The Impact of Firm Performance on Macroeconomic Outcomes: Evidence from Serial Entrepreneurs*

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Abstract

Why are some firms more successful than others and how does this shape aggregate outcomes? To address these questions, we use unique administrative data, exploiting information on serial entrepreneurs (owners of multiple firms) as impersonations of business success. First, we document that serial entrepreneurs are three times more likely to own high-growth firms ("gazelles") and that their businesses disproportionately contribute to aggregate productivity growth, job creation and business dynamism. Second, we show that the success of serial entrepreneurs can largely be traced back to two key sources: their innate characteristics (primarily education and ability) and lower indebtedness of their firms.

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"Be not afraid of greatness. Some are born great, some achieve greatness, and some have greatness thrust upon 'em" - Twelfth Night, Act 2 Scene 5.

1 Introduction

There are enormous differences in firm performance and these have macroeconomic consequences. For instance, while large established firms shut down very rarely, as many as 3/4 of new businesses do not make it past their first year of existence, destroying jobs along the way.[1] Similarly, while the median firm does not create jobs, a small group of young, fast growing, firms (so called "gazelles") is responsible for over half of aggregate output, productivity and employment growth (see Haltiwanger et al., 2017). However, much less is known about *why* some firms are more successful than others and how this shapes aggregate outcomes.

To address these questions, we use unique administrative data and exploit information on serial entrepreneurs – owners of multiple businesses – as observable impersonations of business success. Firms of serial entrepreneurs provide a window through which to gauge why certain groups of businesses succeed and how they can impact the macroeconomy. Our results, therefore, offer two distinct contributions. First, they put forward new evidence of the macroeconomic importance of serial entrepreneurs – a topic not well understood empirically or theoretically. Second, they provide a new lens through which to understand the sources of firm success more generally. We discuss the implications of our results for existing research on business dynamism and its macroeconomic impact at the end of this paper.

More specifically, in this paper we document that firms of serial entrepreneurs disproportionately contribute to *aggregate* productivity growth, job creation, business dynamism and the firm size distribution. This is partly because – relative to other business owners – serial entrepreneurs are three times more likely to own gazelles. Importantly, we also provide novel evidence on the reasons behind their success. Two sets of driving forces stand out as key for understanding the superior performance of firms of serial entrepreneurs: innate characteristics of the entrepreneurs themselves (especially education and ability) and more favorable financial conditions of their firms

[1]These values are based on quarterly data from the Business Employment Dynamics of the U.S. Bureau of Labor Statistics.

(especially lower indebtedness).[2]

In order to obtain these results, we make use of a unique administrative employer-employee matched panel dataset from Portugal, the Quadros de Pessoal (QP), which covers the universe of private sector firms (with at least one employee) and their workers. A key advantage of the QP – which runs from 1986 to 2017 – is that it explicitly identifies business owners and tracks them over time. This is true not only for sole proprietors and partnerships, but for all businesses in our dataset.

We define serial entrepreneurs as business owners who simultaneously own at least two firms at some point within our sample.[3] We then categorize firms accordingly: serial entrepreneur (SE) firms are owned by serial entrepreneurs, while regular (R) firms are all other businesses. At first glance, serial entrepreneurs and their businesses may not inspire great interest from a macroeconomic perspective. Only about 3.5% of all business owners are serial entrepreneurs and their firms represent 13.5% of all businesses. However, we show that serial entrepreneur firms considerably outperform regular businesses: they are larger, grow faster, exit less often and are more productive. These "serial entrepreneur premia" – versions of which have been documented in other studies – provide a prelude to our key results.[4]

We begin by documenting that businesses of serial entrepreneurs contribute disproportionately to *aggregate* productivity growth, employment and job creation. Specifically, despite accounting for less than 14% of all firms, serial entrepreneur businesses alone are responsible for a fifth of aggregate productivity growth and almost one quarter of all job creation and employment.

Next, we turn to analyzing the impact of serial entrepreneur firms on overall business dynamism. As other economies, Portugal is also characterized by so-called "up-or-out" dynamics by which young firms face high rates of exit, but surviving young businesses display strong growth. Our results show that serial entrepreneur businesses play a dominant role in shaping these up-or-out dynamics. Specifically, we document that, compared to regular businesses, SE firms enter larger and grow faster throughout

[2]While we are not the first to observe that firms of serial entrepreneurs outperform other businesses (see for example Chen, 2013; Lafontaine and Shaw, 2016; Shaw and Sørensen, 2019, 2022; Brandt et al., 2022), we are (to our knowledge) the first to document their disproportionate macroeconomic importance and to simultaneously consider a range of explanatory factors including, in particular, financial factors.

[3]The Appendix discusses differences between our definition of serial entrepreneurs – often dubbed as "portfolio" entrepreneurs in the literature – and "sequential" entrepreneurs, that is those who own multiple businesses with an intermittent spell of non-entrepreneurship.

[4]See for example Chen (2013); Lafontaine and Shaw (2016); Shaw and Sørensen (2019); Brandt et al. (2022) for other studies of serial entrepreneurship.

their life-cycle. In contrast, regular firms are characterized by higher exit rates. This job creation prowess of SE firms is related to the fact that, compared to regular business owners, serial entrepreneurs are about three times more likely to own high-growth firms, so called “gazelles.”[5] Moreover, even among the very select group of gazelles, those owned by serial entrepreneurs are larger and less likely to shut down compared to those owned by regular owners.

The documented differences in size and growth rates are then reflected in the firm size distribution. In particular, the size distribution of SE firms has a thicker right tail, i.e. it is skewed towards larger businesses. For instance, while less than 3% of all regular firms employ more than 20 workers, this threshold is surpassed by about 13% percent of serial entrepreneur firms. In addition, the size distribution of SE firms fans out faster as businesses age – a pattern which has been linked to the severity of financial constraints (see Cabral and Mata, 2003).

Taking the above facts together points towards differences in the growth potential between regular and serial entrepreneur firms. Therefore, the last part of our analysis is devoted to investigating the possible sources of such differences. We focus on two broad categories: learning (see for example Lazaer, 2005; Lafontaine and Shaw, 2016) and selection (see for example Sedláček and Sterk, 2017; Shaw and Sørensen, 2022).

Focusing on learning first, our data offers a natural way of isolating the impact of learning on firm performance. In particular, we do so by separately analyzing the performance of “first” (FSE) and “subsequent” (SSE) businesses of serial entrepreneurs. Intuitively, FSE firms are those businesses which entrepreneurs owned *before* they could be classified as serial entrepreneurs. In contrast, SSE businesses are the cause of the serial entrepreneur classification and constitute the second and following firms of serial entrepreneurs. Under the presumption of learning by business owners, subsequent firms of serial owners should outperform their “first” business.

Indeed, our results suggest that learning plays a role in explaining some of the estimated serial entrepreneur premia. In particular, compared to first SE firms, subsequent SE businesses are about a quarter larger.[6] That said, learning does not seem to be the only driver of success. In fact, already first SE businesses considerably outperform

[5]We define gazelles according to the Eurostat-OECD definition (see European Commission, 2007) as young businesses which report average annual growth rates above 20% for at least three consecutive years. The Appendix shows that similar results are obtained with alternative definitions of gazelles which follow Decker et al. (2017).

[6]This result is consistent with evidence from Denmark focusing on young serial entrepreneurs (see Shaw and Sørensen, 2022).

regular firms suggesting that selection also plays a role.

Therefore, we consider a range of aspects on which serial entrepreneurs (and their firms) may be selecting – entrepreneur characteristics, employee characteristics and financial factors. In order to incorporate the latter, we merge our baseline QP data with the "Sistema de Contas Integradas das Empresas" (SCIE) which contains balance sheet and income statement information.

