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Firm dynamics and business cycle: What doesn't kill you makes you stronger?

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Abstract

This paper analyses the impact of recessions and booms on firm performance. We look at 70,000 firms in over 100 countries between 1986 and 2014 and document the trends in firm entry over the business cycle. Our paper confirms some standard facts about firm dynamics: employment growth is decreasing with size and age; entry rate is pro-cyclical while the exit rate is counter-cyclical. For example, in case of advanced economies, 97 per cent of employment creation is by firms between the ages of 0 and 5 years, while for developing and emerging economies, it is 86 per cent of all employment. Our main results are: first, we do see selection effects of recessions, particularly when we look at employment, sales and capital. Specifically, when a firm enters the market during good times, they tend to have lower employment and capital than firms that enter the market during bad times. Second, when we look at total factor productivity (TFP), we don't see a clear "cleansing effect" of recessions – more productive firms entering the market while less productive leaving. Third, the effects of entering during a boom or a recession tend to persist for a long time, over 15 years. Fourth, we find notable differences between income groups – while recessions tend to create stronger firms in the advanced economies, booms tend to create stronger ones in case of the emerging economies. Lastly, the effects of recessions on firms tend to vary by sector.

Key words: business cycles, entry and exit, firm performance, total factor productivity

JEL classification: D22, E32, L25, O4

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1. Introduction

According to the Bureau of Statistics (BLS), 85 per cent of the jobs created in the U.S. economy are in the private sector; similar is the story in other advanced economies. Furthermore, most jobs that are created in the private sector tend to be from young businesses. For example, in the U.S., between 1988 and 2011, almost all of the private sector jobs were created by enterprises that were less than 5 years old (Kauffman Foundation, 2014). Indeed, several studies have shown the importance of young firms for aggregate job creation; see for e.g. Bartelsman, Haltiwanger and Scarpetta (2009), Haltiwanger, Jarmin and Miranda (2013) and Fort, Haltiwanger, Jarmin and Miranda (2013). Furthermore, market conditions during firm entry tend to determine firms' economic and financial performance and the effects tend to last much longer than commonly understood. In particular, Sedlacek and Sterk (2014) show that the starting conditions when firms enter the market tend to have a persistent impact on employment creation by new firms. They look at the Business Dynamics Statistics (BDS) in the U.S. to show that recessions and booms tend to have a differential impact on firms and the impact persists.

Meanwhile, recessions also tend to have a "cleansing effect" – i.e., firms that are not as productive cannot survive during recessions and the ones that do survive tend to have persistently higher productivity – but, the empirical evidence is far from being conclusive regarding entry. On the one hand, Lee and Mukoyama (2012) find evidence in favour of "cleansing effect" and a selection mechanism where only larger firms (in terms of sales and employment) enter during recessions. On the other hand, Sedlácek and Sterk (2014) find that firms entering during recession present persistently lower employment than its counterparts; under one of the authors' model specification, the fact is explained by having lower productivity, which then leads to smaller optimal size (evidence against either "cleansing effect" or the selection mechanism). Regardless of the specification for the second model, the opposite results in terms of employment, given their persistence and the potential aggregate consequences, the issue merits closer examination.

Most studies that look at firm dynamics during business cycle tend to focus on the U.S. and make use of Business Dynamics Statistics (BDS) or the National Establishment Time Series (NETS) – for e.g, Haltiwanger, Jarmin and Miranda (2013) and Neumark, Wall and Zhang (2010). There are a few papers that have examined firm dynamics in Europe – for e.g. Moscarini and Postel-Vinay (2012) look at the "cleansing effects" of recessions in Denmark and France (and compare it with the U.S.). However, a cross country study that examines a large set of countries is lacking in the literature. Our paper fills this gap by examining the impact of "recessions" and "booms" on firm performance – we look at 70,000 firms in over 100 countries between 1986 and 2014 by making use of novel dataset called FactSet.

We identify "booms" and "recessions" by employing a double indicator methodology: GDP growth above or below average and the cyclical component of GDP obtained by the Hodrick and Prescott filter.[1] A "boom" is defined as the period with higher GDP growth rate than the average and a positive cyclical component of HP filtered GDP (this is akin to GDP being above trend). While a "recession" is defined as the period with lower GDP growth rate than the average and a negative cyclical component of HP filtered GDP. This is an extension of the identification procedure of Lee and Mukoyama (2012); the authors use only the growth rate whilst acknowledging different identification results using the HP filter. Our extension has two advantages: first, it diminishes the dependency on the type of filter; and second, it allows for more distinct business cycle phases to be identified – the boom and recessions subsamples will be less alike, this is a positive trait as the objective is to identify the effect of such

[1] GDP level and its growth rate are obtained from the World Development Indicators database.

differences. Stylized facts presented in the paper show that entrants during recessions tend to have higher total factor productivity (TFP), total sales, employment and capital. Entry and job creation rates are pro-cyclical – i.e., more firms enter during booms than in recessions and job creation rate is higher during booms than in recessions. Also, young firms (less than 5 years old) tend to be the job creators across all regions, which is in line with the findings in the literature (Haltiwanger, Jarmin and Miranda, 2013; Neumark, Wall and Zhang, 2010).

Our main results are five-fold: first, we do see selection effects of recessions, particularly when we look at employment, sales and capital. In other words, when a firm enters the market during good times, they tend to have lower employment and capital than firms that enter the market during bad times.[2] Second, when we look at total factor productivity (TFP) using two different methods – standard Cobb-Douglas and the Olley & Pakes modification– we don't see a clear "cleansing effect" of recessions. Third, the effects of boom or recession tend to persist for a long time, over 15 years. This is in line with the literature on labour market dynamics (albeit we see opposite effect on firms compared to workers) where workers that enter into employment during recessions tend to have persistently lower earnings than the ones that enter during booms. Moreover, since the effects of recessions and booms persist for a long time, this has relevance for policy. Fourth, we find significant differences between advanced economies and emerging economies – opposite effects of booms and recessions. Lastly, there are sectoral differences, but these are mainly in terms of the magnitude of the impact rather than the signs.

The rest of the paper is organized as follows: Section 2 provides a literature review of studies that have looked at firm dynamics over the business cycle. In particular, it focusses on the theoretical and empirical evidence behind the effects of recessions. Section 3 describes the firm-level database used for this study called FactSet; it examines the reliability of the database by comparing the trends obtained using FactSet and broader trends. Furthermore it presents some summary statistics from FactSet that is relevant for better understanding firm dynamics vis-à-vis job creation and employment outcomes. Section 4 talks about the empirical methodology used in the paper while Section 5 presents the results, section 6 robustness checks (highlights the disagreement in the literature irrespective of the data used) and section 7 concludes.

[2] Note that we are always considering entrants, thus survival only can influence the persistence results, but certainly not the first year results

2. Literature Review

2.1. Job creation and destruction at entry and exit margins

Studies show that a large bulk of job creation and destruction in an economy takes place at the entry and exit margins for firms (Caballero and Hammour, 1994; Foster, Haltiwanger and Krizan (2000). Empirical literature seems to support this finding. For e.g., Davis, Haltiwanger and Schuh (1996) show that 20 per cent of job destruction and 15 per cent of job creation is due to exit and entry of firms. When we look at five year changes, this rises to 40 per cent of job created/destroyed stems from exit and entries (Baldwin, Dunne and Haltiwanger, 1995). Foster, Haltiwanger and Syverson (2013) show that new businesses are typically much smaller than their established industry competitors and that this size gap closes slowly. Also, exiting businesses have lower prices and lower productivity than incumbents or entrants. Foster et al (2005) say that both productivity and prices are important determinants of firm survival, but, the demand variation across producers seem to be the most important factor. The authors argue looking into the determinants of variation in demand across businesses would be key in better understanding productivity dynamics.

Moscarini and Postel-Vinay (2012), using data across Denmark, France and United States, find that large firms tend to shed more jobs than small firms when unemployment rate is above trend and create more jobs when unemployment is below trend. In other words, large firms show higher negative correlation between job creation and aggregate unemployment than small firms. This pattern is not only visible at entry and exit margins, but also for incumbents. Furthermore, the authors show that the finding holds within sector more than across sectors. Meanwhile, decisions made by firms at the time of entry regarding scale and fixed cost incurred tend to have a direct impact on their economic performance and longevity. Abbring and Campbell (2004), using a small sample of bars in Texas in the U.S., find that 40 per cent of the sales variance is due to pre-entry scale decisions and the effect of scale on sales persists over time. After entry, the authors find that bars tend to exit only after very unfavourable shocks. Also, an entrepreneur tends to delay her exit decision until her posterior beliefs about profitability remains true.

Ottaviano (2011) introduced exogenous technology shocks to a two-sector growth model to show that during booms or upswings the entry rate is higher and more firms survive after entry, but surviving firms are on average less efficient and smaller. The opposite is true during downswings and exits are counter cyclical while entries are pro-cyclical. According to Ottaviano (2011), this has a dampening effect of technology shocks on aggregate output per workers and welfare. This also works through another channel due to variable demand elasticity – keeping the number of incumbents constant, in an upswing there is reallocation towards less efficient firms because the elasticity of demand falls more for high-price firm than for low-price ones. Furthermore, he shows that the dampening effect of technology shocks depends on firm heterogeneity; existing models of firm dynamics might overstate the impact of cyclical exit and counter-cyclical entry on the aggregate dynamics as it is the "small and inefficient firms" that tend to follow this pattern more.

Sedlacek (2011) finds that compared to old firm, employment growth in young firms tends to be more volatile, which then contributes to the unemployment increases during and after recessions and boosting employment growth during expansions. Furthermore, he shows that entrants are more important determinants of aggregate unemployment rate – for example, in the recent recession the lower than average entry rate alone accounted for one-fifth of the observed increase in unemployment rate. Sedlacek (2011) presents a theoretical model that mimics these empirical findings and provides answers to policy questions salient for job creation: government should ease barriers to firm entry (as business

start-ups are crucial for overall job creation and increased productivity) and supporting existing firms disrupts the selection process of successful firms and leads to lower productivity and output.

Clementi and Palazzo (2013) analyse if entry and exit play an important role in aggregate dynamics and find that they tend to propagate the effects of aggregate disturbances. Furthermore, a positive aggregate shock leads to an increase in entry while a negative shock leads to a decline in entry. Entrants tend to be smaller than the incumbents but are the major source of job creation and tend to grow much faster as well. Meanwhile, they show that aggregate productivity reverts back to unconditional mean; the younger cohorts of firms continue to expand which tends to generate larger expansion than it would be without entry or exit.

