0.455
74. Other business activities	0.883	0.882	0.763	0.550
80. Education	0.980	0.980	0.884	0.218
85. Health and social work	0.958	0.947	0.786	0.426
90 Sewage and refuse disposal	0.702	0.709	0.582	0.704
91. Activities of membership organizations	0.982	0.968	0.970	0.332
92. Recreational, Cultural and sporting actives	0.989	0.986	0.853	0.684
93. Other service actives	0.931	0.927	0.837	0.608

Note 1: LS refers to the Cobb-Douglas production function approach to measuring productivity; TL refers to the TFP estimates based on the translog production function, and LP refers to the Levinsohn and Petrin(2003) semiparametric estimator; all estimation are based on value added as output.
Note 2: The figures reported in the table are Spearman rank correlation coefficients.
Note 3: All correlation coefficients are statistically significant at 1% level.

Table 5a: Is TFP growth a determinant of HG incidence? – Manufacturing sectors

	Static Probit Model			Random effect Panel Probit Model		
VARIABLES	All firms	New firm, <=5years	Incumbents, >5 years	All firms	New firm, <=5years	Incumbents, >5 years
Productivity						
TFP growth$_{it}$	0.144***	0.230***	0.132***	1.167***	0.742***	1.198***
	(0.00724)	(0.0302)	(0.00736)	(0.0587)	(0.180)	(0.0666)
Firm characteristics						
Age$_t$	-0.00135***	-0.0373***	-0.00104***	-0.0235***	-0.621***	-0.0183***
	(0.000135)	(0.0106)	(0.000129)	(0.00200)	(0.0883)	(0.00197)
Size$_{t-1}$	-3.47e-05***	-0.00021***	-2.87e-05***	-0.00043***	-0.00199***	-0.00039***
	(8.83e-06)	(6.61e-05)	(8.49e-06)	(0.000113)	(0.000735)	(0.000114)
Intangible assets ratio$_{t-1}$	0.104***	0.0792	0.0830***	1.537***	1.119	1.257***
	(0.0263)	(0.0808)	(0.0305)	(0.333)	(0.950)	(0.390)
Average wage$_{t-1}$	0.000711***	0.000284	0.000848***	0.00641***	0.00322	0.00864***
	(0.000230)	(0.000515)	(0.000194)	(0.00190)	(0.00557)	(0.00207)
Cash flow$_{t-1}$	-1.73e-07	7.99e-06	-6.34e-07	-2.08e-05*	-4.05e-05	-2.16e-05*
	(1.04e-06)	(6.14e-06)	(1.01e-06)	(1.08e-05)	(5.98e-05)	(1.13e-05)
Export$_{t-1}$	0.00484	-0.0549**	0.00843*	0.0889	-0.476*	0.155**
	(0.00514)	(0.0259)	(0.00509)	(0.0748)	(0.280)	(0.0786)
MNE	0.00852	0.00452	0.00858	0.244	0.106	0.225
	(0.0118)	(0.0715)	(0.0114)	(0.154)	(0.772)	(0.155)
Regional characteristics						
Unemployment rate	0.000595	-0.0123	0.00121	-0.000788	-0.145	0.0130
	(0.00191)	(0.0102)	(0.00189)	(0.0216)	(0.100)	(0.0227)
Air	-3.49e-07**	-1.56e-06*	-2.86e-07*	-3.82e-06	-1.46e-05	-2.66e-06
	(1.67e-07)	(9.26e-07)	(1.62e-07)	(2.36e-06)	(1.00e-05)	(2.40e-06)
Patent	2.83e-05	-0.000125	3.81e-05	0.000165	0.000282	0.000502
	(5.41e-05)	(0.000289)	(5.33e-05)	(0.000635)	(0.00298)	(0.000666)
GDP growth	-0.000160	0.000782	-0.000239	-0.000820	0.00840	-0.00245
	(0.000182)	(0.000868)	(0.000182)	(0.00228)	(0.00934)	(0.00241)
Observations	32,045	2,074	29,965	32,045	2,080	29,965

Note: 1.All regressions include year dummy and NACE 2-digit industrial sector dummies
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5b: Is TFP growth a determinant of HG incidence? – Service sectors

	Static Probit Model			Random effect Panel Probit Model		
VARIABLES	All firms	New firm, <=5years	Incumbents, >5 years	All firms	New firm, <=5years	Incumbents, >5 years
Productivity						
TFP growth$_{it}$	0.233***	0.392***	0.206***	1.760***	1.956***	1.822***
	(0.00627)	(0.0243)	(0.00586)	(0.0334)	(0.110)	(0.0400)
Firm characteristics						
Age$_t$	-0.00269***	-0.0398***	-0.00160***	-0.0338***	-0.473***	-0.0236***
	(0.000161)	(0.00664)	(0.000129)	(0.00137)	(0.0418)	(0.00136)
Size$_{t-1}$	2.58e-06	-2.05e-05	3.32e-06	6.61e-05**	-0.000122	6.44e-05*
	(3.24e-06)	(2.05e-05)	(2.83e-06)	(3.25e-05)	(0.000145)	(3.37e-05)
Intangible assets ratio$_{t-1}$	0.0660***	-0.112**	0.0615***	0.876***	-0.740**	0.859***
	(0.0138)	(0.0447)	(0.0149)	(0.133)	(0.319)	(0.168)
Average wage$_{t-1}$	0.00041***	0.00121***	0.00031***	0.00374***	0.00755***	0.00371***
	(7.70e-05)	(0.000270)	(7.06e-05)	(0.000404)	(0.00152)	(0.000426)
Cash flow$_{t-1}$	-1.26e-06**	1.32e-06	-1.30e-06***	-1.88e-05***	7.03e-06	-1.96e-05***
	(4.99e-07)	(3.08e-06)	(4.53e-07)	(4.47e-06)	(1.92e-05)	(4.78e-06)
Export$_{t-1}$	0.00547	-0.0172	0.00962***	0.0616	-0.169	0.122***
	(0.00340)	(0.0171)	(0.00320)	(0.0376)	(0.130)	(0.0398)
MNE	0.0254***	0.111**	0.0210***	0.358***	1.069***	0.325***
	(0.00804)	(0.0470)	(0.00727)	(0.0788)	(0.326)	(0.0807)
Regional characteristics						
Unemployment rate	0.000363	0.00829	-0.000558	-0.0237**	0.0330	-0.0339***
	(0.00132)	(0.00649)	(0.00126)	(0.0117)	(0.0451)	(0.0128)
Air	-1.69e-08	7.68e-07*	-6.18e-08	-6.06e-07	4.51e-06	-8.65e-07
	(8.85e-08)	(4.12e-07)	(8.43e-08)	(9.74e-07)	(3.17e-06)	(1.05e-06)
Patent	4.83e-05	0.000525***	5.39e-06	-0.000196	0.00295**	-0.000530
	(3.97e-05)	(0.000190)	(3.84e-05)	(0.000365)	(0.00136)	(0.000399)
GDP growth	0.000220**	4.43e-05	0.000222**	0.00501***	0.00331	0.00557***
	(9.92e-05)	(0.000481)	(9.46e-05)	(0.000962)	(0.00344)	(0.00104)
Observations	78,588	7,999	70,589	78,588	7,999	70,589

Note: 1.All regressions include year dummy and NACE 2-digit industrial sector dummies
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6a: Robustness Check: Dynamic Probit models – Manufacturing sectors