Equipped with this unique merged dataset, we estimate the fraction of serial entrepreneur premia which can be accounted for by our explanatory factors. Three findings stand out. First, entrepreneur characteristics alone can account for between 27 and 43% of the estimated serial entrepreneur premia. Within these, the most important factors are entrepreneur education and past wages – a proxy of entrepreneurs' ability.[7] Interestingly, whether or not owners are also managers of their business seems to matter less for the estimated premia.

Next, financial factors are the second most important determinant of the superior performance of SE firms. In particular, lower indebtedness of serial entrepreneur firms alone can explain between 20 and 50% the exit and growth premia. Moreover, financial factors remain to explain some of the SE premia even when we restrict our analysis to first SE firms only. This suggests that serial business owners enter entrepreneurship with a healthier balance sheet to begin with. Quantitatively, however, the contributions of financial factors to the estimated SE premia are stronger among subsequent firms of serial entrepreneurs. This suggests that the initial success of the first businesses of serial entrepreneurs helps make the financial position of their subsequent firms even more comfortable, allowing them to thrive further.

Finally, quantitatively the weakest contributors to the estimated SE premia are characteristics of employees in SE firms. Nevertheless, the ability to attract more experienced and more educated workers explains about a third of the growth premium of serial entrepreneurs.

Our paper is related to several strands of the literature. First, although limited high-quality data makes studies of serial entrepreneurship relatively rare, the current paper is not the first to study the topic (see for example Chen, 2013; Lafontaine and Shaw, 2016; Shaw and Sørensen, 2019; Brandt et al., 2022). To the best of our knowledge, however, we are the first to study the *macroeconomic* impact of serial entrepreneurs and their contribution to overall business dynamism. Second, our paper contributes to the

[7]These findings are consistent with other work suggesting education and selection on ability as important for firm dynamics (see for example Chen, 2013; Queiró, 2022).

literature studying the link between firm growth and various explanatory factors such as entrepreneur or worker age, business location or name, human capital of founders or workers (see for example Ouimet and Zarutskie, 2014; Guzman and Stern, 2015; Belenzon et al., 2017; Smith et al., 2019; Azoulay et al., 2020; Choi et al., 2021; Queiró, 2022; Azoulay et al., 2022).[8] We add to these the focus on serial entrepreneurship. Finally, we also discuss how our results relate to broader research on firm dynamics and the role of firm heterogeneity for aggregate outcomes (see for example Haltiwanger et al., 2013; Decker et al., 2017).

The remainder of the paper is structured as follows. The next section describes our data and provides definitions of key variables. Section 3 reports results pertaining to the impact of serial entrepreneurs on the macroeconomy and on business dynamism in particular. Section 4 analyzes potential sources of the superior performance of serial entrepreneur firms and discusses the implications of our results for existing macroeconomic models with business dynamism. The final section concludes.

2 Data, Definitions and Basic Descriptive Statistics

We begin by describing our primary data source and laying out the definitions of key variables. Before presenting our central results in the next section, we show basic descriptive statistics concerning business dynamism and serial entrepreneurship. In what follows, we use the terms entrepreneur and (business) owner interchangeably.

2.1 Business Dynamism Data

Our main data source is Quadros de Pessoal (QP), a Portuguese census of private sector employees conducted each October by the Ministry of Employment, Solidarity and Social Security (MESSS). It is an extremely rich administrative employer-employee matched panel dataset with information at the firm, establishment and individual levels. A unique advantage of the QP for our purposes is that it contains information not only on workers, but also on business *owners*.

The survey covers the universe of firms with at least one employee and their

[8] A connected set of papers studies businesses funded by venture capital or angel investors, which suggests that both more experienced capital providers and entrepreneurs tend to start more successful businesses and that access to finance seems to positively influence firm success (see for example Kaplan and Schoar, 2007; Gompers et al., 2010; Kerr et al., 2014).

workers.[9] It is conducted on an annual basis and our sample runs from 1986 to 2017. Reporting into the QP is mandatory for all businesses that have at least one paid employee as of the survey reference week. Moreover, by law, the questionnaire needs to be available in a public space at the establishment. The administrative nature of the data and its public availability implies a high degree of coverage and reliability.

Firm Entry, Exit and Longitudinal Linkages. The QP dataset is longitudinal in nature. Each firm or establishment entering the database is assigned a unique identifying number by the MESSS. In addition, the MESSS carries out other control checks to make sure that the units which have previously reported in the database are not assigned a different identification number.

Business entry (birth) is then defined as a new identifying number which was not present in the survey in the preceding year. This definition applies to both firms and establishments, given that the two are tracked separately in the survey. Symmetrically, business exit (death) is defined as an identifying number in the preceding year which no longer exists in the current year.[10]

Thanks to these longitudinal linkages inherent to the database, we are able to connect firm-level characteristics with an individual business owner and track owners, their businesses and the workers within these businesses over time.[11] This, in turn, allows us to separately characterize firm dynamics of businesses with different owners. As will become clear below, we focus on the distinction between "serial" entrepreneurs – owners of multiple businesses – and all other "regular" business owners.

Individual and Business Characteristics. Over our 1986 - 2017 sample period, we have information on roughly 2 million workers who are observed between one and thirty times, with roughly 200,000 unique firm identifiers for their jobs in the survey

[9] The data does not contain information on civil servants, self-employed and workers who are unemployed or out of the labor force in the survey week. For our analysis, we also drop businesses from the agricultural sector, where coverage is low.

[10] This way of tracking entry, continuation and exit of businesses aligns with similar datasets in other countries, for example such as that in the Longitudinal Business Database of the U.S. Census Bureau (see for example Jarmin and Miranda, 2002). Note that businesses in the QP also report a founding date. However, cross-checking such founding dates with reported activity in the survey (and business birth as defined above) reveals many discrepancies and we, therefore, do not use this information for measuring firm entry.

[11] This feature of the QP is rare. For instance, Choi et al. (2021) use U.S. Census Bureau data and study the role of "founding teams" for the performance of young firms. In their data, however, founders of the majority of corporations are not directly observable (though they can be proxied).

week.[12] The firm-level information contained in our dataset includes the sector of economic activity, geographical location, legal structure, employment, gross sales and founding year.

For some of our analysis in Section 4, pertaining to firms' financial factors, we merge our QP data with information in Sistema de Contas Integradas das Empresas (SCIE). The latter contains firm-level information on balance sheets and income statements. To preserve the coverage and definition of variables, we focus on the years 2010 - 2017 when using the SCIE.

Finally, at the worker level the QP has information on age, gender, education, occupation, date of hire, salary, job title and hours of work. Crucial to our study is a unique variable – situação profissão ("professional status") – which identifies an individual as either an owner of a business, a salaried worker, or both.

2.2 Identifying Serial Entrepreneurs and Their Firms

We now describe how we measure the key concept of this paper – serial entrepreneurship. As explained in the previous subsection, the QP dataset is uniquely equipped for this purpose. Specifically, using the "professional status" variable in the QP, we identify *business owners* as individuals who own a given firm.

"Serial" Entrepreneurs. We identify serial entrepreneurs as individuals who – at any given point in our sample – own some fraction of more than one firm. The group of serial entrepreneurs can be further categorized into (i) sequential and (ii) portfolio serial entrepreneurs.

Sequential serial entrepreneurs are individuals who experience gaps between business ownership, that is individuals who cease to be involved in a business before obtaining ownership of another. In contrast, portfolio serial entrepreneurs are individuals who own multiple businesses at the same time. For our baseline analysis, we focus on portfolio serial entrepreneurs. Therefore – unless explicitly stated otherwise – in what follows we use the term "serial entrepreneur" to indicate a portfolio business owners.