On the contrary, Baily, Hulten and Campbell (1992) find that firm entry and exit play only a minimal role in productivity growth at the industry level. They show that "increasing output shares in high-productivity plants and the decreasing shares of output in low-productivity plants are very important to the growth of manufacturing productivity". The authors also find that manufacturing plants that are better managed and have higher productivity growth, tend to stay at the top for longer periods.

Empirical studies have shown that within industry dispersion of labour productivity is larger than that for total factor productivity (Bartelsman, Haltiwanger and Scarpetta, 2013). Bartelsman, Haltiwanger and Scarpetta (2013) show that within-industry distributions of productivity and size are closely related but there is considerable heterogeneity across countries. This relationship is stronger in the case of advanced economies and for Central and Eastern European countries the relationship becomes stronger as the countries transitioned towards market economy.

2.2. "Cleansing effect" of recessions

Theoretical literature on firm dynamics and business cycles shows that recessions could have a "cleansing effect" while at the same time, booms could have an "insulation effect" (Caballero and Hammour, 1994). First, "cleansing effect" means that firms that were not as productive before could be even more unprofitable during a downturn and hence leave the market and make way for ones that are productive and managed well. This is very much in line with the Schumpeterian "creative destruction" phenomenon (Schumpeter, 1939, 1942). Second, "insulation effect" means that firms that are not as productive are insulated because of booms, which create enough demand for even the most unproductive firms and allow them to weather the downturn; Caballero and Hammour (1994) show that the structure of the adjustment cost determines whether there is even an "insulation effect". Furthermore, studies show that job destruction is cyclically more responsive than job creation hence the "insulating effect" does not seem perfect (Caballero and Hammour, 1994; Davis and Haltiwanger, 1990, 1992).

Lee and Mukoyama (2012) examine the patterns of entry and exit over the business cycle in terms of employment & productivity and find that entry rates differ significantly during booms and recessions. They show that differences in productivity and employment are larger for entering plants than for exiting plants -- in particular, firms that enter during booms are 25 per cent smaller and 10-20 per cent less productive than the ones that enter during recessions. The authors show that such differences are relatively small for exiting firms, either during booms or recessions. Lee and Mukoyama in effect refute the "cleansing effect" of recessions – that is, firms that are not as productive tend to leave during recessions. In fact, they show that the exit rates are similar during both recessions and booms, and that there is no difference between exiting plants in terms of employment or productivity. Moreover, the authors argue that productive firms do not necessarily exit during recessions; while only highly productive firms can enter during recessions. Firms that enter during recessions differ from the ones

that enter during booms indicates that there are barriers to entry during recessions, which could then have long-run impact on the broader economy (Lee and Mukoyama, 2012). Selection on the entry margin is more important that on the exit-margin.

On the other hand, Caballero and Hammour (1994) find that recessions have "cleansing effect" – getting rid of the unproductive firms, the so called pruning of the economy. They also provide a "pit-stop" view of recessions when firms can engage in productivity enhancing activities because of lower opportunity costs; several studies corroborate this finding, for e.g. Davis and Haltiwanger (1990), Aghion and Gilles Saint-Paul (1991), Gali and Hammour (1991) and Hall (1991). Foster, Haltiwanger and Krizan (2000) show that exit and entry are important sources of aggregate productivity growth. In fact, they find evidence in favour of "cleansing effect" of recessions – exit of low productivity firms. It should be noted that the authors consider only a small subset of service sector – the automobile repair shop sector in the U.S.

Foster, Grim and Haltiwanger (2014) find that reallocation during the Great Recession (2008-09) differed markedly from previous recessions. In particular, job creation fell more during the Great Recession than in previous recessions. Furthermore, they lend support to the "cleansing effect" of recessions – less productive firms were more likely to exit while more productive firms were likely to stay and grow. But this pattern is not as strong for the Great Recession, i.e., it is not as productivity enhancing as in prior recessions. Indeed, the authors show that "the gap in growth rates and exit rates between high productivity and low productivity businesses decreases rather than increases with large increases in unemployment in the Great Recession." Lastly, Foster, Grim and Haltiwanger (2014) show that the firm level effects translate into the aggregate (industry) level but relatively smaller during the Great Recession. The authors posit that the effect of financial collapse during the recent recession might have a role to play. Indeed, there are some studies that show that recessions could have "cleansing effect" only in the absence of financial constraints (Barlevy, 2003).

2.3. Is productivity pro-cyclical or counter cyclical?

"Cleansing effect" of recessions implies that labour productivity is counter-cyclical but measured productivity is pro-cyclical (Caballero and Hammour, 1994). But, measured productivity was pro-cyclical mostly in the 1980s; lately it has been counter cyclical with the Great Recession being an excellent example of this change. Berger (2012) examines the puzzling fact that in recent down-turns productivity has been markedly less cyclical while employment creation remains cyclical. Berger's quantitative model shows that firms tend to grow "fat" during booms and turn "lean" during recessions. In other words, during upswings they employ unproductive workers but they shed these workers in recessions, thus entering the recovery period with greater ability to meet increase in demand without additional hiring. In particular, the model explains 55 per cent of the cyclicality of average labour productivity and 4 quarters of jobless recovery during the Great Recession.

Indeed, *acyclical* productivity in the US has become a stylized fact -- the literature has turned to theoretical explanations. Galí and van Rens (2014) suggest that a reduction in labour market frictions, which would alleviate the need for labour hoarding, could explain the decline in the cyclicality of labour productivity. Garin, Pries, and Sims (2013) argue that an increase in the importance of re-allocative shocks (relative to aggregate shocks) could explain the new pattern for labour productivity. In the Schumpetarian (1939) tradition of creative destruction, these re-allocative shocks boost aggregate labour productivity by shifting employment to more productive sector. Each of the theories outlined above has implications for the behaviour of productivity during recessions, and many of them also address the issue of jobless recoveries. Traditional labour hoarding theory is consistent with jobless

recoveries (excess labour retained during a recession postpones the need for hiring) but inconsistent with productive recessions (productivity falls as firms hoard labour).

On the other hand, models that emphasize reduced labour market frictions (Galí and van Rens, 2014) are designed to explain productive recessions but do not provide an explanation for jobless recoveries. Other models suggest a positive link between productive recessions and jobless recoveries. Models of structural change (Groshen and Potter, 2003; Garin, Preis and Sims, 2013) emphasize both productivity improvements from reallocation during a recession and long lasting structural unemployment during the ensuing recovery. Another branch of the literature suggests that firms accumulate inefficiencies during long expansions and then restructure during a recession (Koenders and Rogerson, 2005; Berger, 2012). Firm-level restructuring yields productivity improvements that delay the need for rehiring during the ensuing expansion. Schreft, Singh, and Hodgson (2005) suggest that increasingly flexible labour markets allow for the use of temporary workers and a just-in-time use of labour that delays the need for permanent hires during a recovery. In a similar spirit, Panovska (2012) emphasizes the ability of firms to adjust hours first during the recovery before committing to new hires. These models can generate productive recessions (as firms aggressively slash hours) followed by jobless recoveries (as firms ramp up hours first, rather than employment). On the other hand Galí, Smets and Wouters (2012) argue that instead of jobless recoveries, the post-modern US recoveries can be characterized as slow (sluggish output growth).

3. Data & Summary Statistics

3.1. Data: FactSet[3]

In a growing trend of private data providers used in academic research, FactSet is one that contains publicly listed firms in over 100 countries, covering the time period between late 1970s and 2014. What makes the database particularly attractive for researchers looking into firm dynamics and labour market outcomes is the data coverage in terms of countries, sectors and period. Indeed, a large number academic studies use FactSet or similar databases. Compustat North America particularly is a popular choice in the finance and macro-finance literature – this database is a subset of FactSet, as coverage of the later has a global scope. Overall, much of the growth in the use of firm level data in the economic literature has relied on databases that retrieve the data from public financial statements; thus the use of FactSet can be considered standard in academic research. For instance, a search in Google Scholar with the key word Compustat returns approximately 37,000 results, 17,500 for 2010 or after. A search for FactSet returns 1,800 results, 1,300 of which for 2010 or after. Thus, Factset is not as popular as Compustat in academic research, but it is starting to become more popular.

One of the limitations of FactSet is that it contains only publicly listed firms, hence it is missing an important component of the production side of the economy -- private companies. Aside from this, the dataset presents further limitations, such as asymmetry in collection between countries and regions, delays in data collection, illogical entries, etc. Despite all the limitations, after a careful cleaning up, we can build a sample that allows us to do sound empirical analysis. Figure 1 (panel A) shows the GDP in current USD from the World Development indicators of the World Bank and total sales figures for all companies using FactSet. As it is expected, the levels from Factset substantially differ from the WDI

[3] The ILO's Research Department has annual subscription to FactSet. Please contact the authors for more information about the data and subscription.

GDP, which is natural given only a fraction of global production is captured by FactSet; and that aggregate sales do not correspond with GDP – aggregate sales are not obtained through a value added approach. Sales for adjusted data are substantially smaller than for unadjusted data – also to be expected as the adjustment removes firms from the database, hence from the total sales. As can be seen in Figure 1, the level of consistency of the data is acceptable. Furthermore, if one is interested in the levels of variables or levels of ratios susceptible to be affected by firm's survivor bias, then the unadjusted version of the data will be more suitable.