	Random effect Panel Probit Model with dynamic term			Dynamic panel estimator, Wooldridge (2005)		
VARIABLES	All firms	New firm, <=5years	Incumbents, >5 years	All firms	New firm, <=5years	Incumbents, >5 years
Productivity						
TFP growth$_{it}$	0.720***	0.278	0.693***	0.512***	-0.0545	0.550***
	(0.0579)	(0.185)	(0.0660)	(0.0624)	(0.217)	(0.0698)
Firm characteristics						
Age$_t$	-0.0122***	-0.897***	-	-0.266***	-1.341***	-0.153***
	(0.00146)	(0.133)	(0.00148)	(0.0310)	(0.184)	(0.0360)
Size$_{t-1}$	-	-	-	-	-0.00414	-
	(0.000109)	(0.000808)	(0.000111)	(0.000234)	(0.00257)	(0.000233)
Intangible assets ratio$_{t-1}$	1.149***	0.428	0.754**	0.608	0.0731	0.372
	(0.281)	(0.817)	(0.347)	(0.495)	(1.923)	(0.548)
Average wage$_{t-1}$	0.00152	0.00628	0.00330*	-0.00680**	0.00903	-
	(0.00174)	(0.00522)	(0.00187)	(0.00275)	(0.0108)	(0.00294)
Cash flow$_{t-1}$	-8.16e-06	-6.26e-06	-1.14e-05	-2.88e-	-0.000137	-2.93e-05**
	(1.09e-05)	(6.18e-05)	(1.14e-05)	(1.38e-05)	(9.27e-05)	(1.45e-05)
Export$_{t-1}$	-0.00386	-0.767***	0.0665	-0.127*	-1.295***	-0.0421
	(0.0582)	(0.274)	(0.0623)	(0.0701)	(0.344)	(0.0731)
MNE	0.139	0.245	0.127	0.0326	-0.0521	0.0424
	(0.120)	(0.737)	(0.123)	(0.125)	(0.754)	(0.127)
Regional						
Unemployment rate	-0.0171	-0.226**	0.00529	-0.0184	-0.237**	0.00190
	(0.0208)	(0.104)	(0.0221)	(0.0214)	(0.105)	(0.0225)
Air	-1.73e-06	-1.35e-05	-6.09e-07	-1.08e-06	-1.43e-05	-4.97e-07
	(1.82e-06)	(9.88e-06)	(1.88e-06)	(1.90e-06)	(1.02e-05)	(1.94e-06)
Patent	0.000315	1.95e-05	0.000662	2.85e-05	4.17e-05	0.000344
	(0.000575)	(0.00280)	(0.000610)	(0.000598)	(0.00289)	(0.000626)
GDP growth	3.98e-05	0.0161*	-0.00209	-0.000228	0.0192**	-0.00240
	(0.00198)	(0.00921)	(0.00211)	(0.00206)	(0.00945)	(0.00218)
State dependence						
HGF$_{it-1}$	2.808***	5.578***	2.818***	2.775***	5.881***	2.786***
	(0.0598)	(0.613)	(0.0629)	(0.0653)	(0.617)	(0.0672)
HGF$_{i1}$				0.177**	-0.509	0.116
				(0.0855)	(0.464)	(0.0887)
Mean covariates						
Age				0.256***	0.724***	0.145***
				(0.0311)	(0.172)	(0.0360)
Size				0.000141	0.00225	9.36e-05
				(0.000270)	(0.00256)	(0.000270)
TFP growth				1.268***	2.641***	0.814***
				(0.156)	(0.521)	(0.193)
Intangible asset ratio				0.441	0.284	0.575
				(0.635)	(2.321)	(0.716)
Average wage				0.0135***	-0.00179	0.0158***
				(0.00309)	(0.0155)	(0.00323)
Cash flow				3.23e-05	0.000192	2.97e-05
				(2.21e-05)	(0.000125)	(2.31e-05)
Export				0.417***	1.401**	0.356***
				(0.134)	(0.666)	(0.138)
Observations	32,045	2,080	29,965	32,045	2,080	29,965

Note: 1. All regressions include year dummy and NACE 2-digit industrial sector dummies.
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6b: Robustness Check: Dynamic Probit models – Service sectors

	Random effect Panel Probit Model with dynamic term			Dynamic panel estimator, Wooldridge (2005)		
VARIABLES	All firms	New firm, <=5years	Incumbents, >5 years	All firms	New firm, <=5years	Incumbents, >5 years
Productivity						
TFP growth$_{it}$	1.529***	1.459***	1.459***	0.973***	1.153***	0.845***
	(0.0239)	(0.0660)	(0.0291)	(0.0308)	(0.0983)	(0.0349)
Firm characteristics						
Age$_t$	-0.0108***	-0.357***	-	-0.591***	-0.235***	-0.591***
	(0.000570)	(0.0282)	(0.000580)	(0.0545)	(0.0175)	(0.0545)
Size$_{t-1}$	-4.28e-06	-	6.25e-06	-0.000743**	-	-0.000743**
	(1.70e-05)	(6.63e-05)	(1.80e-05)	(0.000325)	(7.05e-05)	(0.000325)
Intangible assets	0.281***	-0.221	0.0663	1.013*	-0.390	1.013*
	(0.0749)	(0.140)	(0.103)	(0.563)	(0.245)	(0.563)
Average wage$_{t-1}$	0.00142***	0.00372***	0.00134***	0.00258	-0.00298***	0.00258
	(0.000223)	(0.000808)	(0.000243)	(0.00200)	(0.000649)	(0.00200)
Cash flow$_{t-1}$	-1.43e-	-2.57e-06	-1.68e-	-6.96e-	-5.23e-	-6.96e-
	(2.75e-06)	(8.92e-06)	(3.01e-06)	(2.53e-05)	(6.02e-06)	(2.53e-05)
Export$_{t-1}$	0.0427**	0.00398	0.0718***	0.130	0.107***	0.130
	(0.0168)	(0.0529)	(0.0184)	(0.105)	(0.0325)	(0.105)
MNE	0.157***	0.409***	0.151***	0.687***	0.224***	0.687***
	(0.0336)	(0.130)	(0.0358)	(0.253)	(0.0646)	(0.253)
Regional						
Unemployment rate	0.00731	0.0329	-0.000582	0.0238	-0.0119	0.0238
	(0.00754)	(0.0217)	(0.00840)	(0.0388)	(0.0119)	(0.0388)
Air	-4.36e-07	1.26e-06	-6.93e-07	-4.53e-07	-1.14e-06	-4.53e-07
	(4.43e-07)	(1.30e-06)	(4.93e-07)	(2.53e-06)	(8.52e-07)	(2.53e-06)
Patent	0.000314	0.00133**	7.93e-05	0.00103	-0.000298	0.00103
	(0.000213)	(0.000623)	(0.000236)	(0.00113)	(0.000350)	(0.00113)
GDP growth	0.000217	-0.000180	0.000346	0.00188	0.00206**	0.00188
	(0.000543)	(0.00158)	(0.000605)	(0.00290)	(0.000931)	(0.00290)
State dependence						
HGF$_{it-1}$	2.080***	2.069***	2.123***	1.322***	0.809***	1.487***
	(0.0179)	(0.0582)	(0.0198)	(0.0237)	(0.0867)	(0.0261)
HGF$_{i1}$				1.514***	3.306***	1.046***
				(0.0452)	(0.198)	(0.0456)
Mean covariates						
Age				0.235***	0.392***	0.224***
				(0.0141)	(0.0538)	(0.0175)
Size				0.000238***	0.000426	0.000306***
				(7.51e-05)	(0.000347)	(7.78e-05)
TFP growth				1.013***	0.650***	1.362***
				(0.0777)	(0.185)	(0.0966)
Intangible asset ratio				-0.127	-1.867***	0.832***
				(0.260)	(0.686)	(0.303)
Average wage				0.00679***	0.00518*	0.00734***
				(0.000804)	(0.00276)	(0.000844)
Cash flow				4.34e-05***	9.17e-05***	4.13e-05***
				(7.95e-06)	(3.03e-05)	(8.38e-06)
Export				0.0287*	-0.0148	0.0303*
				(0.0173)	(0.0763)	(0.0176)
Observations	78,588	7,999	70,589	78,588	7,999	70,589