Practically, to identify serial owners in our data we count the number of businesses

[12]Worker level data are not available for the years of 1990 and 2001 and, therefore, we interpolate firm-level values for these years.

for which an individual is recorded as an owner in every year of our sample.[13] Next, we define an individual to be a (portfolio) serial entrepreneur if he or she simultaneously owns more than one business at *any* moment within our sample. It is important to note that under this definition, serial entrepreneurship is viewed as a "permanent characteristic" (fixed effect) of individuals. As will become clear, this definition of serial ownership will be particularly useful for our analysis of potential channels in Section 4. Nevertheless, the Appendix shows that our results are similar when we use a time-varying definition that categorizes individuals as serial owners only for those years in which they own multiple firms.

"Regular" Entrepreneurs. We define "regular" entrepreneurs as business owners who complement serial entrepreneurs, that is all business owners who are not classified as (portfolio) serial entrepreneurs. Therefore, as explained above, this definition of regular business owners also includes sequential serial owners. The Appendix documents that the business performance of sequential owners is in fact very close to that of firms owned by individuals who only ever own one business (see also Shaw and Sørensen, 2019). This, therefore, explains our primary focus on portfolio owners only.

Firms of Regular and Serial Entrepreneurs. Our primary units of observation are firms and we will use business and firm interchangeably throughout the paper. That said, certain parts of our analysis also make use of establishment-level information of the QP. When doing so, we will be explicit in distinguishing firms and establishments.

A key feature of our analysis is that we categorize firms by the characteristics of their owners. In particular, we classify businesses as "serial entrepreneur (SE) firms" if at any point in their life-cycles *at least one* of their owners is involved in multiple companies, i.e. classified as a serial business owner. All other businesses are classified as "regular (R) firms". Note that $2/3$ of all firms in the Portuguese economy have only one owner. Nevertheless, the Appendix shows that our results are similar when we restrict our definition to firms which are *solely* owned by serial entrepreneurs.

Discussion: Right Censoring, Selection on Survival and M&As. Having described the main concepts in this paper, we now discuss potential concerns arising from our

[13] As is typical in the literature, when measuring worker characteristics we restrict our sample to individuals aged 16 to 70. Fewer than 1% of all owners fall outside these bounds.

specific definitions. The first two are common to all studies of serial entrepreneurship, while the third is specific to our macroeconomic focus.

First, our results may be biased because of right censoring. Specifically, business owners may be classified as "regular", despite the fact that they will start a second business in the future, *outside* our sample period. While this feature only likely creates a downward bias in estimates of the importance of serial owners (i.e. our results may be viewed as lower bounds), we provide an explicit robustness check using a truncated sample in the Appendix.

Second, studying serial entrepreneurship implies focusing on a select group of businesses. Intuitively, SE firms are more likely to display lower exit rates because first businesses of serial entrepreneurs need to survive before the owner starts another firm. Exceptions may be serial entrepreneurs who found multiple startups at the same time. Nevertheless, it remains an open question whether SE businesses contribute quantitatively to macroeconomic outcomes – precisely one of the questions addressed in this paper. Indeed, we view serial entrepreneurship as an *observable proxy* for underlying sources of firm performance, which we explicitly study in Section 4. Our approach is, therefore, analogous to the study of the macroeconomic impact of "high-growth" firms which relies on identifying such businesses with observed, realized, growth outcomes (see for example Haltiwanger et al., 2017).

Finally, to accurately quantify the macroeconomic contribution of SE firms, it is important to account for mergers and acquisitions (M&As). Intuitively, expansions (or entry) of SE firms via M&A activity should not be counted as contributions to aggregate job creation since they are exactly offset by exit of the acquired business.[14] However, M&As are not a quantitative concern in Portugal. Mata and Portugal (2004) report that M&As account for less than 1% of all business shutdowns. In addition, while M&A activity is not directly observable in our data, we provide an estimate by using worker tenure information. In particular, we consider a new firm to be the result of a merger or acquisition if any of its workers report having tenure larger than 1 year at the time of startup. Only about 3% of all startups in our sample would be classified as M&As according to this proxy.[15]

[14]In the data, the identification numbers of the firms involved in the M&A operation are transmitted to the resulting firm, while the others disappear. Therefore, the acquired businesses are counted as exits in the data.

[15]Even when restricting attention to SE startups only, the fraction with workers reporting tenure larger than 1 year is about 6%. Therefore, while SE firms seem to be more often associated with M&A activity, the absolute number of such cases remains quantitatively small.

2.3 Outcome variables

Ultimately, our main units of observation are firms. To describe the performance of a group of firms, we focus on four distinct variables: size, growth, productivity and exit rates. We now explicitly define these outcome variables as well as our definition of high-growth firms, a key concept for studying business dynamism.

Firm Size, Growth, Job Creation and Destruction. Because of the ease and quality of measurement, we focus on employment, E, as our baseline measure of firm size. This notion of firm size is consistent with a range of existing studies (see for example Moscarini and Postel-Vinay, 2012; Haltiwanger et al., 2013) and allows us to directly analyze the impact on aggregate job creation, often a key policy interest.

We follow Davis et al. (1996), henceforth DHS, and measure firm growth in firm i and period t, g_{it}, as

$$g_{it} = \frac{(E_{it} - E_{it-1})}{X_{it}}, \tag{1}$$

where $X_{it} = 1/2(E_{it} + E_{it-1})$. Conveniently for our purposes, the DHS firm growth rate can be defined for different levels of aggregation:

$$g_t = \sum_s \frac{X_{st}}{X_t} g_{st} = \sum_s \left(\frac{X_{st}}{X_t} \sum_{i \in s} \left(\frac{X_{it}}{X_{st}} \right) g_{it} \right), \tag{2}$$

where $X_t = \sum_s X_{st} = \sum_s \sum_{i \in s} X_{it}$ and where s denotes a particular group of firms – our primary focus will be on serial entrepreneur and regular businesses, $s = \{SE, R\}$. The same concepts can also be used to define job creation (JCr) and destruction rates (JDr):

$$JCr_t = \sum_s \left(\frac{X_{st}}{X_t} \sum_{i \in s, g_{i,t} \geq 0} \left(\frac{X_{it}}{X_{st}} \right) g_{it} \right), \tag{3}$$

$$JDr_t = \sum_s \left(\frac{X_{st}}{X_t} \sum_{i \in s, g_{i,t} < 0} \left(\frac{X_{it}}{X_{st}} \right) g_{it} \right). \tag{4}$$

Productivity and Exit. Since accurate estimates of firm-level productivity are hard to obtain, we focus on the simplest measure of labor productivity $q_{i,t} = Z_{i,t}/E_{i,t}$, where $Z_{i,t}$ are sales of firm i in period t.

Finally, in our analysis we also focus on firm exit rates, $D_{s,t}$. For a group of firms, s, We define the exit rate as the number of businesses which shut down in a given year relative to incumbent firms:

$$D_{s,t} = \frac{(\text{\# of exiting firms})_{s,t}}{(\text{\# of firms})_{s,t}}. \tag{5}$$

As discussed above, exit rates of SE firms may be subject to a survival bias and, therefore, we interpret results pertaining to firm exit with caution.

High-Growth Firms ("Gazelles"). Part of our analysis focuses on high-growth firms, so called gazelles. We follow the Eurostat-OECD (see European Commission, 2007) definition of gazelles as businesses up to 5 years old, with a minimum of 10 employees (at some point in the firm's existence), and with average annualised growth of at least 20% per year, over a three year period. As with the definition of serial ownership, we treat the term gazelle as a permanent characteristic – a fixed effect – of a particular business. That is, once a young business satisfies the requirements to be classified as a high-growth firm, we continue to refer to such businesses as gazelles even beyond the age of 5 and even if their subsequent growth slows. This allows us to gauge how high-growth firms differ from other businesses throughout their life-cycles.