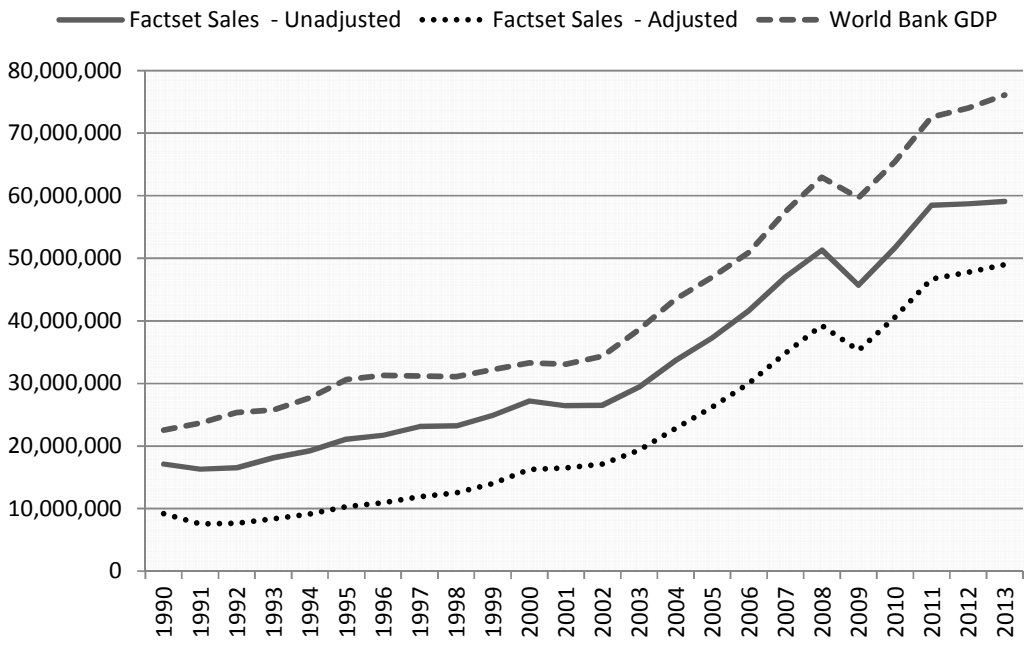
Meanwhile, Figure 1 (panel B), presents a similar exercise – growth rates of the world GDP and total sales from FactSet. Two salient features from this figure are worth mentioning: i) the growth rate of FactSet data is more volatile than the GDP data; in (broadly defined) expansion years the growth rate of sales is above GDP, whereas in (broadly defined) contraction years it is below. ii) The second fact is the poor performance of the unadjusted data towards the end of the sample (2014 is excluded from Figure 1); this is not surprising; data collection requires time, and most recent years will be disproportionately affected. The problem is evident in 2014, before that, the discrepancy is not exceptional compared to the rest of the sample, nonetheless some bias appears to be present. Thus when analysing the end of the sample and particularly 2014, it is convenient to use adjusted data. Nonetheless in some occasions, since it is a ratio that is of interest unless a serious reporting bias affects the data – which can be the case – unadjusted data can be consistent enough.

Meanwhile, when we examine the GDP growth figures and compare that to sales growth from FactSet, one period that stands out is 1995-2000. During this period, firms reported by FactSet saw significant changes in growth figures but the global GDP growth, albeit positive and strong during this period, does not nearly mimic the trend from FactSet. This might be reflective of the tech boom in the US and since FactSet is comprised of only publicly listed firms, the discrepancy might be due to this. Furthermore, it could also be the case that more firms went public during this period, riding the wave of tech boom. In any case, this needs to be investigated further and when we do the empirical analyses using FactSet we will need to make adjustments for this period to get a true picture of firm dynamics and employment creation.

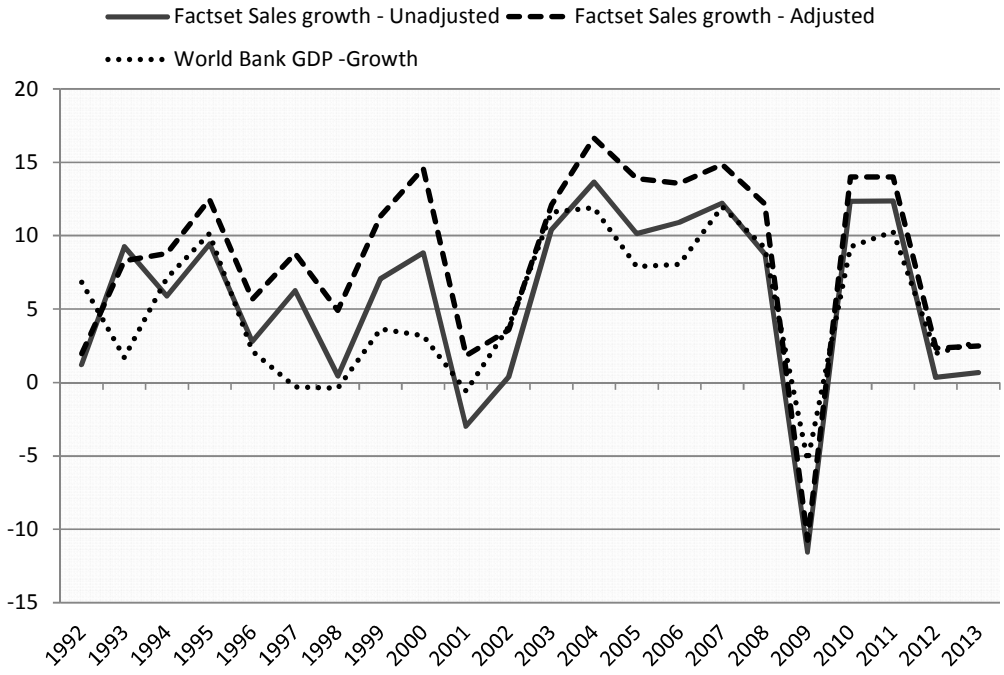
After cleaning up the database for descriptive trends and analysis – where the key criteria was availability of employment information – the total sample we have is 71,672 firms, out of which 18,918 are in the United States (see the Appendix for details on sample selection strategy). Countries with more than 5,000 firms include Canada, Japan and the United Kingdom. Meanwhile, countries with more than 3,000 firms include China and India; over 2,000 firms include Australia, Korea and Taiwan; likewise, over 1,000 firms include France, Germany, Hong Kong and Malaysia (see the Appendix for firm break down for other countries).

Figure 1: World GDP from the WDI vs. aggregate sales from Factset

Panel A: Levels



Panel B: Growth



Note: Adjusted data refers to data that excludes firms which at some point of the sample period stopped having entries in the database (due to disappearance or delays in data collection). Unadjusted data refers to the data that does not leave out non-reporting firms from the sample. Source: Authors' calculations based on FactSet and the World Bank.

3.2. Summary Statistics

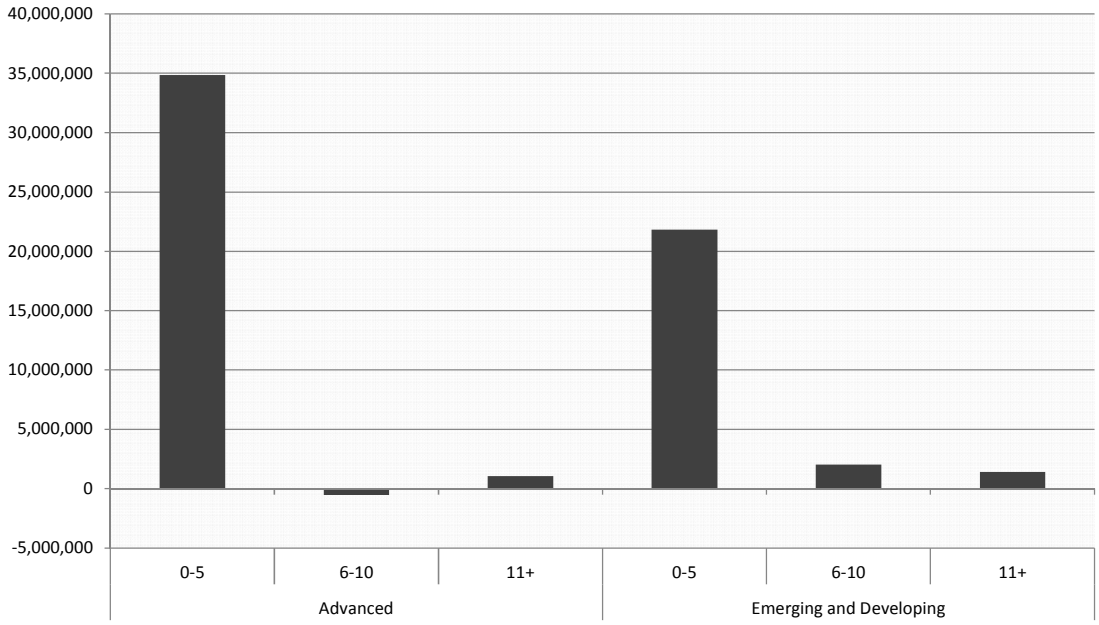
Employment creation by firm size reveals that small and medium sized firms have seen the most significant growth rates in employment. Take for example the late 1990s, when employment growth for small firms hovered around 50 per cent while for medium firms it was around 25 per cent. Large firms did well during this period as well, but there was a drop in 1997 and 1998, reflective of the Asian financial crisis. It should be noted that for small firms, which have less than 50 employees, going from 10 to 15 employees in a year amounts to a 50 per cent growth rate; while for large firms, which are 250 employees plus, it amounts to 2 per cent growth rate in employment. Also, it is not at all a surprise that the aggregate employment growth follows the same path as the one for large firms.

Employment growth hovered around 0 per cent in early 2000 for large firms, which is reflective of the burst of tech dotcom bubble. In case of small and medium sized firms, even though the employment growth was not as strong as in the late 1990s, it was stronger than for large firms. This trend continued until mid to late 2000, after which employment growth in small and medium sized firms entered into negative territory and has not really recovered. Employment growth among large firms seems to have recovered since the Great Recession, notwithstanding the recent slowdown, for small and medium firms it has not recovered yet.

When we examine employment creation by the age of firms, we see that young firms tend to account for a large share of job creation across all regions. For example, in case of advanced economies, 97 per cent of employment creation is by firms between the ages of 0 and 5 years, while for developing and emerging economies, it is 86 per cent of all employment (Figure 2). Our findings confirm the empirical finding in the literature on firm dynamics that small and young firms create most of the employment in an economy. However, based on our descriptive trends, we cannot disentangle whether it is the size or the age that matter more, for that we would need to conduct an empirical analysis.

Meanwhile, we see that firm death rate is high among small firms, but also there are more small firms entering the market across all regions. Here we have defined death rate as firms inactive within first year of establishment over total active firms and birth rate as firms active within first year of establishment over total active firms. Since early 2000, for small and medium sized firms the death rate has stayed between 2.5 and 3.5 per cent, with the exception of 2002. During the crisis years, 2008-10, it was around 3.5 per cent. For large firms, the death rate did not show much variation during this period. Also, when we look at the birth rate, leading up to the crisis in 2008, it was over 10 per cent for small firms, but it has been on a downward trend since then, currently below 5 per cent. Similarly, for medium sized firms it was around 7 per cent leading up to the Great Recession, now it is close to 2 per cent. For large firms, it was close to 5 per cent before the crisis, now it is below 1 per cent.