Note: 1. All regressions include year dummy and NACE 2-digit industrial sector dummies.
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7a: High growth experience and TFP growth: Quantile regression analysis Manufacturing sectors

Dep: TFP growth	(1)	(2)	(3)	(4)	(5)
VARIABLES	q10	q25	q50	q75	q90
High Growth Firm					
HGF_{it-1}	0.0283***	0.0457***	0.0655***	0.120***	0.208***
	(0.00524)	(0.00403)	(0.00353)	(0.00590)	(0.00728)
Firm characteristics					
Age_t	0.000549***	0.000274***	3.46e-05	-0.00022***	-0.00072***
	(8.45e-05)	(5.06e-05)	(2.88e-05)	(3.80e-05)	(7.87e-05)
$Size_{t-1}$	2.65e-05***	8.84e-06***	-1.32e-05***	-3.55e-05***	-6.14e-05***
	(3.34e-06)	(2.12e-06)	(9.74e-07)	(2.52e-06)	(5.37e-06)
Intangible assets $ratio_{t-1}$	-6.71e-07	-4.37e-07	8.54e-07***	1.21e-06*	2.57e-06**
	(1.22e-06)	(4.31e-07)	(2.82e-07)	(6.56e-07)	(1.17e-06)
Average $wage_{t-1}$	0.0724**	0.0227	0.0148	0.0466*	0.105**
	(0.0283)	(0.0230)	(0.0129)	(0.0279)	(0.0447)
Cash $flow_{t-1}$	-0.00542***	-0.00293***	-0.00165***	-0.00156***	-0.00204***
	(0.000295)	(0.000242)	(0.000160)	(0.000221)	(0.000489)
$Export_{t-1}$	-0.0206	-0.00519	0.0110***	0.0282***	0.0445***
	(0.0131)	(0.00516)	(0.00375)	(0.00534)	(0.00987)
MNE	0.0377***	0.0179***	0.00878**	0.00639	0.00809
	(0.0105)	(0.00493)	(0.00418)	(0.00421)	(0.0126)
Regional characteristics					
Unemployment rate	-0.00715***	-0.00341**	-0.00179*	-0.00151	-0.00123
	(0.00163)	(0.00149)	(0.000952)	(0.000933)	(0.00222)
Air	3.78e-07**	2.24e-07***	5.98e-08	-5.22e-08	-9.45e-08
	(1.67e-07)	(8.26e-08)	(6.08e-08)	(6.50e-08)	(1.46e-07)
Patent	-3.50e-05	-2.52e-05	-4.61e-05*	-2.95e-05	-4.73e-05
	(4.91e-05)	(3.46e-05)	(2.62e-05)	(3.06e-05)	(5.86e-05)
GDP growth	0.000511***	0.000279**	0.000206**	0.000363***	0.000528**
	(0.000132)	(0.000119)	(8.48e-05)	(9.66e-05)	(0.000262)
Observations	32,045	32,045	32,045	32,045	32,045

Note: 1. The quantile regression results presented in this table have as dependent variable the **growth** of TFP, controlling for NACE 2-digit level sector dummy and year dummy.
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7b: High growth experience and TFP growth: Quantile regression analysis

Service sectors

Dep: TFP growth	(1)	(2)	(3)	(4)	(5)
VARIABLES	q10	q25	q50	q75	q90
High Growth Firm					
HGF_{it-1}	0.0142**	0.0387***	0.0611***	0.119***	0.178***
	(0.00554)	(0.00223)	(0.00290)	(0.00375)	(0.00749)
Firm characteristics					
Age_t	0.000559***	0.000185***	-0.00016***	-0.00063***	-0.00149***
	(8.81e-05)	(3.71e-05)	(3.15e-05)	(2.70e-05)	(5.34e-05)
$Size_{t-1}$	8.06e-06***	2.17e-06***	-3.97e-06***	-1.19e-05***	-2.55e-05***
	(2.32e-06)	(8.27e-07)	(5.64e-07)	(9.03e-07)	(1.66e-06)
Intangible assets $ratio_{t-1}$	0.0784***	0.0400***	0.0213***	0.0428***	0.204***
	(0.0194)	(0.00830)	(0.00649)	(0.0147)	(0.0415)
Average $wage_{t-1}$	-0.00297***	-0.00157***	-0.00066***	-0.00056***	-0.00081***
	(0.000170)	(8.64e-05)	(5.54e-05)	(6.70e-05)	(8.79e-05)
Cash $flow_{t-1}$	1.53e-06**	1.19e-06***	1.17e-07	-9.75e-07***	-2.30e-07
	(6.54e-07)	(3.07e-07)	(1.22e-07)	(2.72e-07)	(6.28e-07)
$Export_{t-1}$	0.00195	0.00137**	0.000970**	0.000952	0.00433
	(0.00286)	(0.000693)	(0.000423)	(0.00131)	(0.00501)
MNE	0.0380***	0.0226***	0.0135***	0.0152***	0.0148**
	(0.00660)	(0.00305)	(0.00244)	(0.00378)	(0.00630)
Regional characteristics					
Unemployment rate	-0.00320	-0.00218**	-0.00115**	0.000636	0.00286**
	(0.00204)	(0.000889)	(0.000502)	(0.000881)	(0.00144)
Air	2.49e-08	1.22e-09	-1.81e-08	7.43e-08	6.90e-08
	(7.49e-08)	(4.42e-08)	(2.30e-08)	(4.60e-08)	(7.23e-08)
Patent	-2.30e-06	-9.01e-06	-2.60e-05**	-1.52e-05	-2.42e-05
	(4.88e-05)	(2.42e-05)	(1.12e-05)	(1.86e-05)	(4.88e-05)
GDP growth	0.000242*	0.000187***	0.000189***	0.000278***	0.000580***
	(0.000125)	(5.59e-05)	(3.60e-05)	(7.17e-05)	(0.000119)
Observations	78,588	78,588	78,588	78,588	78,588

Note: 1. The quantile regression results presented in this table have as dependent variable the **growth** of TFP, controlling for NACE 2-digit level sector dummy and year dummy.
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8a: Channels of productivity enhancement through HGF experience: Manufacturing sector