While informative for our purposes, other definitions of gazelles have been used in the literature. For example, Haltiwanger et al. (2017) define gazelles as businesses which exhibit an annual growth rate above 25% in any given year. This definition is not conditional on firm age, nor is it used as a "fixed effect." In the Appendix, we show that our results are similar when using this alternative definition of high-growth firms.

2.4 Basic Descriptive Statistics

Before moving to our central results, we first provide basic descriptive statistics of firm dynamics and serial entrepreneurship in the Portuguese economy. We return to these patterns in more detail in Section 3.

Average Firm Life-Cycle Dynamics. Since a key focus of our analysis is centered around firms' life-cycle dynamics, we begin by describing average up-or-out patterns – the process in which young businesses face high exit rates, but surviving young firms exhibit fast growth. Specifically, while annually about 10% of the youngest Portuguese firms in our sample shut down, this fraction drops by a fifth to about 8% by the time businesses reach the age of 6 years. At the same time, surviving startups almost double in size in the same time-period of 6 years. These "up-or-out" patterns are consistent with those found in the U.S. (see Haltiwanger et al., 2013) and other developed economies (see for example Calvino et al., 2015).

Gazelles in the Portuguese Economy. As pointed out by Haltiwanger et al. (2017), the growth prowess of young businesses is predominantly driven by a small fraction of high-growth gazelles. Under the Eurostat-OECD definition of high-growth firms, about 9% of all businesses are gazelles in Portugal.

That said, given their superior growth performance, this group of firms alone accounts for almost a third of aggregate employment and almost a half of all job creation. Therefore, also in Portugal the relatively rare group of gazelles plays an influential role in determining aggregate patterns. These patterns are broadly consistent with those in the U.S. economy (see Haltiwanger et al., 2017), albeit our approach uses a different definition of gazelles – as noted above.

Prevalence of Serial Entrepreneurship. Let us now provide basic descriptive statistics on the core aspect of our analysis – serial entrepreneurship. The next section studies the characteristics of serial entrepreneurs and their firms in more detail.

Using our (once-and-for-all) definition of (portfolio) serial entrepreneurship, we find that only 3.5% of all business owners can be classified as serial entrepreneurs. The average number of businesses a serial entrepreneur owns is 1.4 and SE firms account for about 13.5% of all businesses.[16] On average, it takes serial entrepreneurs about 6 years to start their second business.

Importantly, Table 1 shows that serial entrepreneurship is not an obscure feature of a particular industry. In contrast, it appears to be widespread throughout the entire economy with the sectoral composition of serial entrepreneur businesses closely matching that of the economy as a whole.[17]

The Serial Entrepreneur Premium. Finally, before investigating the *macroeconomic* impact of serial entrepreneurs and their businesses, let us document the firm-level differences in various measures of performance between SE and R businesses.

[16]Under the year-on-year definition of serial entrepreneurship, SE firms account for 4.7% of all businesses.

[17]The exception seems to be "Real estate and other activities" in which serial entrepreneurship is more prevalent.

Table 1: Sectoral composition of serial entrepreneur firms

	All	Serial
Wholesale and retail trade	33.0	33.8
Manufacturing	16.8	15.6
Construction	13.7	11.4
Accommodation and food services	11.6	8.7
Real estate and other activities	11.3	17.6

Notes: The columns show, respectively, "all" and "serial" entrepreneur businesses. The values report the shares (in %) of each group of businesses across five broad industries in which almost 90% of all firms operate.

To formalize such differences, we estimate the following regression

$$y_{i,t} = \alpha + \beta \mathbb{1}_{i \in SE} + \gamma F_{i,t} + \epsilon_{i,t}, \tag{6}$$

where $y_{i,t}$ is an outcome variable of interest, $\mathbb{1}_{i \in SE}$ is an indicator function which is equal to one if business i is a serial entrepreneur firm and zero otherwise. In addition, we also include a range of control variables, $F_{i,t}$.

We dub the coefficient β as the average "serial entrepreneur premium" in regards to variable y. In what follows, we estimate these serial entrepreneur premia for four firm-level variables of interest, $y_{i,t}$: log size, growth, log productivity and exit rates. Finally, in our estimation we include the following control variables, $F_{i,t}$: firm age, industry and year fixed effects.

Table 2 reports the results from our estimation. In the first and second columns, respectively, the table shows the unconditional averages of our four variables of interest for the groups of serial entrepreneur and regular firms. Unconditionally, serial entrepreneur businesses markedly outperform regular firms. They are much larger, exit less often (keeping in mind the issue of selection when studying SE firms as discussed above), grow faster and are more productive.

The third column then reports estimates of the respective serial entrepreneur premia, β. The estimates show that, even conditional on other control variables, serial entrepreneur firms outperform regular businesses. Importantly, the estimated premia are not only statistically significant, but they are also quantitatively large. In particular, our results suggest that on average SE businesses are almost 50% larger, their exit rates are about 25% lower, they grow at a pace which is 20% faster and they are 23% more

Table 2: Serial owner premia

	Regular	Serial	SE Premium
Size (workers)	5.4	10.9	0.48^{***}
Exit (in %)	8.0	5.4	-1.93^{***}
Growth (in %)	8.9	9.8	1.81^{***}
Productivity (aggregate = 1)	0.82	1.17	0.23^{***}

Notes: The columns show, respectively, the unconditional averages of regular and serial entrepreneur firms and the SE premium estimated from regression (6). The rows depict, respectively, average (employment) size, exit rates, (employment-weighted) net employment growth and average labor productivity scaled by labor productivity of all firms. Ordinary Least Squares estimates with robust standard errors clustered at the firm level in parentheses. *** stands for statistical significance at the 1% level.

productive compared to regular businesses.[18]

These patterns are consistent with previous studies which analyze different countries or industries and typically focus only one or two of the dimensions we examine (see for example Chen, 2013; Lafontaine and Shaw, 2016; Shaw and Sørensen, 2019).

3 Macroeconomic Impact of Serial Entrepreneurs

This section documents the importance of serial entrepreneurs for *macroeconomic* outcomes which – to the best of our knowledge – has not been put forward empirically or theoretically. Three key messages emerge out of our analysis. First, SE firms are important for aggregate job creation and productivity growth. Second, SE businesses shape aggregate business dynamism. Finally, a key reason behind the previous two findings is that SE firms are disproportionately represented among high growth firms.

3.1 Aggregate Productivity Growth and Job Creation

Economists have long strived to identify groups of firms which are most important for driving aggregate outcomes (see for example Birch, 1981; Guzman and Stern, 2015; Haltiwanger et al., 2017). It is in this context that we present one of our headline results that firms of serial entrepreneurs contribute disproportionately to aggregate productivity growth and job creation.

[18] In regards the firm exit, the serial entrepreneur premium is estimated at about 1.9 percentage points. This is about 25% of the unconditional average exit rate of 8% among regular businesses. Similarly in the case of firm growth, the serial entrepreneur premium is estimated at 1.8 percentage points which is about 20% of the unconditional average growth rate of 8.9% among regular firms.