Figure 2: Net job creation by the age of firms



Source: Authors' calculations based on Factset.

4. Empirical Methodology

4.1. Estimating total factor productivity

In order to calculate total factor productivity (TFP) we use the neoclassical production function used by Baily, Hulten and Campbell (1992). Here, Y_{it} is the real gross output for *i* firm in year *t*, K_{it}, L_{it} and M_{it} are capital, labour and intermediate inputs. Output is proxied by sales, capital by plant and equipment, labour by the number of employees, and intermediate inputs by cost of goods sold minus labour expenses.[4]

$$Y_{it} = F(K_{it}, L_{it}, M_{it})$$

As in most studies in the literature, we use two methods for calculating TFP (see Baily, Hulten and Campbell, 1992 for a discussion of both). The first one is the standard Cobb-Douglas method where look at the value added by each firm and calculate the residual, where value added is $Y_{it} - M_{it}$. Intermediate inputs are directly subtracted from sales. It can be expressed as the following:

$$lnTFP_{it} = ln(Y_{it} - M_{it}) - \alpha_L lnL_{it} - \alpha_K lnK_{it} - c$$

where c is a constant. The second one is called Olley and Pakes method, which is substantially more convoluted. The basic structure is the same as the standard Cobb-Douglas case, however Olley and Pakes assume that the productivity in each period is observed before some input decisions and exiting

[4] Cost of goods sold is the costs of operations, as such they do not include overhead expenses amongst others. Therefore intermediates are approximated as the total costs involved in production of the goods minus labour expenses. Total labour expenses are used due to data availability.

decisions gives rise to endogeneity issues. For instance labour input can increase, and exit probability decrease, as a response to an observed productivity shock by the firm, but unobserved by the researcher. The methodology controls for the effects of simultaneity by use of an auxiliary variable that is positively related to productivity – for this study we use investment proxied by capital expenditure. The details of the method can be found in the seminal paper by Olley and Pakes (1996).

4.2. Estimating the selection effect of recessions

We identify "booms" and "recessions" by employing a double indicator methodology: GDP growth above or below average and the cyclical component of GDP obtained by the HP-filter. A "boom" is defined as the period with higher GDP growth rate than the average and a positive cyclical component of HP filtered GDP (this is akin to GDP being above trend). While a "recession" is defined as the period with lower GDP growth rate than the average and a negative cyclical component of HP filtered GDP. In order to understand the effects of recessions and booms, we first use the following basic panel specification:

$$\ln(Y_{it}) = \beta D_{jt} + \varepsilon_{it} \; \forall (i,t) \in \Omega$$

Where Ω is the set of new entrants; the condition defines that only pairs (i,t) belonging to the set are considered. This simply indicates that the regression is only carried out in the subsample of the first year of existence of each firm in the sample. D_{jt} takes a value of 1 if the country is classified as having a boom in that year, and 0 if it is considered to be in recession. The country indexed by *j*, is the one to which firm *i* belongs. The dependent variable is one of the following variables:

$$Y_{it} = \begin{pmatrix} TS_{it} \\ EMP_{it} \\ CAP_{it} \\ TFP_{it} \end{pmatrix}$$

TS_{it} refers to total sales, EMP_{it} refers to employment, CAP_{it} refers to capital, and TFP_{it} refers to total factor productivity. Meanwhile, D_{it} refers to a dummy variable for the state of economy – booms and recessions.

As it is standard in the literature, we repeat the estimation including a set of relevant controls, in the following manner:

$$\ln(Y_{it}) = \beta D_{jt} + \upsilon_j + \upsilon_k + \upsilon_t + \varepsilon_{it} \; \forall (i,t) \in \Omega$$

where υ_j is the country control, υ_k the sector control, and υ_t the year control. We don't employ other controls in our regressions – such as finance measures relevant for firms (debts, interest payment, tangible/intangible assets etc.), tax measures (income tax, foreign country tax etc.) and globalization measures (sales abroad, assets abroad etc.) – because we are looking at the first year of entry for firms. Presumably, firms have taken into account all these factors (state variables) before they make the decision to enter the market. Also, we don't have sales (employment, capital equipment) going back in time because the firms were not existence before time $t = 0$.

The interpretation of the regression model is straightforward in both cases, with or without controls (country, sector and year) – the estimation of β will indicate the difference in conditional means between the group of firms entering during booms compared to during recessions.

It is very common to consider panel data to include an individual fixed effect, for instance the simplest FE panel data model would be:

$$Y_{it} = \alpha_i + \varepsilon_{it}$$

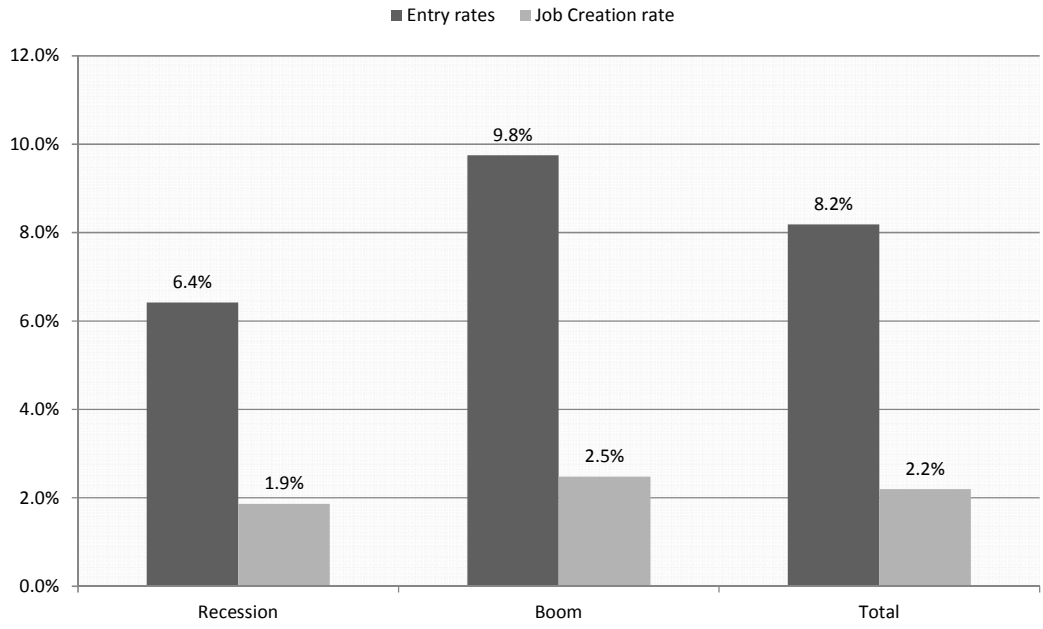
In this framework such an exercise cannot be carried out. The reason is that since the set of observations is restricted to new entrants, $(i,t) \in \Omega$, we only have one observation available for each firm, thus it is meaningless to estimate a fixed effect and an error term.[5]

5. Results

5.1. Stylized facts based on definition of booms and recessions

Our sample suggests that entry and job creation rates are pro-cyclical, thus suggesting possible selection mechanisms. In particular, entry rate of firms during booms is 9.8 per cent while during recessions it is 6.4 per cent (Figure 3). Nonetheless, the difference in job creation rate between booms and recessions is not as stark – 2.5 per cent vs. 1.9 per cent. For the total sample period, entry rate is 8.2 per cent while the job creation rate is 2.2 per cent. As Figure 4 shows, entrants during recessions tend to have higher sales, employment and capital. Indeed, employment and sales are between 7 and 8 per cent higher during recessions and investment in capital is 13 per cent higher as well.[6] In case of TFP, the difference between booms and recessions is very small.

Figure 3: Entry and entrants' job creation rates: booms vs. recessions

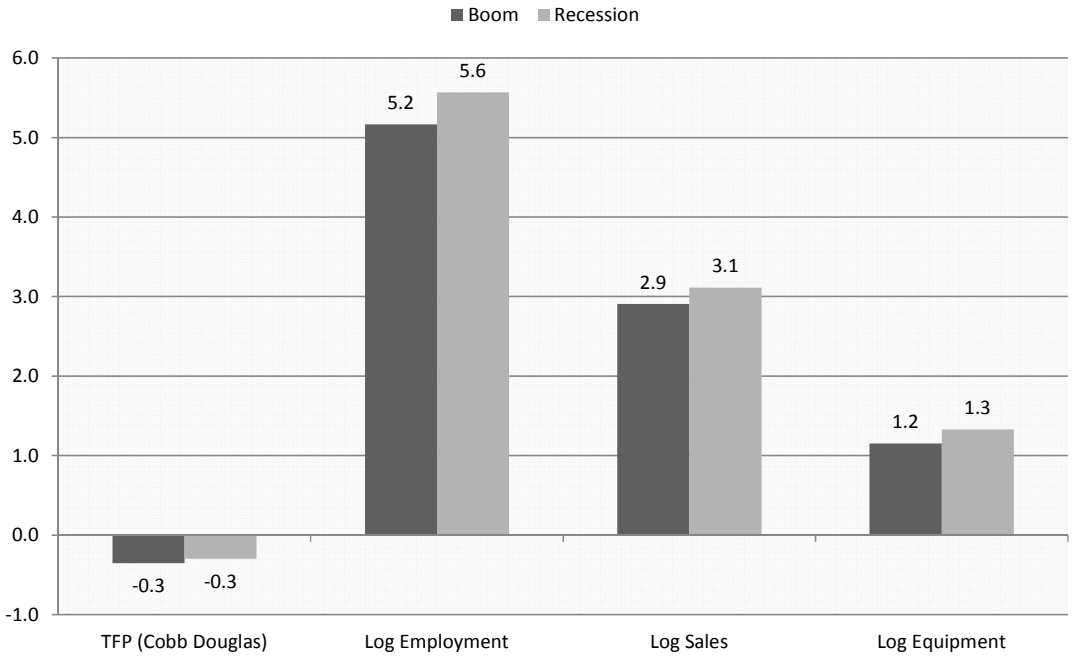


Note: the y-axis refers to the % of the respective ratio: entry rate = new entrants /total active firms; job creation = employment among new entrants/ total employment
Source: Authors' calculations based on Factset.

[5] If one estimates both terms, the trivial solution of 0 errors and a fixed effect equal to the observation is obtained.

[6] The percentage difference is in terms of the natural logarithm of the variables, therefore the difference in levels is substantially higher.