Dep: TFP growth	(1)	(2)	(3)	(4)
VARIABLES	OLS	F.E. estimation	OLS	F.E. estimation
High growth experience	0.1000***	0.196***	0.183***	0.267***
	(0.00537)	(0.0134)	(0.0355)	(0.0539)
Age_t	-3.98e-05	0.0225***	4.48e-05	0.0225***
	(6.40e-05)	(0.00672)	(6.41e-05)	(0.00661)
Growth experience*Age			-0.000807***	-0.000939
			(0.000273)	(0.000693)
$Size_{t-1}$	-2.75e-06	-0.000122***	-8.87e-07	-0.000118***
	(3.48e-06)	(2.83e-05)	(3.47e-06)	(3.01e-05)
Growth experience*Size			-2.19e-05	6.16e-05
			(1.36e-05)	(5.17e-05)
Cash $flow_{t-1}$	6.51e-08	-6.00e-06***	7.04e-08	-6.04e-06***
	(6.56e-07)	(1.25e-06)	(6.57e-07)	(1.22e-06)
Growth experience*Cash			-2.86e-08	2.63e-06
			(2.24e-06)	(3.71e-06)
Intangible assets $ratio_{t-1}$	0.0757***	0.0870	0.0157	0.0444
	(0.0214)	(0.0667)	(0.0192)	(0.0725)
Growth exp*Intangible			0.212***	0.125
			(0.0638)	(0.136)
Average $wage_{t-1}$	-0.00324***	-0.0117***	-0.00262***	-0.0104***
	(0.000539)	(0.00138)	(0.000520)	(0.00139)
Growth exp*Wage			-0.00377***	-0.00601***
			(0.000785)	(0.00149)
$Export_{t-1}$	-0.000480	-0.00200	-0.00126	-0.00251
	(0.00162)	(0.00281)	(0.00186)	(0.00309)
Growth exp*Export			0.00463	0.0753*
			(0.00535)	(0.0421)
MNE	0.0150**		0.00471	
	(0.00684)		(0.0242)	
Growth exp*MNE			-0.00471	0.05201
			(0.02418)	(0.0566)
Unemployment rate	-0.00208	-0.00909***	-0.00218	-0.0104***
	(0.00144)	(0.00346)	(0.00149)	(0.00345)
Growth exp*Unemploy			-0.00340	-0.00572***
			(0.00420)	(0.00201)
Air	3.34e-07***	6.16e-06**	2.40e-07**	4.63e-06*
	(9.56e-08)	(2.41e-06)	(9.44e-08)	(2.37e-06)
Growth exp*Air			7.90e-07**	2.19e-06***
			(3.38e-07)	(8.50e-07)
Patent	2.60e-05	-1.99e-05	-5.18e-05	-0.000174
	(3.62e-05)	(0.000116)	(3.78e-05)	(0.000117)
Growth exp*Patent			0.000541***	0.00108***
			(0.000124)	(0.000179)
GDP growth	0.000485***	0.00101	0.000477***	0.00105
	(0.000136)	(0.00112)	(0.000136)	(0.00113)
Growth exp*GDP growth			0.000460	0.000619
			(0.000374)	(0.000694)
Constant	0.0538***	-0.271	0.0434***	-0.258
	(0.0147)	(0.188)	(0.0150)	(0.186)
Hausman test for fixed-effects vs random-effects model, p-value		0.000		0.000
Observations	31,579	31,579	31,579	31,579
R-squared	0.086	0.122	0.093	0.132
Number of new firms		8,164		8,164

Note: 1.All regressions include year dummy and NACE 2-digit industrial sector dummies
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8b: Channels of productivity enhancement through HGF experience: Service sector

Dep: TFP growth	(1)	(2)	(3)	(4)
VARIABLES	OLS	F.E. estimation	OLS	F.E. estimation
High growth experience	0.128***	0.216***	0.106***	0.334***
	(0.00291)	(0.00863)	(0.0190)	(0.0438)
Age_t	-0.000364***	-0.0126***	-0.000105**	-0.0113***
	(5.14e-05)	(0.00421)	(4.65e-05)	(0.00418)
Growth experience*Age			-0.00192***	-0.00305***
			(0.000255)	(0.000546)
$Size_{t-1}$	-8.92e-06***	-9.82e-05***	-6.77e-06***	-9.40e-05***
	(1.95e-06)	(1.28e-05)	(2.03e-06)	(1.61e-05)
Growth experience*Size			-1.30e-05**	2.24e-05
			(6.37e-06)	(1.97e-05)
Cash $flow_{t-1}$	4.66e-07	-4.17e-06***	1.09e-06***	-2.51e-06***
	(3.80e-07)	(8.33e-07)	(3.96e-07)	(8.72e-07)
Growth experience*Cash			-2.98e-06***	-3.49e-06*
			(1.04e-06)	(2.09e-06)
Intangible assets $ratio_{t-1}$	0.0656***	0.0360	0.0527***	0.00497
	(0.0125)	(0.0431)	(0.0113)	(0.0415)
Growth exp*Intangible			0.0423	0.0843
			(0.0315)	(0.0769)
Average $wage_{t-1}$	-0.00123***	-0.00364***	-0.00103***	-0.00289**
	(0.000176)	(0.000959)	(0.000214)	(0.00114)
Growth exp*Wage			-0.000481*	-0.00161
			(0.000290)	(0.00113)
$Export_{t-1}$	0.000450	0.000199	0.000271	0.000261
	(0.000347)	(0.000586)	(0.000787)	(0.001000)
Growth exp*Export			6.67e-05	-0.000108
			(0.000914)	(0.00122)
MNE	0.0198***		-0.00656	
	(0.00446)		(0.0122)	
Growth exp*MNE			0.00656	0.0690***
			(0.0121)	(0.03183)
Unemployment rate	-0.000193	-0.00165	-0.000629	-0.00390*
	(0.000903)	(0.00213)	(0.000872)	(0.00211)
Growth exp*Unemploy			0.00187	-0.0111***
			(0.00259)	(0.00104)
Air	5.48e-08	2.43e-06	-1.96e-08	3.68e-06**
	(4.98e-08)	(1.56e-06)	(4.80e-08)	(1.56e-06)
Growth exp*Air			3.47e-07**	-1.30e-06***
			(1.59e-07)	(4.56e-07)
Patent	-6.56e-06	9.31e-05	-0.000108***	-4.64e-05
	(2.47e-05)	(6.87e-05)	(2.47e-05)	(6.66e-05)
Growth exp*Patent			0.000514***	0.00117***
			(7.76e-05)	(0.000104)
GDP growth	0.000289***	-0.000776	0.000190**	-0.000528
	(7.59e-05)	(0.000557)	(7.81e-05)	(0.000582)
Growth exp*GDP growth			0.000367**	-0.000735*
			(0.000180)	(0.000404)
Constant	0.0436***	0.388***	0.0469***	0.351***
	(0.00721)	(0.0945)	(0.00769)	(0.0941)
Hausman test for fixed-effects vs random-effects model, p-value		0.000		0.000
Observations	78,588	78,588	78,588	78,588
R-squared	0.053	0.067	0.057	0.080
Number of new firms		22,181		22,181

Note: 1.All regressions include year dummy and NACE 2-digit industrial sector dummies.
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 9a: Is TFP level a determinant of HG incidence? – Manufacturing sectors