Contributions to Aggregate Productivity Growth. First, we turn our attention to the contribution of serial entrepreneur firms to *aggregate* productivity growth. Towards this end, we follow Foster et al. (2001) and define industry-specific productivity by

$$Q_{jt} = \sum_{s} \sum_{i \in s} \omega_{it} q_{it} \tag{7}$$

where Q_{jt} is the productivity index of industry j in year t, s is a subset of all businesses (in our case serial entrepreneur and regular firms, i.e. $s = \{SE, R\}$), ω_{it} is the employment share of firm i in industry j (shares $\omega_{it} \geq 0$ sum to one), and q_{it} is the logarithm of labor productivity at the firm level. Denoting the set of continuing, new and exiting firms with C, N and X, respectively, we decompose the change in industry-level productivity as

$$\Delta Q_{jt} = \sum_{s} \left[\begin{array}{c} \overbrace{\sum_{i \in C_s} \omega_{i,t-1} \Delta q_{it}}^{\text{within}} + \overbrace{\sum_{i \in C_s} (q_{i,t-1} - Q_{j,t-1}) \Delta \omega_{it}}^{\text{between}} + \overbrace{\sum_{i \in C_s} \Delta q_{it} \Delta \omega_{it}}^{\text{cross}} \\ + \underbrace{\sum_{i \in N_s} \omega_{i,t} (q_{i,t} - Q_{j,t-1})}_{\text{entry}} - \underbrace{\sum_{i \in X_s} \omega_{i,t-1} (q_{i,t-1} - Q_{j,t-1})}_{\text{exit}} \end{array} \right]. \tag{8}$$

where we follow Foster et al. (2001) and Baily et al. (1992) and compute the above decomposition for every industry-year pair in our data and aggregate up to the entire economy using gross output weights.

In the above decomposition, the first three terms relate to continuing businesses. The first, "within", term measures the contributions of productivity changes at the firm-level, for a given mix of businesses. The "between" term reflects changing market shares, i.e. the contribution to industry-wide productivity growth stemming from a reallocation of market shares from (on average) relatively less to relatively more productive businesses. The third, "cross", term encompasses the combination of the previous two, whereby a reallocation of market shares towards businesses which display increases in firm-level productivity contributes positively to aggregate productivity growth. The last two terms reflect the contributions of entry and exit. In particular, the entry (exit) of firms with above (below) average productivity contributes to aggregate productivity growth.

The first row of Table 3 reports average aggregate productivity growth over our sample period and the contributions of the separate components from the decomposition in (8). The second and third rows show the contributions of serial entrepreneurs in

Table 3: Aggregate productivity growth decomposition

	Total	Within	Between	Cross	Entry	Exit
Aggregate	7.1	13.8	3.0	−8.5	−2.4	1.2
Serial entrepreneur firms: level	1.4	3.2	0.4	−2.0	−0.2	0.0
Serial entrepreneur firms: share of aggregate	19.7	23.2	13.3	23.5	8.3	0.0

Notes: The table reports values (in %) from the productivity growth decomposition in (8). The first row reports aggregates, the second and third rows reports the contribution of serial entrepreneur firms only in levels and as a share of the aggregate, respectively.

levels and as a share of the respective components of aggregate productivity growth.

Consistent with other studies (see for example Dias and Robalo Marques, 2021; Reis, 2013), our decomposition reveals that aggregate productivity growth is predominantly driven by within-firm growth. Importantly for the focus of our paper, the results suggest that serial entrepreneur firms are important for aggregate productivity growth. In particular, despite accounting for less than 14% of firms, they alone are responsible for over 23% of the within component of aggregate productivity growth.

Next, note that the contribution of firm entry to aggregate productivity growth is negative overall (top row, second-to-last column). This indicates that in our sample, startups are somewhat less productive than incumbent firms. While this holds true also for startups of serial entrepreneurs, it does so to a considerably smaller extent. This is because – consistent with the estimated serial entrepreneur premia – SE startups are more productive than regular new firms.

Finally, relatively less productive firms tend to shut down overall which contributes positively to aggregate productivity growth (last column). In contrast, exiting SE firms are roughly as productive as incumbents and, therefore, exit of SE firms has no quantitative impact on aggregate productivity growth. Put together, firms of serial entrepreneurs account for almost 20% of aggregate productivity growth.

Contributions to Aggregate Employment, Job Creation and Destruction. Next, we document that serial entrepreneur firms also contribute disproportionately to aggregate employment and job creation.

Specifically, Table 4 shows that while SE businesses represent less than 14% of all firms, they alone employ more than 23% of the workforce. This is consistent with our estimated premia which show that serial entrepreneur firms are considerably larger compared to regular businesses. Table 4 further reports that serial entrepreneur firms also create (and to a lesser extent also destroy) a disproportionate amount of jobs.

Table 4: Contributions to aggregates (in %): Regular and serial entrepreneur firms

	Firms	Employment	Job creation	Job destruction
Regular	86.5	76.6	77.3	81.6
Serial entrepreneur	13.5	23.4	22.7	18.4

Notes: The table shows, respectively, the contributions (in %) of "regular" and "serial entrepreneur" businesses to the aggregate number of firms, employment, job creation and job destruction.

In particular, firms of serial entrepreneurs are responsible for 23% of all job creation and about 18% of all job destruction. These values are already suggestive of a *net* job creation prowess of serial entrepreneur firms to which we turn next.

3.2 Business Dynamism

Having shown that SE firms are quantitatively important for macroeconomic outcomes, we now focus on how they shape average business dynamism patterns. In this subsection, we analyze indicators which measure firm and worker churn – so called up-or-out dynamics. Specifically, we document life-cycle patterns of job creation, destruction and the distribution of firm-level (net) growth rates. These variables not only underlie the aggregate job creation patterns discussed above, but they have also been shown to be important indicators of *aggregate* productivity-enhancing factor reallocation (see Haltiwanger et al., 2013).

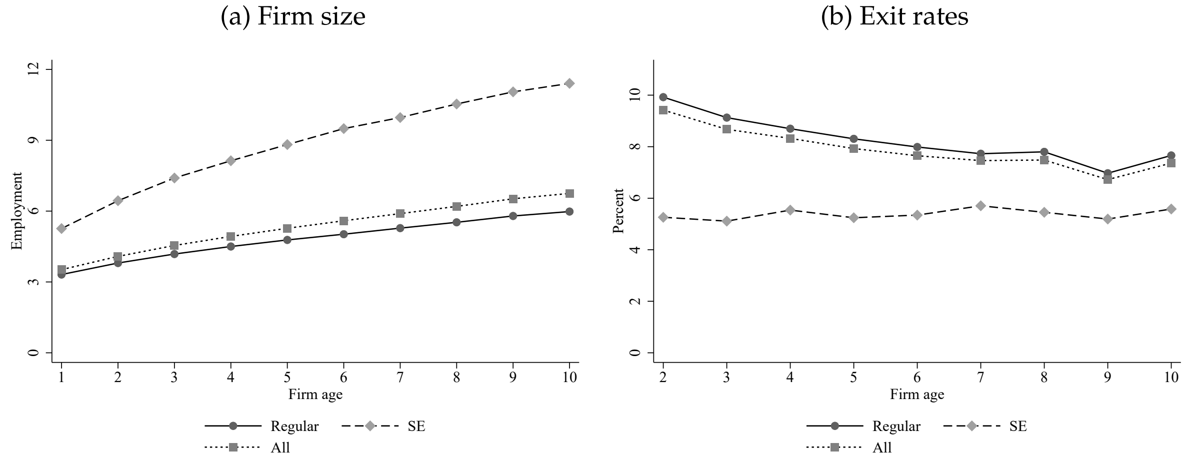
Up-or-Out Dynamics. As discussed in Section 2.4, existing empirical evidence points to strong "up-or-out" dynamics in developed economies. We, therefore, begin our analysis by investigating life-cycle patterns of firm size and exit.

Figure 1 depicts life-cycle profiles for average firm size and exit rates by firm age.[19] It does so separately for all, regular and serial entrepreneur firms. As documented in 2.4, *on average* young businesses exit more often, but surviving young firms almost double in size in the first ten years of their existence.These average patterns, however, hide a dramatic difference between the life-cycle patterns of regular and serial entrepreneur firms, consistent with the serial entrepreneur premia estimated in Table 2.