Figure 4: Difference between firms that enter during booms vs. recessions

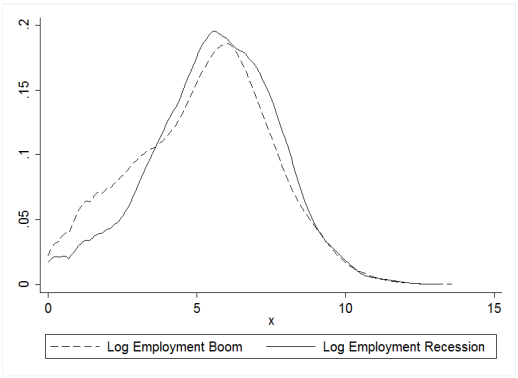


Note: the y-axis refers to the units of each variable; not comparable across variables. These are averages across our sample of firms.
Source: Authors' calculations based on Factset.

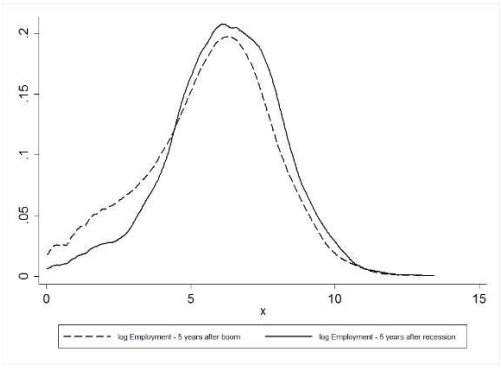
Figure 5 shows the Kernel density estimates of variables of interest – employment, sales and TFP – during booms and recessions; dotted lines indicate booms while the solid lines indicate recessions. As it can be seen from the left hand side panels, employment distribution shows a fatter left tail during booms than during recessions – this indicates that during booms a larger number of smaller firms (in terms of employment) tend to enter the market, while smaller number of smaller firms enter during recessions. This evidence is compatible with the selection effect. The rest of the variables present a similar pattern, nonetheless the magnitude of the selection is much lower (the difference in the tails is reduced). Qualitatively however, it can be said that during recessions entrants are larger in terms of employment and sales and have larger productivity – albeit the difference in TFP is barely visible. Right hand side panels in Figure 5 plots the distribution of variables of interest of those new entrants 5 years later. As it can be seen the differences between booms and recessions persist substantially in the case of sales and employment.

Figure 5: Selection effect of recessions: Contemporaneous (left) and 5-year (right)

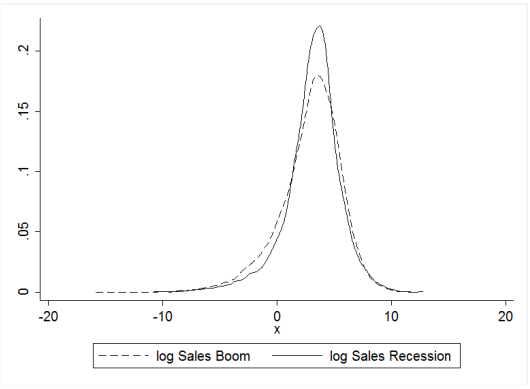
Panel A: Log Employment (t)



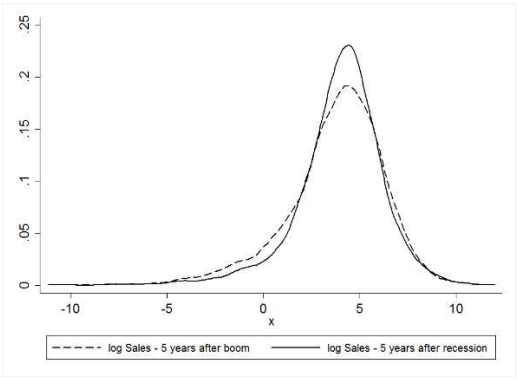
Panel B: Log Employment (t+5)



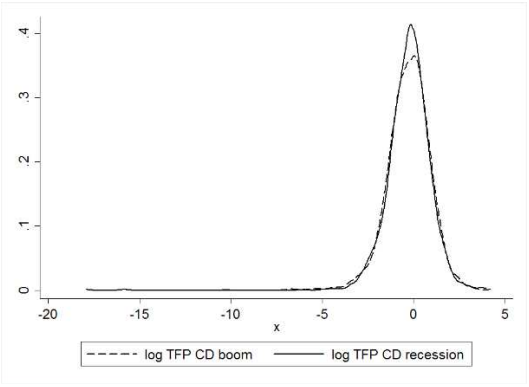
Panel C: Log sales (t)



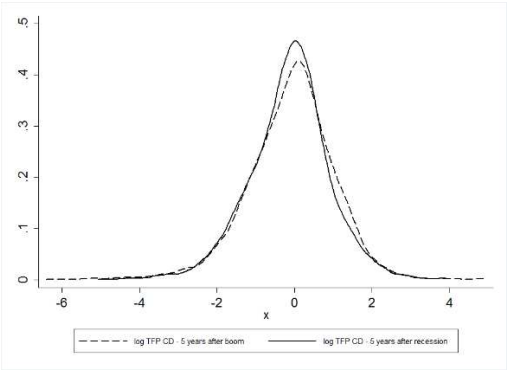
Panel D: Log sales (t+5)



Panel E: TFP (t)



Panel F: TFP (t+5)



Notes: The charts refer to Kernel Density estimates – dotted lines denote good times and solid lines denote bad times. Source: Authors' calculations based on Factset.

In order to further test our hypothesis of selection effects of recessions, we use a t-test of means comparison across groups for the variables of interest. The distributions observed in the above figures are approximately corroborated by the test – all the variables except the estimates for TFP are significantly higher during recessions (Table 1). The magnitude of the differences is large, for instance in terms of employment. The difference of 0.4 in terms of log implies that the average employment for entrants during recessions is 50 per cent higher than during booms.

Table 1: Means comparison (t-test)

Variable	Number Observations		Average		Difference	% Difference over booms	p-value
	Boom	Recession	Boom	Recession			
Log Employment	11,478	7,015	5.16	5.57	0.40	49.9	0.00
Log Sales	19,788	12,257	3.11	2.90	0.21	23.3	0.00
Log Capital	15,239	8,501	2.00	2.29	0.29	33.8	0.00
TFP (Cobb Douglas)	2,597	1,732	-0.26	-0.25	0.01	1.4	0.36
TFP (Olley and Pakes)	2,597	1,732	-0.86	-0.83	0.03	3.1	0.21

5.2. Baseline regressions

Now we use the regression approach – which is consistent with a t-test of means with unequal variances – to see whether booms and recessions have a differential impact on our variables of interest. As indicated earlier, the following specification is where D_{jt} is 1 during booms and 0 during recessions:

$$\ln(Y_{it}) = \beta D_{jt} + \varepsilon_{it} \; \forall (i,t) \in \Omega$$

To assess the persistence of the effects, illustrated in the density plots above, we run the regression for the period of entry and the following years. Thus the regression model becomes:

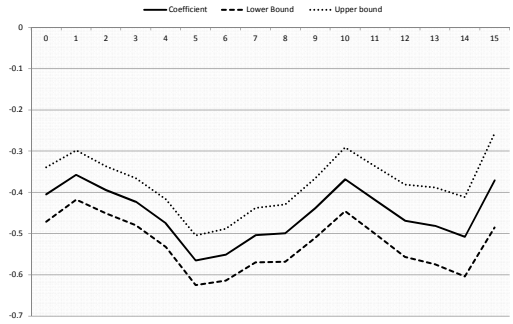
$$\ln(Y_{i,t+f}) = \beta D_{jt} + \varepsilon_{it} \; \forall (i,t) \in \Omega$$

where f = 0,1, 2 , …,15 indicates the number of periods that the dependent variable is forwarded. The interpretation is straightforward, the estimate of β will indicate the difference in means conditional on entering during a recession or a boom. For instance obtaining a negative coefficient for (log) employment implies that firms entering during a boom are on average smaller in terms of employment during entry. When the left hand side variable enters as forward values, the interpretation is very similar. The estimate of β indicates the difference between entrants during booms or recessions, f years after. For example, a negative estimate of the slope, for f =10 and log employment, indicates that firms entering during booms *remain* smaller than firms entering during recessions after 10 years. Results concerning the longest horizons (10-15) should be taken with care, as the sample size is greatly reduced as many firms have not been in the database for 10 years or more.

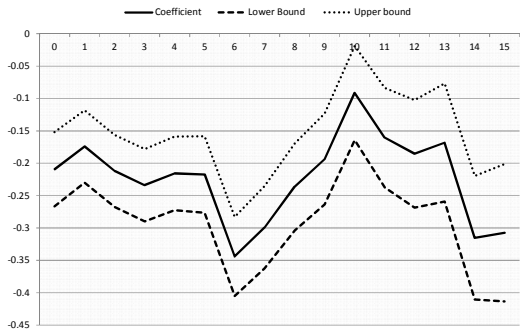
Figure 6 shows the results in four panels for employment, sales and TFP using two methods. Our results indicate that firms that enter the market during good times will have lower employment than the ones that enter during bad times and this effect persists for 15 years. Indeed, in period zero (year of entry) entrants during booms are smaller in employment (negative coefficient estimate and statistically significant) and in year 1, firms that are one year old are still smaller (as the coefficient remains negative and statistically significant). In other words, firms that entered during good times are smaller than firms that entered during bad times. And this effect is simply the result of persistence in level and not persistence in growth rates. For e.g., consider a firm with 250 employees (one that entered during good times) vs. 500 employees (one that entered during bad times) – if employment at these two firms grow at 10 per cent per year, the second firm will remain larger many years later. In terms of sales, the story is similar (panel B, Figure 6). Meanwhile, with productivity, the effect of entering during good or bad times is not clear and the coefficient estimates are largely insignificant (panels C and D).