	Static Probit Model			Random effect Panel Probit Model		
VARIABLES	All firms	New firm, <=5 years	Incumbents,> 5years	All firms	New firm, <=5 years	Incumbents, >5years
Productivity						
TFP level$_{it}$	-0.0292***	-0.0844***	-0.0208***	-0.622***	-1.017***	-0.528***
	(0.00508)	(0.0193)	(0.00540)	(0.0447)	(0.218)	(0.0481)
Firm characteristics						
Age$_t$	-0.00143***	-0.0541***	-0.00107***	-0.0237***	-0.652***	-0.0179***
	(0.000138)	(0.0104)	(0.000130)	(0.00202)	(0.0877)	(0.00199)
Size$_{t-1}$	-2.06e-05***	-5.76e-05	-2.01e-05***	-0.000147*	-0.000125	-0.000185**
	(6.65e-06)	(4.18e-05)	(6.60e-06)	(8.86e-05)	(0.000391)	(9.37e-05)
Intangible assets ratio$_{t-1}$	0.113***	0.0812	0.0910***	1.550***	1.327	1.302***
	(0.0247)	(0.0742)	(0.0288)	(0.307)	(0.870)	(0.354)
Average wage$_{t-1}$	0.000637**	0.000825	0.000629**	0.00681***	0.0146	0.00689***
	(0.000252)	(0.000567)	(0.000272)	(0.00152)	(0.0111)	(0.00156)
Cash flow$_{t-1}$	1.07e-06	4.13e-06	5.66e-07	-1.19e-05	-5.88e-05	-1.08e-05
	(7.73e-07)	(4.24e-06)	(7.57e-07)	(8.23e-06)	(4.70e-05)	(8.62e-06)
Export$_{t-1}$	0.00751	-0.0466*	0.0115**	0.184**	-0.267	0.248***
	(0.00524)	(0.0262)	(0.00518)	(0.0756)	(0.281)	(0.0793)
MNE	0.0179	0.0652	0.0160	0.462***	0.983	0.392**
	(0.0127)	(0.0757)	(0.0123)	(0.154)	(0.798)	(0.155)
Regional characteristics						
Unemployment rate	0.000124	-0.00806	0.000666	-0.00890	-0.144	0.00335
	(0.00191)	(0.00969)	(0.00190)	(0.0213)	(0.100)	(0.0223)
Air	-2.53e-07	-1.94e-06**	-1.78e-07	-2.28e-06	-1.42e-05	-8.10e-07
	(1.68e-07)	(9.40e-07)	(1.64e-07)	(2.35e-06)	(1.04e-05)	(2.37e-06)
Patent	4.50e-05	-7.99e-05	5.65e-05	0.000351	0.000692	0.000764
	(5.45e-05)	(0.000280)	(5.37e-05)	(0.000627)	(0.00298)	(0.000653)
GDP growth	-3.58e-05	0.000418	-0.000110	0.00184	0.00653	0.000406
	(0.000182)	(0.000847)	(0.000183)	(0.00226)	(0.00934)	(0.00237)
Observations	33,534	2,179	31,348	33,534	2,186	31,348

Note: 1.All regressions include year dummy and NACE 2-digit industrial sector dummies.
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
3. The corresponding table for TFP growth in the main text is Table 5a.

Table 9b: Is TFP level a determinant of HG incidence? –Service sectors

	Static Probit Model			Random effect Panel Probit Model		
VARIABLES	All firms	New firm, <=5 years	Incumbents,>5 years	All firms	New firm, <=5 years	Incumbents, >5years
Productivity						
TFP level$_{it}$	-0.0407***	-0.128***	-0.0205***	-0.727***	-0.968***	-0.557***
	(0.00340)	(0.0101)	(0.00330)	(0.0255)	(0.0799)	(0.0289)
Firm characteristics						
Age$_t$	-0.00317***	-0.0586***	-0.00187***	-0.0439***	-0.694***	-0.0303***
	(0.000191)	(0.00617)	(0.000157)	(0.00171)	(0.0449)	(0.00170)
Size$_{t-1}$	-1.20e-06	-1.05e-05	-1.68e-06	0.000109***	-9.22e-05	5.44e-05
	(3.97e-06)	(1.90e-05)	(3.66e-06)	(3.77e-05)	(0.000167)	(3.94e-05)
Intangible assets ratio$_{t-1}$	0.0816***	-0.119***	0.0711***	0.930***	-1.304***	0.822***
	(0.0167)	(0.0439)	(0.0191)	(0.151)	(0.370)	(0.187)
Average wage$_{t-1}$	0.000592***	0.00208***	0.000440***	0.00443***	0.00945***	0.00352***
	(0.000116)	(0.000371)	(9.35e-05)	(0.000477)	(0.00177)	(0.000501)
Cash flow$_{t-1}$	1.23e-06**	1.13e-05***	-2.35e-07	-2.07e-06	4.69e-05**	-5.68e-06
	(5.95e-07)	(2.74e-06)	(5.67e-07)	(4.81e-06)	(2.22e-05)	(5.14e-06)
Export$_{t-1}$	0.0185***	0.0397**	0.0182***	0.317***	0.372**	0.311***
	(0.00430)	(0.0178)	(0.00415)	(0.0466)	(0.159)	(0.0484)
MNE	0.0526***	0.159***	0.0424***	0.831***	1.722***	0.742***
	(0.0108)	(0.0463)	(0.00994)	(0.1000)	(0.447)	(0.101)
Regional characteristics						
Unemployment rate	0.00153	0.0115*	0.000281	-0.0290**	0.0420	-0.0382***
	(0.00155)	(0.00643)	(0.00154)	(0.0125)	(0.0520)	(0.0135)
Air	6.76e-08	8.26e-07**	-1.95e-09	1.21e-06	6.04e-06	1.03e-06
	(1.09e-07)	(4.18e-07)	(1.07e-07)	(1.18e-06)	(3.78e-06)	(1.25e-06)
Patent	0.000107**	0.000583***	5.24e-05	0.000190	0.00346**	-8.48e-05
	(4.75e-05)	(0.000190)	(4.71e-05)	(0.000401)	(0.00157)	(0.000431)
GDP growth	0.000436***	0.000190	0.000398***	0.0108***	0.00854**	0.0110***
	(0.000119)	(0.000476)	(0.000117)	(0.00111)	(0.00407)	(0.00119)
Observations	83,904	8,625	75,279	83,904	8,625	75,279

Note: 1.All regressions include year dummy and NACE 2-digit industrial sector dummies.
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
3. The corresponding table for TFP growth in the main text is Table 5b.

Table 9c: Robustness Check: Dynamic Probit Models –Manufacturing sectors

	Random effect Panel Probit Model with dynamic term			Dynamic panel estimator, Wooldridge (2005)		
VARIABLES	All firms	New firm, <=5years	Incumbents, >5 years	All firms	New firm, <=5years	Incumbents, >5 years
Productivity						
TFP $Level_{it}$	-0.208***	-0.225***	-0.191***	-0.751***	-0.712***	-0.746***
	(0.0262)	(0.0825)	(0.0282)	(0.0499)	(0.186)	(0.0529)
Firm characteristics						
Age_t	-0.00303***	-0.237***	-0.00256***	-0.141***	-0.543***	-0.124***
	(0.000715)	(0.0554)	(0.000744)	(0.0180)	(0.0876)	(0.0213)
$Size_{t-1}$	-0.000179***	-2.58e-05	-0.000205***	-0.00112***	-0.00595***	-0.00100***
	(5.41e-05)	(0.000166)	(5.79e-05)	(0.000150)	(0.00132)	(0.000155)
Intangible assets $ratio_{t-1}$	0.306*	0.0123	0.308	-0.279	0.994	-0.539
	(0.163)	(0.330)	(0.200)	(0.400)	(1.058)	(0.436)
Average $wage_{t-1}$	0.00324***	0.00408**	0.00322***	-4.84e-05	0.00873	-0.000152
	(0.000705)	(0.00199)	(0.000757)	(0.00111)	(0.00702)	(0.00121)
Cash $flow_{t-1}$	-7.57e-07	-7.59e-06	-8.03e-07	-3.80e-05***	-6.58e-05	-3.61e-05***
	(5.68e-06)	(2.26e-05)	(5.91e-06)	(9.22e-06)	(4.06e-05)	(9.57e-06)
$Export_{t-1}$	0.0953***	-0.0699	0.115***	0.0531	-0.368**	0.0755**
	(0.0318)	(0.110)	(0.0336)	(0.0330)	(0.144)	(0.0347)
MNE	0.0530	0.828***	0.0102	-0.0348	0.693**	-0.0768
	(0.0626)	(0.258)	(0.0651)	(0.0639)	(0.277)	(0.0664)
Regional characteristics						
Unemployment rate	0.000844	-0.0281	0.00458	0.00197	-0.0193	0.00486
	(0.0135)	(0.0456)	(0.0143)	(0.0138)	(0.0485)	(0.0145)
Air	-5.65e-08	-1.91e-06	8.62e-08	-3.25e-07	-2.77e-06	-3.02e-07
	(9.56e-07)	(4.15e-06)	(9.84e-07)	(9.73e-07)	(4.56e-06)	(1.00e-06)
Patent	0.000479	-0.000346	0.000544	0.000276	-0.000983	0.000315
	(0.000353)	(0.00129)	(0.000370)	(0.000362)	(0.00140)	(0.000379)
GDP growth	-0.000422	0.00247	-0.000860	-0.00123	0.00452	-0.00178
	(0.00115)	(0.00395)	(0.00122)	(0.00118)	(0.00424)	(0.00125)
State dependence						
HGF_{it-1}	2.833***	3.343***	2.794***	2.963***	4.354***	2.922***
	(0.0326)	(0.127)	(0.0345)	(0.0398)	(0.291)	(0.0405)
HGF_{i1}				-0.192***	-0.937***	-0.205***
				(0.0498)	(0.267)	(0.0544)
Mean covariates						
Age				0.138***	0.364***	0.121***
				(0.0181)	(0.0813)	(0.0213)
Size				0.000923***	0.00587***	0.000794***
				(0.000146)	(0.00133)	(0.000153)
TFP growth				0.678***	0.567**	0.684***
				(0.0595)	(0.223)	(0.0632)
Intangible asset ratio				0.663	-1.273	1.101**
				(0.458)	(1.235)	(0.495)
Average wage				0.00519***	-0.00600	0.00553***
				(0.00164)	(0.0108)	(0.00169)
Cash flow				4.30e-05***	7.48e-05	4.06e-05***
				(1.08e-05)	(4.71e-05)	(1.13e-05)
Export				0.0267	0.459	0.0237
				(0.0198)	(0.296)	(0.0207)
Observations	33,534	2,186	31,348	33,534	2,186	31,348