The left panel of Figure 1 shows that SE firms not only start up more than 1.5 times larger than regular businesses, but they also grow by 122% (on average) within

[19]Figure 1 reports "raw" numbers. In the Appendix, we show that these results are very similar when controlling for the industry composition and geographical location of R and SE firms.

Figure 1: Size and exit profiles by age



Notes: The left panel shows average firm size by age, while the right panel shows average exit rates by age. Both panels depict all, regular and serial entrepreneur businesses.

ten years of their existence. In contrast, regular businesses on average grow by 86% between startup and the age of 10.

The right panel of Figure 1 displays exit rates of the three groups of firms. The rate at which SE firms shut down is not only considerably lower on average, but it is also essentially flat over the course of their life-cycle. Once again, however, readers will recall that exit patterns of SE firms are (at least partly) mechanically lower because serial entrepreneurship requires a certain degree of survival.

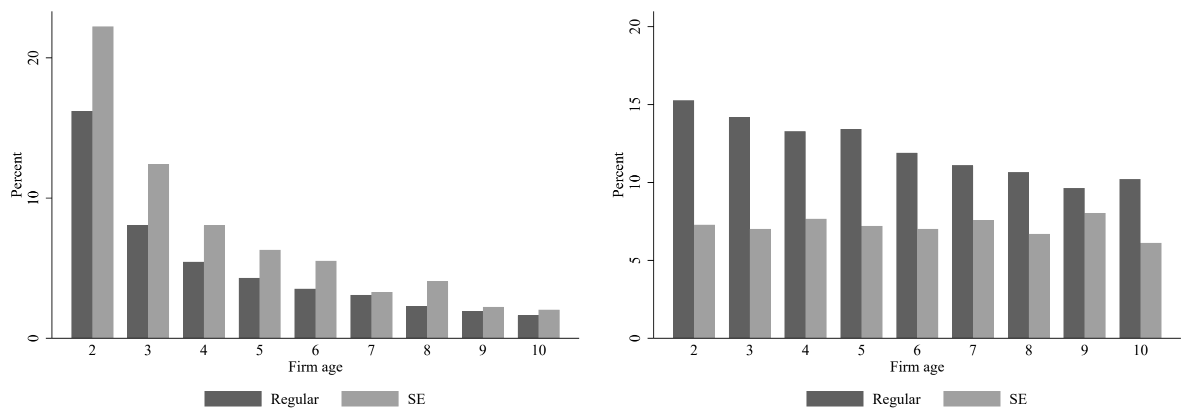
Importantly, Figure 1 allows us to gauge the importance of SE firms for aggregate up-or-out dynamics. We do so by comparing life-cycle profiles of all firms to those of regular businesses, since the latter depicts how the aggregate patterns would look like in the absence of serial entrepreneur firms.

If it were not for SE firms – and ignoring general equilibrium effects – the average life-cycle profile of firm size would be much flatter, especially for older businesses. Specifically, while average startup size would fall by about 6% in the absence of SE firms, 10 year old firms would on average be more than 12% smaller. In contrast, average exit rates would increase by about 5% (0.4 percentage points) in the absence of SE firms.

Job creation, destruction and excess reallocation. Next, Figure 2 shows how the stark differences in up-or-out dynamics between R and SE firms are reflected in their job

Figure 2: Up-or-out dynamics

(a) Net Job Creation of Continuers (b) Job Destruction from Exit



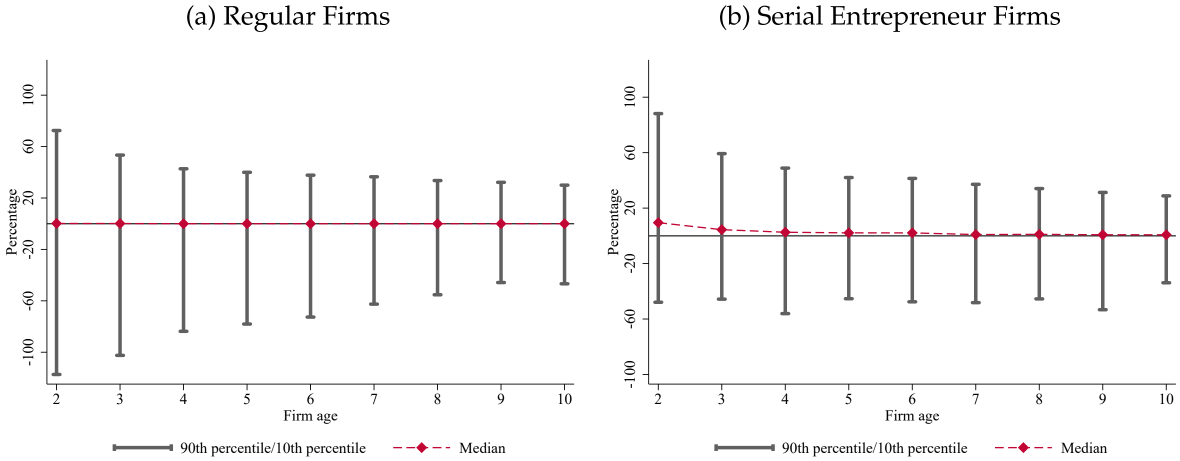
Notes: The figure shows net job creation (NJC) rates of continuing businesses (panel a), and job destruction (JD) rates from exit (panel b). Both as a function of business age and separately for regular and serial entrepreneur (SE) firms.

creation and destruction patterns. Specifically, the left panel of Figure 2 depicts net job creation of continuing firms, while the right panel shows job destruction from exit. In both panels, we separately depict the values for serial entrepreneur and regular businesses.

Two patterns stand out. First, net job creation by continuing regular businesses is about a fifth lower compared to that by serial entrepreneurs. This holds true essentially across the entire firm life cycle. Second, reflecting the flat exit rates of SE firms documented above, job destruction from exit is also essentially constant among SE firms. This evidence combined documents that SE firms are important drivers of aggregate business dynamism.

Interestingly, gross job creation rates are comparable between regular (29%) and serial entrepreneur firms (28%). However, serial entrepreneur firms destroy fewer jobs (13%) compared to regular businesses (17%). Therefore, the net job creation prowess of serial entrepreneur firms can be attributed primarily to their lower destruction rates. This, in turn, also leads to larger excess job reallocation – total job reallocation minus realized net employment growth (see Davis and Haltiwanger, 1992) – among regular firms (34%) compared to serial entrepreneur businesses (26%).

Figure 3: Employment growth distributions



Notes: The figure shows employment growth distributions of continuing businesses for regular (left panel) and serial entrepreneur firms (right panel). Both as a function of business age and employment-weighted. Specifically, the figure depicts the 10th and 90th growth percentiles in each age category together with the median.

Growth distributions over the life-cycle. We now zoom in on the "up-" part of business dynamism and analyze net job creation and its distribution over firms' life-cycles. Figure 3 shows the distribution of employment growth rates among regular (left panel) and serial entrepreneur firms (right panel) by age.