Figure 6: Persistence of the effects – without controls

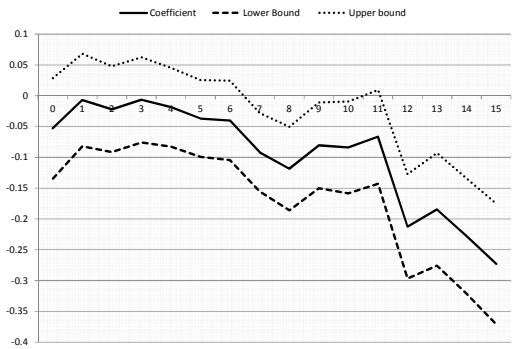
Panel A: Employment



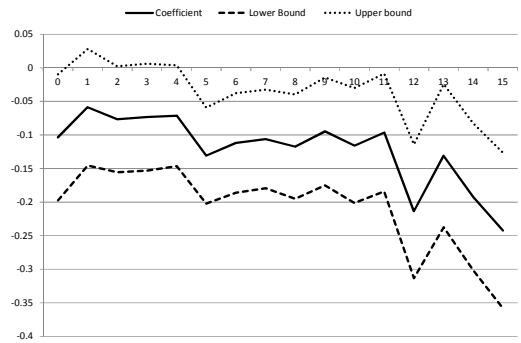
Panel B: Sales



Panel C: TFP (Cobb-Douglas)



Panel D: TFP (Olley and Pakes)



Note: The middle line in each panel refers to the coefficient estimate, the one above it refers to the upper bound and the one below it refers to the lower bound.
Source: Authors' calculations based on Factset.

We carry the same exercise with controls; we estimate the following equation:

$$\ln(Y_{i,t+f}) = \beta D_{jt} + \upsilon_j + \upsilon_k + \upsilon_t + \varepsilon_{it} \; \forall (i,t) \in \Omega$$

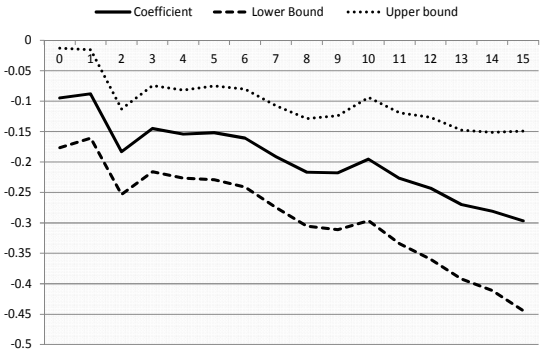
As discussed above, the controls are for country, year and sector. Given important differences in the variables of interest across these three categories, controlling for them can have a large impact, as indeed turns out to be the case.

It should be noted that we see instability in results depending on which regressor we condition and this is likely due to biases in the data collection in FactSet. Existent firms in early years tend to be much larger in terms of employment (and sales) than the entrants during more recent years because the FactSet coverage increases with time and smaller firms are underrepresented in the beginning of the sample. This can easily cause bias in the estimate of cyclical effects. For instance due to the global financial crisis and its aftermath, years identified as recessions are more frequent toward the end of the sample. In the previous setting, the higher frequency of recession years in the end of the sample will be associated with average smaller firms. Thus the results would be attributed to cyclical variation what is in all likelihood sample selection bias. This problem can be addressed by simply adding a year control, which will take into account these large yearly differences. Similar issues can arise across countries, as large differences between countries in entrants' variables of interest are present in the database. Given

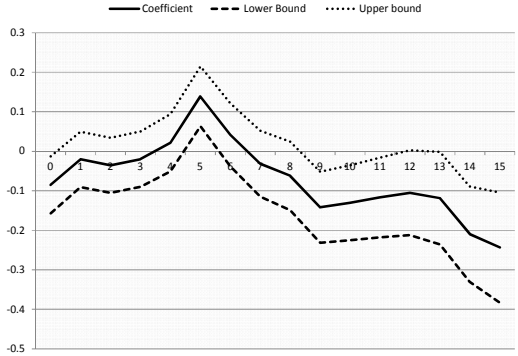
this, results based on the regressions which include controls will be more robust to sample selection issues. Indeed, as Figure 7 shows, there are substantial differences compared to the previous exercise. In particular, employment results remain valid, indicating a strong selection effect during recessions in favour of larger entrants, while sales do not appear to show a clear pattern. Lastly, the results for TFP are again largely non-significant, nevertheless over the medium term after entry there is a significantly positive coefficient for both measures (panels C and D). This implies *smaller* TFP for entrants during recessions, this is consistent with larger employment and capital and similar sales (compared to entrants during booms).

Figure 7: Persistence of the effects – with controls

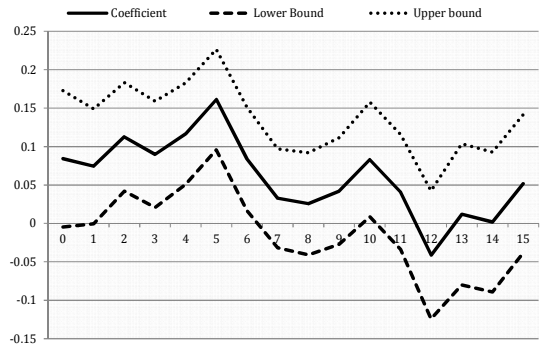
Panel A: Employment



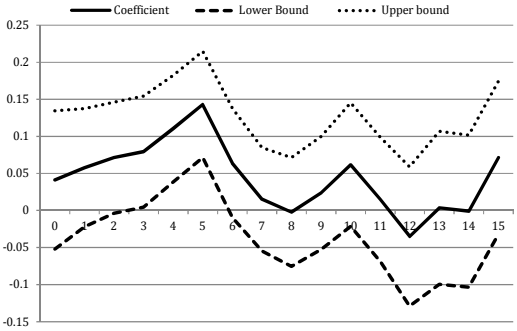
Panel B: Sales



Panel C: TFP (Cobb-Douglas)



Panel D: TFP (Olley and Pakes)



Note: The middle line in each panel refers to the coefficient estimate, the one above it refers to the upper bound and the one below it refers to the lower bound.
Source: Authors' calculations based on Factset.

5.3. Regressions with controls: By income groups and sectors

In order to further shed light on our results, we substituted the year controls with trend controls because the cycle indicator only contains variations of the cycle within a country and as the sample is reduced, instability in the results arises.[7] Therefore the model we estimated is the following:

$$\ln(Y_{i,t+f}) = \beta D_{jt} + \upsilon_j + \upsilon_k + t + \varepsilon_{it} \; \forall (i,t) \in \Omega$$

Table 2 presents the results of the division by income groups: advanced and emerging economies. As it is evident, the results are opposite for the two groups – the coefficient estimates are negative for the advanced economies and positive for the emerging ones (except for employment, but it is not significant for the latter group). What this essentially means is that selection effects are different: i) among the advanced economies, firms born during recessions tend to be larger than the ones born during booms; ii) while in case of the emerging economies, firms born during recessions tend to be smaller than the ones born during booms.

Meanwhile, consistent with a larger sample size, the global result tends to coincide with the advanced economies one – see the Appendix for number of firms by country (it is much larger for the advanced economies than the emerging and developing ones). Furthermore, the persistence of these differential effects is similar to the case of the global analysis – in other words, the effects are notably persistent (Figure 8).

Table 2: Difference between advanced and emerging economies

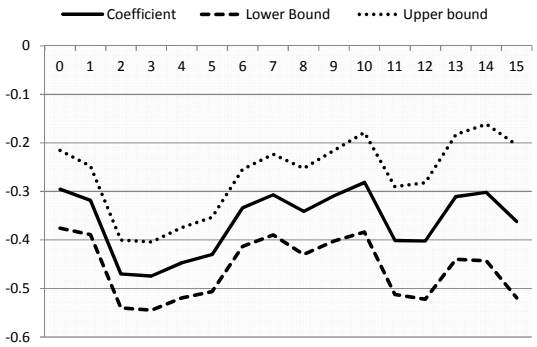
		Regressor: Cyclical Dummy		Controls			
Income Group	Dependent Variable	Coefficient	t-statistic	Country	Year	Sector	Number obs
Advanced	Log Employment	-0.30***	-7.25	yes	trend	yes	12,903
Emerging		-0.03	-0.6	yes	trend	yes	5,260
Advanced	Log Capital	-0.55***	-10.48	yes	trend	yes	15,295
Emerging		0.18***	3.56	yes	trend	yes	7,711
Advanced	Log Sales	-0.52***	-12.54	yes	trend	yes	20,110
Emerging		0.42***	10.78	yes	trend	yes	11,078

Standard errors in parenthesis (*p<1, **p<0.05, ***p<0.01)

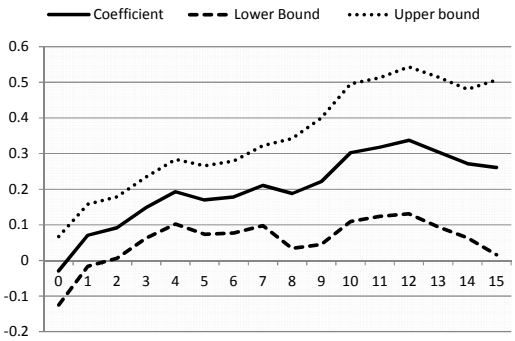
[7] We believe that the subsamples tend to have a negative effect on the estimations: First, it obviously reduces observations available, and the reduction can be crucial as the indicator of the cycle is a country level one and not a firm level one (thus much less degrees of freedom are present). Second, to the extent that subdivisions group produces more similar behaviour of the cyclical indicator including year controls can be deeply misleading. For instance considering the extreme case in which all the countries in the subsample present recessions and booms during the same years, in this case the cyclical indicator is perfectly collinear with the year controls.