Note: 1. All regressions include year dummy and NACE 2-digit industrial sector dummies.
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
3. The corresponding table for TFP growth in the main text is Table 6a.

Table 9d: Robustness Check: Dynamic Probit Models –Service sectors

	Random effect Panel Probit Model with dynamic term			Dynamic panel estimator, Wooldridge (2005)		
VARIABLES	All firms	New firm, <=5years	Incumbents, >5 years	All firms	New firm, <=5years	Incumbents, >5 years
Productivity						
TFP $Level_{it}$	-0.189***	-0.253***	-0.147***	-1.085***	-0.969***	-1.067***
	(0.0134)	(0.0342)	(0.0152)	(0.0337)	(0.0846)	(0.0376)
Firm characteristics						
Age_t	-0.00410***	-0.274***	-0.00215***	-0.147***	-0.430***	-0.128***
	(0.000557)	(0.0249)	(0.000573)	(0.00984)	(0.0352)	(0.0123)
$Size_{t-1}$	-4.94e-05**	-0.000152**	-4.42e-05**	-0.000390***	-0.000776***	-0.000367***
	(2.01e-05)	(7.29e-05)	(2.08e-05)	(6.43e-05)	(0.000267)	(6.63e-05)
Intangible assets $ratio_{t-1}$	0.0323	-0.173	-0.101	-0.453**	-0.179	-0.736***
	(0.0861)	(0.154)	(0.111)	(0.190)	(0.402)	(0.221)
Average $wage_{t-1}$	0.00169***	0.00481***	0.00136***	0.000352	0.00267*	0.000118
	(0.000251)	(0.000969)	(0.000271)	(0.000456)	(0.00157)	(0.000486)
Cash $flow_{t-1}$	3.89e-07	8.66e-06	-2.98e-06	-2.93e-05***	-4.90e-05***	-2.71e-05***
	(3.04e-06)	(9.29e-06)	(3.24e-06)	(5.22e-06)	(1.76e-05)	(5.47e-06)
$Export_{t-1}$	0.118***	0.238***	0.109***	0.0812***	0.161***	0.0741***
	(0.0184)	(0.0557)	(0.0196)	(0.0189)	(0.0594)	(0.0201)
MNE	0.222***	0.366***	0.209***	0.138***	0.236*	0.130***
	(0.0370)	(0.137)	(0.0384)	(0.0376)	(0.142)	(0.0390)
Regional characteristics						
Unemployment rate	0.0209**	0.0469**	0.0151*	0.0169**	0.0372	0.0133
	(0.00833)	(0.0231)	(0.00901)	(0.00853)	(0.0240)	(0.00919)
Air	-7.45e-09	1.02e-06	-1.96e-07	-4.74e-07	6.65e-07	-6.43e-07
	(4.83e-07)	(1.35e-06)	(5.22e-07)	(4.97e-07)	(1.42e-06)	(5.35e-07)
Patent	0.000667***	0.00138**	0.000521**	0.000432*	0.000915	0.000350
	(0.000231)	(0.000662)	(0.000248)	(0.000238)	(0.000691)	(0.000255)
GDP growth	0.000363	-0.000694	0.000563	-5.75e-05	-0.000559	5.55e-05
	(0.000602)	(0.00165)	(0.000652)	(0.000616)	(0.00171)	(0.000665)
State dependence						
HGF_{it-1}	2.804***	3.135***	2.741***	2.919***	3.703***	2.859***
	(0.0183)	(0.0542)	(0.0198)	(0.0221)	(0.0938)	(0.0230)
HGF_{i1}				-0.179***	-0.624***	-0.191***
				(0.0250)	(0.0842)	(0.0277)
Mean covariates						
Age				0.143***	0.218***	0.125***
				(0.00989)	(0.0304)	(0.0123)
Size				0.000346***	0.000627**	0.000332***
				(6.71e-05)	(0.000283)	(6.93e-05)
TFP growth				1.036***	0.850***	1.047***
				(0.0370)	(0.0909)	(0.0413)
Intangible asset ratio				0.504**	-0.107	0.832***
				(0.217)	(0.461)	(0.250)
Average wage				0.00205***	0.00182	0.00205***
				(0.000592)	(0.00180)	(0.000630)
Cash flow				3.17e-05***	5.98e-05***	2.66e-05***
				(6.25e-06)	(1.99e-05)	(6.63e-06)
Export				-0.000193	-0.0169	-0.000100
Observations	83,904	8,625	75,279	83,904	8,625	75,279

Note: 1. All regressions include year dummy and NACE 2-digit industrial sector dummies.
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
3. The corresponding table for TFP growth in the main text is Table 6d.