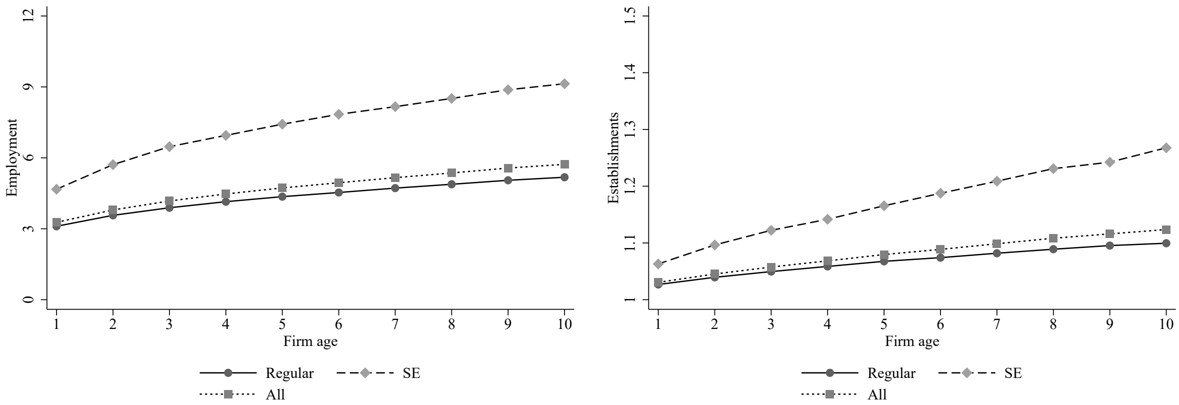
As is clearly visible from the figure, the entire growth distribution of serial entrepreneur firms is shifted towards faster growth rates, compared to regular firms – and this holds true throughout firms' life-cycles. Specifically, the lower end (10th percentile) of the growth distribution among regular firms ranges between about -120% and -50%.[20] In contrast, the 10th percentile among SE firms hovers around -50%. In addition, the upper end (90th percentile) of the growth distribution is considerably higher for serial entrepreneur firms, especially early on in firms' life-cycles.

These two effects combined give rise to a higher median growth rate of SE firms. Specifically, the median serial entrepreneur firm at age 10 still displays a slightly positive growth rate. In contrast, the median regular firm essentially does not grow – independent of its age.

[20] Recall the definition of employment growth follows the Davis et al. (1996) methodology in which firm exit is associated with -200% employment growth.

Figure 4: Margins of growth

(a) Size of single-establishment firms (b) Establishments per firm



Notes: The figure shows the average size of single-establishment firms (left panel) and the average number of establishments per firm (right panel). It does so for regular, serial entrepreneur (SE) and all firms.

Margins of growth. Before moving on, we investigate the margins of firm growth. In particular, we focus on when and how businesses tend to open more establishments ("extensive margin") or when and how they choose to employ more workers per establishment ("intensive margin").

Let us begin by investigating intensive margin growth. We do so first by focusing on single-establishment firms only, where intensive margin growth is the only option. The left panel of Figure 4 shows that single-establishment serial entrepreneur firms not only start larger but also grow faster compared to their regular counterparts. In particular, employment growth is almost a third faster among serial entrepreneur firms (8.3% on average over the first ten years) compared to regular firms (6.3%).[21] These patterns closely mimic those of all firms (see Figure 2), suggesting that extensive margin growth is quantitatively not that important. Indeed, multi-establishment firms are quite rare in Portugal.

Specifically, only about 1.7% of all regular firms have multiple establishments at startup, while this fraction is about 3.5% for serial entrepreneur businesses. Nevertheless, conditional on having multiple establishments, serial entrepreneur businesses tend

[21]In contrast, multiple-establishment regular businesses tend to expand their workforce *per establishment* at a somewhat faster pace (3.5% vs 3% among serial entrepreneur multi-establishment firms). However, it remains the case that serial entrepreneur multi-establishment firms enter larger. This holds true even per establishment.

to open somewhat more establishments over the course of their life-cycle than regular firms, see the right panel of Figure 4. Interestingly, both types of multi-establishment firms tend to enter with roughly the same average number of establishments (around 2.7). However, by the time firms reach the age of 10 years, multi-establishment serial entrepreneur firms have 3.5 establishments on average, while regular multi-establishment businesses operate about 20% few establishments – just under 3 on average.

3.3 Gazelles and the Firm Size Distribution

The previous two subsections documented that SE firms are important for aggregate job creation, productivity growth and business dynamism, despite accounting for less than 14% of all businesses. We now turn to analyzing the implications for the firm size distribution.

First, we now turn our attention to an important sub-group of businesses – high-growth firms, so called "gazelles". This focus builds on established evidence that while rare, gazelles are important for aggregate outcomes (see Haltiwanger et al., 2017). Second, we report the implications of our findings for the firm-size distribution. Understanding the latter is of importance as it can inform about underlying frictions inhibiting firm growth (see for example Cabral and Mata, 2003; Hsieh and Klenow, 2014) as well as serving as a key target disciplining macroeconomic models (see for example Hopenhayn and Rogerson, 1993; Sterk ⓡ al., 2021). We discuss the latter in more detail at the end of the paper.

Prevalence and Importance of Gazelles for Aggregate Job Creation. To begin with, Table 5 confirms the findings in Haltiwanger et al. (2017) that gazelles contribute disproportionately to aggregate employment and job creation also in Portugal. In particular, the first column of Table 5 shows that while only about 9% of all firms in Portugal can be classified as gazelles according to the Eurostat-OECD definition, these firms alone account for almost a third of employment and more than 40% of newly created jobs in the entire economy.

The second and third columns of Table 5 then show the contributions of regular and serial entrepreneur gazelles to the overall patterns of high-growth firms. Two patterns stand out.

First, the table documents that about 29% of all high-growth firms are owned by serial entrepreneurs. Given that serial entrepreneur firms account for less than 14% of

Table 5: Contribution of high-growth firms to aggregates (in %)

	All	Regular	Serial
Firms	8.6	70.9	29.1
Employment	31.1	67.3	32.7
Job creation	44.2	67.8	32.2

Notes: The table reports characteristics of all high-growth firms (first column) and those owned "regular" and "serial" entrepreneurs (second and third columns). Shares are in % of all businesses in the first column, while they are a fraction of all high-growth firms in the second and third columns (hence, shares for regular and serial gazelles add to 100%).

all firms, this implies that serial entrepreneurs are almost three times more likely to own a gazelle compared to regular business owners.[22]

Second, high-growth firms owned by serial entrepreneurs account for slightly more aggregate employment and job creation relative to their firm share. Specifically, while SE gazelles account for 29% of all high-growth firms, they account for 32% of workers and all jobs created in high-growth businesses.

Serial Entrepreneur Premia Among Gazelles. The previous paragraphs showed that even among the very select group of high-growth firms, those owned by serial entrepreneurs seem to slightly outperform those owned by regular business owners. To estimate these premia formally, we again turn to regression (6), but restrict the sample of firms to only include gazelles.

Table (6) shows estimated serial entrepreneur premia for the sub-group of high-growth firms. The table documents that indeed even in this select group of firms, gazelles of serial entrepreneurs are 15% larger and about 25% less likely to shut down. In contrast, there are no statistical differences between gazelles owned by regular and serial entrepreneurs when it comes to growth rates and productivity.

Up-Or-Out Dynamics Among Gazelles. Before turning to implications for the firm-size distribution, we document up-or-out dynamics of high-growth firms. Figure 5 plots average size and exit profiles for the groups of SE and R gazelles. The shaded areas in the figure indicate the five-year window used to define gazelles. Recall, however, that

[22] The probability that a firm of a particular group of entrepreneurs, $i \in \{R, SE\}$, is a gazelle can be expressed as $Pr(\text{gazelle}|i) = \frac{\#\text{gazelles}}{\#\text{all firms}} \times \frac{\#\text{i-type gazelles}}{\#\text{gazelles}} / (\frac{\#\text{i-type firms}}{\#\text{all firms}})$. For regular and serial entrepreneurs these values are, respectively, $Pr(\text{gazelle}|R) = 0.09 \times 0.71/0.86 \approx 0.07$ and $Pr(\text{gazelle}|SE) = 0.09 \times 0.29/0.14 \approx 0.19$.