Figure 8: Persistence of the effects: Advanced (left) vs. Emerging Economies (right)

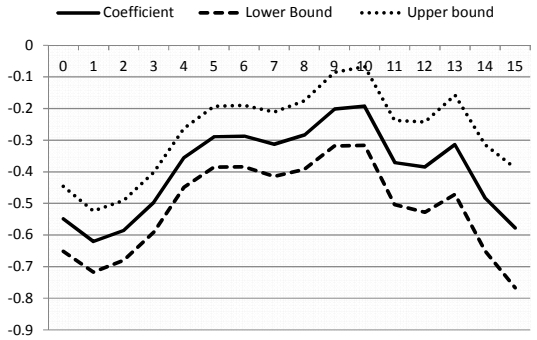
Panel A: Employment



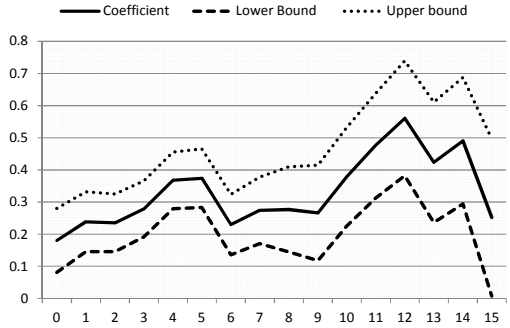
Panel B: Employment



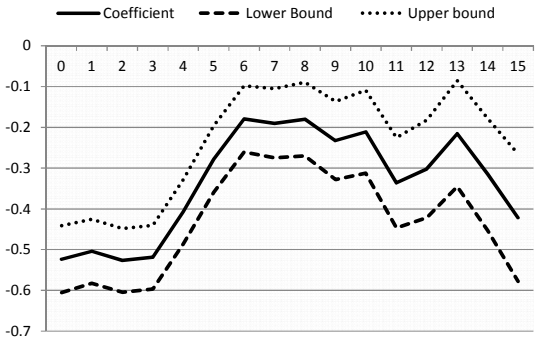
Panel C: Capital



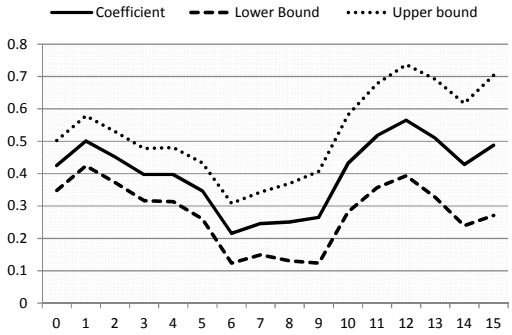
Panel D: Capital



Panel E: Sales



Panel F: Sales



Source: Authors' calculations based on Factset.

Table 3 presents the results of the division by sector, using only data for the advanced economies.[8] Our results show that some of the sectors have coefficients substantially different from others and some sectors present coefficients not significantly different from zero expressed as ns (these sectors tend to have smaller number of firms to being with). Meanwhile, we also looked into whether sectoral

[8] Developing economies have less observations and further breaking down by sector delivers generally non-significant results.

differences in the intensity of finance (measured by leverage in our case) -- we considered an interaction between the cyclical dummy and aggregate leverage by country and year. As

Table 4 shows, the interaction term is not always significant, but the general pattern inferred for employment, capital and sales is a positive interaction term. This positive interaction can be interpreted as following: the entrant's variable of interest (employment, capital or sales) tends to be larger during recessions, but less so in high leverage sector-country pairs.

Table 3: Results by sector (advanced economies)

Dependent Variable:	Log Employment		Log Capital		Log Sales	
Regressor cyclical dummy	Coefficient	No. of Obs	Coefficient	No. of Obs	Coefficient	No. of Obs
Accommodation and restaurants + Other community, social and personal service activities	-0.43**	868	-0.69***	1,058	-0.69***	1,296
Construction	ns	557	-0.46*	705	-0.31*	860
Financial Activities	ns	1,919	-0.45*	908	-0.46***	3,372
Health and social work activities	ns	232	-1.34***	260	-0.63*	346
Manufacturing	-0.27***	4,484	-0.63***	5,507	-0.37***	6,509
Mining and quarrying	-0.39***	1,008	-0.59***	2,539	-1.12***	1,459
Other Services	-1.32***	290	ns	290	-0.50***	1,125
Real estate, business and administrative activities	ns	800	ns	849	-0.77***	1,104
Transport, storage and communication	-0.25**	2,021	-0.54***	2,342	-0.59***	2,984
Utilities (Electricity, gas , etc)	ns	212	ns	263	ns	303
Wholesale and retail trade; repair of motor vehicles, motorcycles andpersonal and household goods	ns	512	ns	574	-0.49**	752
Note: includes only advanced economies.						
Standard errors in parenthesis (*p<1, **p<0.05, ***p<0.01)						

Table 4: Interaction between cyclical dummy and leverage

Dependent Variable:	Log Employment			Log Capital			Log Sales		
	Coefficient	t-statistic	Number Obs	Coefficient	t-statistic	Number Obs	Coefficient	t-statistic	Number Obs
Cyclical dummy	-0.53**	-2.51		-0.74***	-2.87		-0.83***	-4.45	
Interaction cyclical dummy leverage	1.20*	1.66	7,667	1.40	1.55	8,966	-1.97***	3.02	10,878
Leverage (by country and sector)	-1.24**	-2.08		-0.84	-1		-0.98*	-1.71	
Note: only advanced economies									
Standard errors in parenthesis (*p<1, **p<0.05, ***p<0.01)									

5.4. Accounting for the magnitude of recessions and booms

Instead of employing a dummy – where D_{jt} takes a value of 1 if the country is classified as having a boom in that year, and 0 if it is considered to be in recession – here we consider the magnitude of booms and recessions. In other words, we consider deviations from average growth rate – here the specification will look like the following:

$$\ln(Y_{it}) = \beta\left(g_{jt} - \bar{g}_j\right) + \varepsilon_{it} \; \forall (i,t) \in \Omega$$

Where, $(g_{jt} - \bar{g}_j)$ is the deviation in growth rate in country *j* in time *t* from the average growth rate in that country and Y_{it} refers to the dependent variables: employment, capital, sales and productivity. Furthermore, as indicated before, Ω is the set of new entrants; the condition defines that only pairs (i, t) belonging to the set are considered. This simply indicates that the regression is only carried out in the subsample of the first year of existence of each firm in the sample. To assess the persistence of the effects, illustrated in the density plots above, we run the regression for the period of entry and the following years. Thus the regression model becomes:

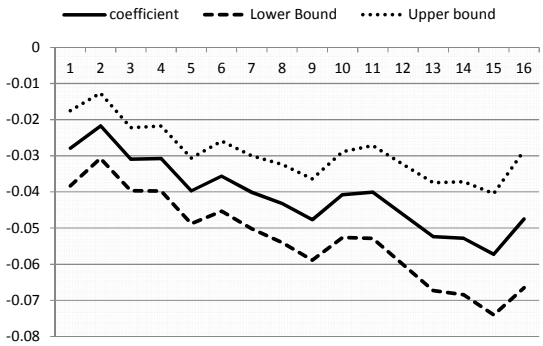
$$\ln(Y_{i,t+f}) = \beta(g_{jt} - \bar{g}_j) + \varepsilon_{it} \; \forall (i,t) \in \Omega$$

where *f* = 0,1, 2 , …,15 indicates the number of periods that the dependent variable is forwarded.

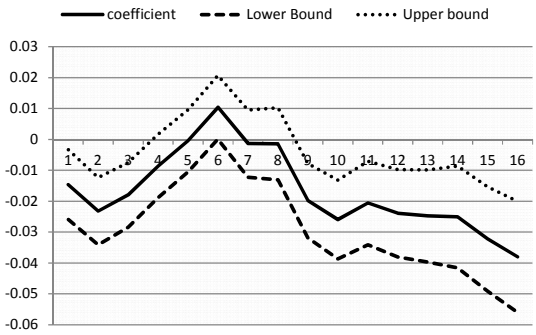
As before, we see that firms' that enter during a period when the growth rate is higher than the average, firm size is smaller in terms of employment and the effects persists over time (Figure 9, panel A). This result is statistically and economically significant. On the contrary, in case of capital, sales and productivity, the effect is not as clear cut (panels B, C and D). Consider the case of capital and sales – at first, the effect of entering during a time when growth is above the average is negative, but then turns positive after year 4 (albeit not always statistically significant), but then turns negative again after year 7 or 8, and remains negative (and statistically significant) thereafter. Lastly, results for productivity are even more confounding and largely insignificant.

Figure 9: Deviations from average growth

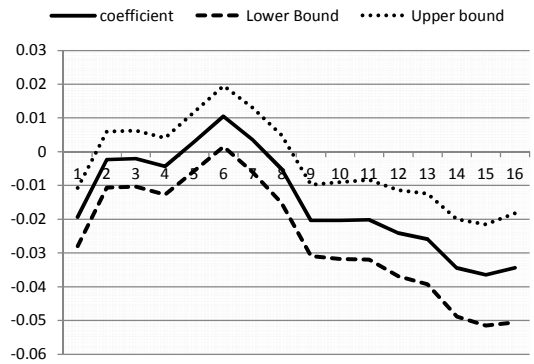
Panel A: Employment



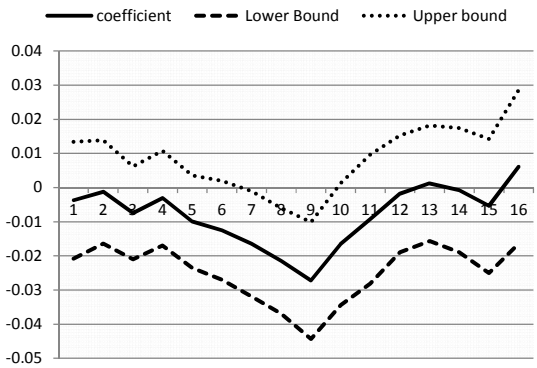
Panel B: Capital



Panel C: Sales



Panel D: TFP



Source: Authors' calculations based on Factset.

6. Robustness checks

Discrepancies in cyclicality of employment of entrants in the literature

As we discussed before, Lee and Mukoyama (2012), using Annual Survey of Manufacturers (ASM) data from the U.S. Census Bureau, find evidence in favour of "cleansing effect" and a selection mechanism where only larger firms in terms of employment enter during recessions. Meanwhile, Sedlácek and Sterk (2014), using Business Development Statistics (BDS), arrive at the opposite conclusion and find that entrants tend to be smaller during recessions. As we saw earlier, our results support the view of Lee and Mukoyama. However, to further shed light on this discrepancy, in this section we look at the BDS data used by Sedlácek and Sterk. Table 5 shows the correlation between entrant size and GDP with various filters.[9] It can be observed that the cyclicality of the variable is not unambiguously obtained from the data. Only in 2 out of the 7 cases the correlation is positive and significantly different than zero.

Table 5: Business cycle and firm size: Using BDS data

Correlation GDP/Entrant Size	Point Estimate	Lower Bound (90% ci)	Upper Bound (90% ci)
Levels (log-lin)	0.20	-0.08	0.46
Only GDP filtered			
Linear filter (detrended)	0.124	-0.213	0.435
HP filter	0.519	0.23	0.724
Growth filter	-0.076	-0.395	0.259
Both filtered			
Linear filter (detrended)	0.52	0.29	0.70
HP filter	0.02	-0.26	0.30
Growth filter	-0.01	-0.29	0.27

Furthermore, we let a year of recession be defined as years of at least one quarter of recession according to standard NBER dating. With this classification we can compute the average of each measure of entry size conditional on being in a recession. As it can be seen in Table 6, regardless of the filter used, entrant size is larger during recessions than in the rest –nevertheless, only in the case of the HP filter the difference is significant (but it is not when we allow unequal variances). As a final note it is worth highlighting that countercyclical entry size is mainly due to smaller firms, which are more likely to be affected by the selection mechanisms.