Table 10a: High growth experience and TFP level: Quantile regression analysis, Manufacturing sectors

Dep: TFP level	(1)	(2)	(3)	(4)	(5)
VARIABLES	q10	q25	q50	q75	q90
High Growth Firm					
HGF_{it-1}	-0.0295	0.0163	0.0731***	0.107***	0.152***
	(0.0215)	(0.0168)	(0.0128)	(0.00987)	(0.0165)
Firm characteristics					
Age_t	0.00113***	0.000816***	0.000514***	0.000427***	0.000297
	(0.000135)	(0.000109)	(0.000143)	(0.000133)	(0.000219)
$Size_{t-1}$	0.000158***	0.000171***	0.000196***	0.000201***	0.000174***
	(1.23e-05)	(8.43e-06)	(1.23e-05)	(1.33e-05)	(1.56e-05)
Intangible assets $ratio_{t-1}$	0.406***	0.490***	0.490***	0.489***	0.464***
	(0.101)	(0.0446)	(0.0337)	(0.0481)	(0.0468)
Average $wage_{t-1}$	0.0205***	0.0253***	0.0280***	0.0300***	0.0314***
	(0.000642)	(0.000538)	(0.000531)	(0.000512)	(0.000632)
Cash $flow_{t-1}$	1.86e-05***	2.19e-05***	2.40e-05***	2.54e-05***	3.25e-05***
	(1.76e-06)	(1.20e-06)	(1.37e-06)	(1.37e-06)	(2.57e-06)
$Export_{t-1}$	0.00238	-0.000308	-0.00395	-0.00794	-0.000586
	(0.00739)	(0.00508)	(0.00532)	(0.00691)	(0.00954)
MNE	0.178***	0.113***	0.131***	0.121***	0.121***
	(0.0182)	(0.00982)	(0.0134)	(0.0105)	(0.0126)
Regional characteristics					
Unemployment rate	-0.0181***	-0.0134***	-0.00736***	-0.00796***	-0.00785***
	(0.00393)	(0.00303)	(0.00260)	(0.00229)	(0.00280)
Air	3.85e-07	4.80e-07*	2.15e-07	2.72e-07	7.92e-07***
	(3.57e-07)	(2.84e-07)	(1.86e-07)	(2.19e-07)	(3.04e-07)
Patent	-0.000142	-0.000173**	-0.000165***	-8.39e-05	-9.45e-05
	(9.81e-05)	(7.54e-05)	(5.72e-05)	(5.72e-05)	(9.11e-05)
GDP growth	0.00171***	0.00165***	0.00160***	0.00171***	0.00185***
	(0.000420)	(0.000255)	(0.000298)	(0.000265)	(0.000337)
Observations	33,750	33,750	33,750	33,750	33,750

Note: 1. The quantile regression results presented in this table have as dependent variable the **level** of TFP, controlling for NACE 2-digit level sector dummy and year dummy.
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
3. The corresponding table for TFP growth in the main text is Table 7a.

Table 10b: High growth experience and TFP level: Quantile regression analysis, Service sectors

Dep: TFP level	(1)	(2)	(3)	(4)	(5)
VARIABLES	q10	q25	q50	q75	q90
High Growth Firm					
HGF_{it-1}	0.0256***	0.0491***	0.0709***	0.108***	0.143***
	(0.00762)	(0.00670)	(0.00535)	(0.00590)	(0.00598)
Firm characteristics					
Age_t	8.80e-05	0.000342***	0.000378***	0.000646***	0.000992***
	(0.000312)	(9.88e-05)	(0.000138)	(0.000146)	(0.000169)
$Size_{t-1}$	0.000112***	0.000114***	0.000170***	0.000248***	0.000286***
	(9.65e-06)	(6.11e-06)	(4.67e-06)	(7.23e-06)	(9.51e-06)
Intangible assets $ratio_{t-1}$	-0.0834	0.140***	0.161***	0.185***	0.141***
	(0.0778)	(0.0334)	(0.0263)	(0.0282)	(0.0282)
Average $wage_{t-1}$	0.0108***	0.0138***	0.0158***	0.0175***	0.0180***
	(0.000512)	(0.000346)	(0.000343)	(0.000263)	(0.000340)
Cash $flow_{t-1}$	4.70e-05***	5.01e-05***	5.28e-05***	5.55e-05***	5.76e-05***
	(1.17e-06)	(7.21e-07)	(5.39e-07)	(9.85e-07)	(1.44e-06)
$Export_{t-1}$	-0.00900***	-0.00714	-0.00562***	-0.00402**	-0.00406***
	(0.00265)	(0.00497)	(0.00174)	(0.00159)	(0.00117)
MNE	0.261***	0.223***	0.198***	0.212***	0.206***
	(0.0223)	(0.0173)	(0.0147)	(0.0112)	(0.0119)
Regional characteristics					
Unemployment rate	-0.00505	-0.000850	-0.00116	0.000417	-0.00286
	(0.00364)	(0.00254)	(0.00165)	(0.00172)	(0.00198)
Air	1.36e-06***	9.84e-07***	9.59e-07***	1.12e-06***	1.45e-06***
	(2.53e-07)	(1.83e-07)	(1.11e-07)	(9.26e-08)	(1.20e-07)
Patent	0.000396***	0.000305***	0.000195***	0.000219***	0.000339***
	(0.000101)	(7.71e-05)	(3.82e-05)	(6.58e-05)	(7.88e-05)
GDP growth	0.00256***	0.00196***	0.00178***	0.00162***	0.00193***
	(0.000278)	(0.000186)	(0.000165)	(0.000143)	(0.000192)
Observations	83,950	83,950	83,950	83,950	83,950

Note: 1. The quantile regression results presented in this table have as dependent variable the **level** of TFP, controlling for NACE 2-digit level sector dummy and year dummy.
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
3. The corresponding table for TFP growth in the main text is Table 7b.

Table 11a: Channels of productivity enhancement through HGF experience: Manufacturing sector

Dep: TFP	OLS	F.E. estimation	OLS	F.E. estimation
High growth experience	0.0745***	0.113***	0.0763***	0.247***
	(0.0157)	(0.0128)	(0.0222)	(0.0252)
Age_t	0.000975***	0.0374***	0.000978***	0.0348***
	(0.000243)	(0.00557)	(0.000251)	(0.00553)
Growth experience*Age			0.000724	-0.000294
			(0.000736)	(0.000579)
$Size_{t-1}$	0.000155***	-9.26e-06	0.000153***	-4.66e-05
	(1.87e-05)	(4.08e-05)	(1.92e-05)	(4.10e-05)
Growth experience*Size			4.76e-05	5.37e-05
			(5.71e-05)	(3.46e-05)
Cash $flow_{t-1}$	2.68e-05***	6.58e-06***	2.59e-05***	5.68e-06***
	(1.95e-06)	(1.51e-06)	(2.03e-06)	(1.49e-06)
Growth experience*Cash			9.27e-06*	4.49e-06
			(5.56e-06)	(4.07e-06)
Intangible assets $ratio_{t-1}$	0.445***	0.0577	0.488***	0.0627
	(0.0630)	(0.0921)	(0.0672)	(0.0933)
Growth exp*Intangible			-0.189	0.0237
			(0.140)	(0.109)
Average $wage_{t-1}$	0.0201***	0.00782***	0.0199***	0.00709***
	(0.00254)	(0.00121)	(0.00280)	(0.00121)
Growth exp*Wage			0.00169	0.00337***
			(0.00286)	(0.00112)
$Export_{t-1}$	0.00429	0.00274	0.00139	0.000575
	(0.00700)	(0.00327)	(0.00726)	(0.00365)
Growth exp*Export			0.0200	0.0126
			(0.0165)	(0.0163)
MNE	0.161***		0.0553	
	(0.0251)		(0.122)	
Growth exp*MNE			0.109	0.0877
			(0.128)	(0.0823)
Unemployment rate	-0.0147***	-0.0107**	-0.0148***	-0.0108**
	(0.00374)	(0.00455)	(0.00374)	(0.00453)
Growth exp*Unemploy			9.57e-05	-0.000758
			(0.0114)	(0.00908)
Air	7.65e-07**	6.67e-06**	7.82e-07**	7.92e-06**
	(3.64e-07)	(3.38e-06)	(3.77e-07)	(3.36e-06)
Growth exp*Air			2.30e-07	-2.70e-07
			(9.93e-07)	(7.65e-07)
Patent	-0.000105	-0.000454***	-0.000140	-0.000422***
	(0.000108)	(0.000158)	(0.000111)	(0.000158)
Growth exp*Patent			0.000331	-0.000196
			(0.000321)	(0.000251)
GDP growth	0.00254***	0.00342**	0.00268***	0.00355**
	(0.000470)	(0.00146)	(0.000482)	(0.00146)
Growth exp*GDP growth			-0.00111	-0.000500
			(0.00107)	(0.000751)
Constant	4.018***	3.307***	4.024***	3.375***
	(0.0563)	(0.172)	(0.0627)	(0.171)
Hausman test for fixed-effects vs random-effects model, p-value		0.000		0.000
Observations	33,750	33,750	33,750	33,750
R-squared	0.574	0.077	0.575	0.090
Number of new firms		9,169		9,169

Note: 1.All regressions include year dummy and NACE 2-digit industrial sector dummies.
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
3. The corresponding table for TFP growth in the main text is Table 8a.

Table 11b: Channels of productivity enhancement through HGF experience: Service sector

Dep: TFP	(1)	(2)	(3)	(4)
VARIABLES	OLS	F.E. estimation	OLS	F.E. estimation
High growth experience	0.0848***	0.0959***	0.288***	0.0722*
	(0.00961)	(0.00597)	(0.0633)	(0.0403)
Age_t	0.000376	-0.000200	0.000289	0.000691
	(0.000285)	(0.00314)	(0.000277)	(0.00314)
Growth experience*Age			0.00166*	0.00265***
			(0.000895)	(0.000478)
$Size_{t-1}$	0.000116***	3.69e-06	0.000125***	-2.04e-06
	(1.20e-05)	(2.24e-05)	(1.38e-05)	(2.26e-05)
Growth experience*Size			-4.81e-05	-1.54e-05
			(2.97e-05)	(1.15e-05)
Cash $flow_{t-1}$	5.63e-05***	6.93e-06***	5.47e-05***	5.86e-06***
	(1.55e-06)	(9.00e-07)	(1.82e-06)	(8.52e-07)
Growth experience*Cash			7.90e-06**	4.19e-06**
			(3.36e-06)	(1.92e-06)
Intangible assets $ratio_{t-1}$	0.0768*	-0.0397	0.120***	-0.00199
	(0.0407)	(0.0377)	(0.0439)	(0.0366)
Growth exp*Intangible			-0.199**	-0.106*
			(0.0816)	(0.0552)
Average $wage_{t-1}$	0.00861***	0.00131***	0.00942***	0.00125***
	(0.00105)	(0.000210)	(0.00149)	(0.000223)
Growth exp*Wage			-0.00279*	8.92e-05
			(0.00163)	(0.000232)
$Export_{t-1}$	-0.00515**	0.000633	-0.00576	-0.000817
	(0.00225)	(0.00106)	(0.00361)	(0.00165)
Growth exp*Export			0.00139	0.00302
			(0.00450)	(0.00192)
MNE	0.253***		0.235***	
	(0.0210)		(0.0357)	
Growth exp*MNE			0.0194	0.0592***
			(0.0407)	(0.0225)
Unemployment rate	-0.00194	-0.0131***	-0.000693	-0.0120***
	(0.00283)	(0.00232)	(0.00298)	(0.00232)
Growth exp*Unemploy			-0.0122*	0.00242
			(0.00667)	(0.00469)
Air	1.55e-06***	1.40e-06	1.41e-06***	1.28e-06
	(2.40e-07)	(1.71e-06)	(2.46e-07)	(1.70e-06)
Growth exp*Air			6.79e-07	-5.01e-07
			(5.46e-07)	(3.40e-07)
Patent	0.000397***	0.000190**	0.000463***	0.000353***
	(9.42e-05)	(7.93e-05)	(0.000101)	(7.98e-05)
Growth exp*Patent			-0.000571***	-0.00102***
			(0.000213)	(0.000136)
GDP growth	0.00304***	-0.000284	0.00307***	-0.000140
	(0.000316)	(0.000602)	(0.000372)	(0.000601)
Growth exp*GDP growth			-4.67e-05	2.64e-05
			(0.000571)	(0.000352)
Constant	4.922***	5.340***	4.885***	5.304***
	(0.0316)	(0.0723)	(0.0404)	(0.0723)
Hausman test for fixed-effects vs random-effects model, p-value		0.000		0.000
Observations	83,950	83,950	83,950	83,950
R-squared	0.499	0.037	0.502	0.044
Number of new firms		24,663		24,663

Note: 1.All regressions include year dummy and NACE 2-digit industrial sector dummies.
2. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
3. The corresponding table for TFP growth in the main text is Table 8b.

ANNEX 1:

Producers Price Indices (PPI) and Consumer Producers Price Indices (SPPI)

PPI

Most of the PPI were obtained from EconStats, and the missing observations, most of which were in the early years were supplemented by using data provided on the ONS website. Before 2007 ONS reports are published using the SIC03 standard whilst reports from 2007 onwards and the EconStats use the SIC07 standard. Therefore the equivalents of the SIC07 codes were found and matched to our data. Another translation of codes from SIC07 to NACE has to be made as the data we are analysing is reported using the NACE standard. There are a small number 4-digit industries for which deflators could not be obtained. In such cases, missing deflators were replaced by the respective 2-digit industry deflators or in some instances by deflators most closely related to them. Furthermore, deflators from early years had the year 2000 as base year and had to be transformed and reported as deflators with the base year 2005.

SPPI

SPPI data were obtained from the ONS website. Deflators for most service industries were very rare. In these instances, the average of the available deflators within their 2-digit industries was used to fill the missing observation within the same industry.

ANNEX 2:

Definition of Variables

Variable name	Description	**Source**
Firm characteristics		
Age	The age of a firm calculated since year of when the company has been incorporated.	Fame
Costs of Goods sold	Costs of goods sold, production, services.Costs directly related to the production of the goods sold + depreciation of those costs.	Fame
Employees	Total number of full time employees of the company (personnel)	Fame
Turnover	Total Operating Revenue (Net sales +Other operating revenue + Stock variations). These figures do not include VAT or excise taxes and similar obligatory payments. (Turnover) is defined in the Balance Sheet account	Fame
Tangible Fixed Assets	All tangible fixed assets, such as building and machinery. The Tangible Fixed Assets are defined in the Balance Sheet account	Fame
Age	The age of a firm calculated since year of when the company has been incorporated.	Fame
Size		Fame
Cash	Cash and cash equivalents is an item on the balance sheet that reports a firm's assets that are cash or can be readily converted into cash. Examples of cash and cash equivalents are bank accounts, marketable securities and Treasury bills.	Fame
Intangible Fixed Assets	All intangible assets such as formation expenses, research expenses, goodwill, development expenses and all other expenses with a long term effect. The Intangible Fixed Assets is a financial label of the Balance Sheet account	Fame
Average Wage	Average Wage (Monetary value) is defined as a ratio: Cost of Employees / Number of Employees	Fame
Exports	The Export Turnover (Monetary value) is a financial label of the Profit & Loss account	Fame
MNE	A firm is defined as a multinational if it owns at least one foreign subsidiary and controls at least 10% of its voting shares.	Fame
Regional characteristics		
Air traffic	Air transport of passengers, by NUTS 2 regions, 1 000 Passengers	Eurostat
GDP growth	Annual percentage change in regional gross domestic product (million EUR), by NUTS 2 regions	Eurostat
PATENTS	Patent applications to the EPO by priority year, by NUTS 2 region, Number of applications per million of inhabitants	Eurostat
UNEMP	Unemployment rate, by NUTS 2 regions	Eurostat

Note: All local factors are taken from Eurostat.