[9] GDP clearly is not mean stationary, therefore considering it in levels is just done for illustration purposes

Table 6: NBER defined periods of recessions and firm size

Average Entrant Size	Recession	No Recession
Level	8.56	8.53
Linear filter (detrended)	0.02	-0.01
HP filter	0.17	-0.06
Growth filter	0.02	-0.01

7. Conclusion

The experience of the Great Recession has shown that for the right set of policy interventions aimed at job creation, it is important to understand the link between firm dynamics and business cycles. There is a considerable debate in the economics literature on the effects of business cycles on firms entering the market. In this paper, we made use of a novel dataset covering over 100 countries and 70,000 firms to show that indeed, small and young firms tend to create most of the employment. The paper shows that firm death rate is high among small firms, but also there are more small firms entering the market across all regions.

Meanwhile, we show that there is a selection effect of recessions – that is, larger firms (in terms of employment, sales and capital) tend to enter the market during recessions than during booms. In other words, during booms a larger number of smaller firms enter, which stands in contrast with recessions. When we look at total factor productivity (TFP), we see the selection effect as well, but it is not as strong and varies (weakens or disappears, and in some cases reversed) depending on the methodology used. In other words, we do not find strong evidence of "cleansing effect" of recessions – more productive firms entering during recessions for the entry margin.

Furthermore, we show that the effects of recessions and booms tend to persist for 10 years or more. However, results concerning the longest horizons (10 to 15 years) should be taken with care as the sample size in FactSet is greatly reduced as many firms have not been in the database for 10 years or more. Lastly, we also find differences between advanced economies and emerging economies – in case of the former, recessions seem to create "good" firms, while in case of the latter booms seem to create "good" firms. It should be noted that the coverage of the sample in emerging and developing economies is poor and as such, firms might not be representative of the average firm and the coverage across years is very uneven. Some of these factors could have biased our findings. Nonetheless, the difference in the effects of business cycles across income groups is of enormous policy relevance and also merits further research.

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Appendix A: Sample Selection – FactSet

In-source selection: The FactSet database has an interface labelled "screening". This interface is one of the possible access pathways to the data for bulk download. The interface permits universe restrictions (type of data to retrieve) and variable selection. It is important to recall that the FactSet database is composed of securities, not firms –albeit some securities will contain the data of firms. In this step the universe was restricted as follows. First only securities which have an assigned economic sector (variable FG_FACTSET_SECTOR) are selected. This step removes securities unrelated to firms, such as financial derivatives or currency exchange rate.

Variable id homogenization: Due to computational burden each variable is better retrieved separately. The id of each security in the FactSet database is in an extremely small number of cases not unique. The duplicates in terms of the id are removed from the sample – maintaining the first observation according to alphabetical and numerical order of the ids. In the variable most affected the number of securities removed is 172 of 119,822. In the variables least affected is 4 of 119,822.

Database merging: The FactSet database is under continuing updates, and downloading the data requires time. This leads to different variables presenting different number of securities. When merging, the sector variables and company name (which were obtained at the same time) is used as the master data. Observations that are not in the master data are removed. In the most affected variables this implied the removal of 23 securities, in the least affected only 1 security was removed. The merged sample contains 119,834 observations.

Removing duplicates: As the data contained are securities, the same firm can have several securities, for instance in account of being traded in different markets. In this step where the duplicates are removed, the data is in a long format, therefore the number of observations is not the number of securities, rather is the number of security-year observation. In the beginning of this step – consistent with the data above – there are 1,198,340 security year observations. In the next step crucial variables to identify duplicates are ensured existence. One crucial variable to identify the duplicates is FF_CO_NAME, the name of the company. Securities with a missing value of this variable are discarded, 81,700 observations are dropped. Securities with missing country are dropped as well (11,600 cases). Finally securities without any employment observations[10] during the whole sample are discarded (528,820 cases). Further discarding is done, removing 99,890 observations that share the same year, name, country and sector. Of those observations with different country and sector (but same year and name) the ones that share the same number of employees are removed, 94011. When possible to choose, the observation of a security is selected before others by having the largest employee and then sales data – consistent with consolidated accounting. Having removed duplicates, the remaining securities are referred to as firms.

Preparing data for trends and econometric analysis: In a first step observations with sales smaller than 0.1$ are set to missing (50,800 cases), as well as firms with 0 employees (4,676 cases). Further conditions are imposed to the rest of the variables, as non-negativity or forbidding that a component exceeds its container. For the econometric analysis the log transformation is used on the unrestricted data, this delivers the same results in terms of employment, but for sales only firms with 0 or less are set to missing (47,625).

[10] This step is the most restrictive one. To remove duplicates using the criteria described, it would suffice to drop securities with all missing values for employment and have another security or more sharing its company name. However as the focus of the use of the database is in labour market outcomes, we have removed all the firms that do not have any entry for employment – since it is the most densely covered labour market indicator.

[11] Securities sharing name, but not country and sector, generally presented a larger amount of coincidence in employment than in sales. Therefore the strictest requirement is used.

Appendix B: Variables and number of firms by country

Table B1: Variable coverage of Factset

Performance Measures	TFP: Sales/ Employment
	Margin: OIBDP/Sales
	Sales
	Employment
	Wages: Labour Expenses/Employees
	Investment by Sales : Capex / Sales
	Firm death rate: Firms with 1st year inactive/Total active firms
	Firm birth rate: Firms with 1st year active/Total active firms
Financial Measures	Equity to Debt Ratio: Total Debt/Total Equity
	Cash and ST of total assets: Cash and Equivalents / Total Assets
	Short Term to Long Term Debt: Short Term Debt /Long Term Debt
	Net Debt to sales: Net Debt / Sales
	Interest expense on debt to sales: Interest Expense / Sales
	Plant and Equip to total assets: Plant and equipment / Total Assets
	Equipment to total assets: Equipment / Total Assets
	Intangible to total assets: Intangible Assets / Total Assets
	Selling General and Admin to Sales: Selling, General and Administrative Expenses/Sales
	ST Recivables to assets: Short term receivables / Assets
Tax Measures	Income Tax to Sales: Income tax / Sales
	Income Tax to Assets: Income Tax/ Total Assets
	Income Tax to Cash: Income Tax / Cash and equivalents
	Income Foreign Tax to Sales: Foreign Income Tax / Sales
	Income Foreign Tax to Assets: Foreign Income Tax /Total Assets
	Income Foreign Tax to Cash: Income Foreign Tax / Cash and Equivalents
"Globalization" measures	Domestic Sales of Total Sales: Domestic Sales / Sales
	Domestic Assets of Total Assets: Domestic Assets / Total Assets
Other	Price to Book Ratio: Market price / Book Value (Weighted by Sales)
	Days held of inventory: Days of inventory (Weighted by Sales)

Table B2: Data sample: country coverage using Factset

Entity	No. of Firms	Entity	No. of Firms	Entity	No. of Firms	Entity	No. of Firms
All countries	**71,672**	Netherlands	396	Bulgaria	111	Serbia	24
United States	18,918	Turkey	393	Cyprus	95	Trinidad and Tobago	22
Japan	5,200	Denmark	371	Czech Republic	93	Cayman Islands	20
United Kingdom	5,049	Spain	353	Romania	90	Malta	20
Canada	5,037	Philippines	307	Luxembourg	87	Zambia	19
China	3,611	Pakistan	299	Morocco	85	Estonia	18
India	3,368	Belgium	297	Colombia	82	Malawi	12
Australia	2,889	Sri Lanka	289	Hungary	70	Lebanon	10
Korea, Republic of	2,163	Chile	287	Tunisia	70	Iraq	8
Taiwan, China	2,157	New Zealand	259	Kenya	58	Tanzania, United Republic of	8
France	1,791	Jordan	242	Slovenia	53	Virgin Islands, British	8
Germany	1,600	Mexico	236	Venezuela	52	Namibia	7
Hong Kong SAR, China	1,532	Finland	227	Qatar	47	Ecuador	7
Malaysia	1,301	Egypt	226	Bahrain	46	Uganda	6
Singapore	928	Kuwait	219	West Bank and Gaza Strip	45	Isle of Man	6
South Africa	907	Austria	201	Mauritius	45	Jersey	4
Sweden	868	Peru	176	Slovakia	44	Barbados	3
Thailand	750	Ireland	169	Bermuda	43	The former Yugoslav Republic of Macedonia	3
Viet Nam	637	Saudi Arabia	169	Lithuania	41	Panama	3
Brazil	631	Nigeria	168	Kazakhstan	40	Costa Rica	2
Israel	628	Ukraine	166	Jamaica	33	Faeroe Islands	2
Poland	627	Portugal	154	Guernsey	31	Bosnia and Herzegovina	2
Italy	583	Oman	131	Zimbabwe	31	Antigua and Barbuda	1
Indonesia	566	Argentina	131	Iceland	30	Bahamas, The	1
Norway	520	United Arab Emirates	126	Côte d'Ivoire	29	Curacao	1
Switzerland	515	Croatia	121	Latvia	26	Georgia	1
Russian Federation	478	Bangladesh	116	Ghana	25	Liberia	1
Greece	443			Botswana	25		

Appendix C: Regression results

Table C1: Regression results, contemporaneous[12]

	Regressor: Cyclical Dummy		Controls			
Dependent Variable	Coefficient	t-statistic	Country	Year	Sector	Number obs
	-0.40***	-12.05	no	no	no	18,493
Log Employment	-0.09**	-2.27	yes	yes	yes	18,493
	-0.21***	-7.16	no	no	no	32,045
Log Sales	-0.08**	-2.31	yes	yes	yes	32,045
	-0.01	-0.36	no	no	no	4,329
TFP (Cobb Douglas)	0.08*	1.86	yes	yes	yes	4,329
	-0.03	-0.79	no	no	no	4,329
TFP (Olley and Pakes)	0.04	0.86	yes	yes	yes	4,329
Standard errors in parenthesis (*p<1, **p<0.05, ***p<0.01)						

[12] Additional tables with the results (particularly for the forwards) can be made available upon request. We did not include them all as it would have made the Appendix too long.