Table 6: Serial entrepreneur premium: High-growth firms

	Regular	Serial	SE Premium
Size (workers)	23.3	28.4	0.15***
Exit (in %)	5.4	3.9	-1.37***
Growth (in %)	14.4	13.1	0.35
Productivity (agg.=1)	0.86	1.13	0.06

Notes: The columns show, respectively, the averages of regular and serial entrepreneur high-growth firms and the SE premium estimated from regression (6). The rows depict, respectively, average (employment) size, exit rates, (employment-weighted) net employment growth and average labor productivity scaled by labor productivity of all firms. Ordinary Least Squares estimates with robust standard errors clustered at the firm level in parentheses. *** stands for statistical significance at the 1% level.

we follow high-growth firms even after that age and even if their growth slows.

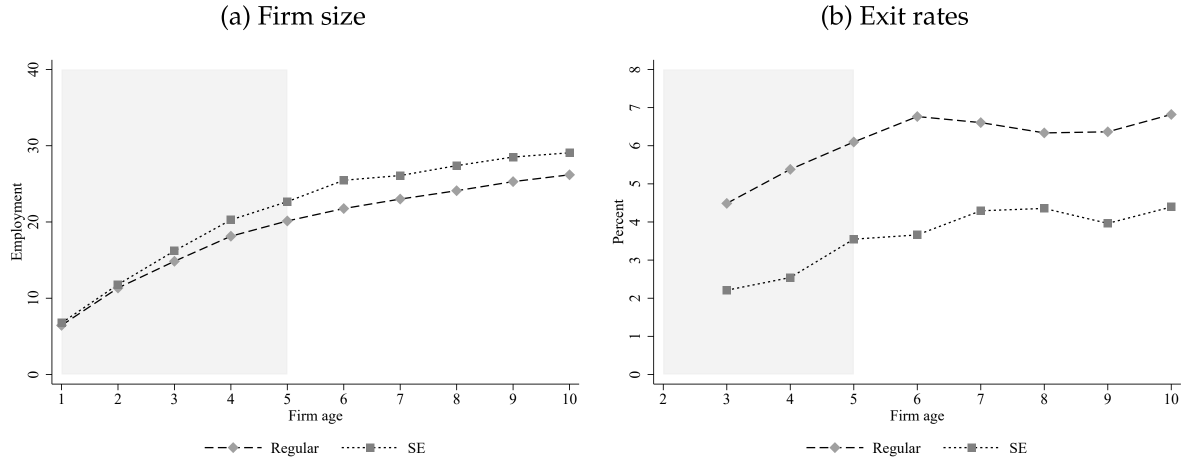
The right panel confirms results from our estimated risk premia – SE gazelles are considerably less likely to shut down.[23] Note that the survival bias inherent to the study of serial entrepreneurship is somewhat less severe in Figure 5. This is because our definition of high-growth firms requires they survive for at least 3 years. Importantly, this applies to *both* R and SE businesses.

The left panel shows how gazelles grow on average over their respective life-cycles. While both SE and R gazelles enter with essentially identical startup sizes, SE gazelles display stronger growth early on in their life-cycle. This opens up a gap in firm size which, from about the age of five, remains relatively stable. For both R and SE gazelles, growth slows after the age of five. This is not surprising, given that this is the cutoff age used in the definition of high-growth firms (i.e. businesses with sustained high growth in the first five years of their existence). Insofar as firm growth is partly driven by favorable – but transitory – shocks, average growth of gazelles will fade after the age of five as such "luck" runs out.

Firm size distributions overall. Let us now turn to investigating the implications of our previous findings for the firm size distribution. As is well known, Portugal (as well as other advanced economies) displays a size distribution which is skewed towards small firms (see for example Haltiwanger et al., 2013; Cabral and Mata, 2003). This pattern holds also within the groups of regular and SE firms. However, the extent is much weaker for firms of serial entrepreneurs. We illustrate this in Figure 6 which

[23]Given the definition of gazelles, we report exit rates only from age 3. They mechanically display an increasing pattern as initially high-growth firms need to survive in order to be classified as high-growth.

Figure 5: High-growth firms: Size and exit profiles by age



Notes: The left panel shows average firm size by age, while the right panel shows average exit rates by age. Both panels depict regular and serial entrepreneur high-growth businesses. We define gazelles as businesses younger than five years which display an annual growth rate of at least 20% for at least 3 years and employ at least 10 workers at some point in their life-time (see European Commission, 2007). Shaded areas indicate the five year period used for defining high-growth firms.

displays the complementary cumulative distribution function in log-log scale, a figure typically used in the literature (see for example Axtell, 2001; Gabaix et al., 2016). The advantage of this particular type of figure is that it also efficiently demonstrate whether the data is consistent with Pareto's Law.

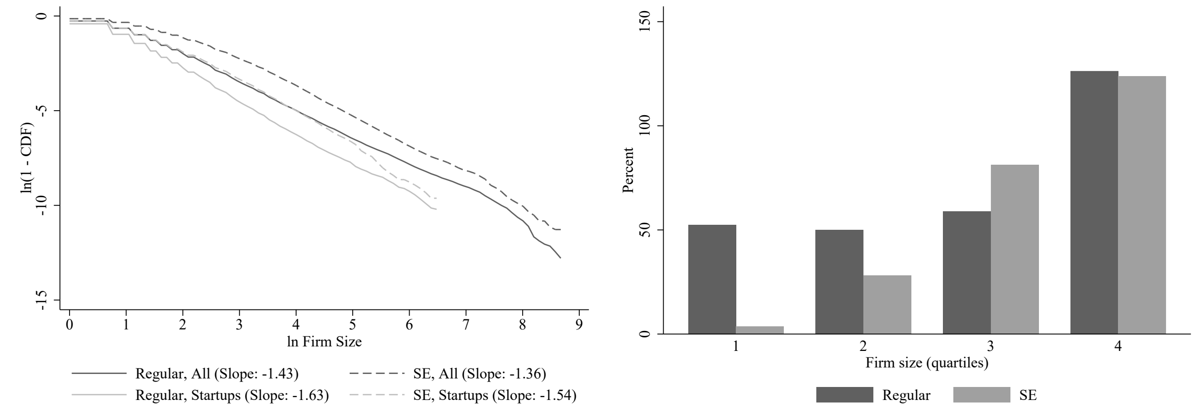
The left panel of Figure 6 shows the firm size distributions of regular and serial entrepreneur firms. It does so separately for startups and all regular and serial entrepreneur firms. First, note that the tails of the size distributions of both (all) regular and serial entrepereneur firms can be approximated by a straight line, indicating Pareto tails.[24] However, serial entrepreneur firms are clearly skewed towards larger businesses. Moreover, this occurs essentially across the entire firm size distribution suggesting that larger average sizes of SE firms are not because of "only" a handful of very large firms. For example, while only 3% of regular firms employ more than 20 workers, this fraction is 13% among SE businesses.

Firm size distributions over the life-cycle. The apparent differences in firm size between regular and SE firms suggest different sources of – or impediments to – firm

[24] See Kondo et al. (2021) for a discussion of the differences between estimating Pareto vs log-normal distributions (or their mixtures).

Figure 6: Firm size distribution and its changes

(a) Firm size distribution (b) Size growth in firm size quartiles



Notes: The figure shows the firm size distribution of regular and serial entrepreneur firms (left panel) and their evolution by plotting the size growth (between startups and 10 year old firms) in the quartiles of the respective distributions (right panel). In the left panel, the horizontal axis displays log(employment), while the vertical axis shows log(1-CDF).

growth among the two types of businesses. One possibility is that serial entrepreneur firms are larger from the onset. The left Panel of of Figure 6 shows that size differences between regular and serial entrepreneur firms indeed exist already at startup. These results, therefore, suggest that SE businesses may enjoy stronger innate characteristics ("ex-ante heterogeneity") or they may face more favorable initial conditions. We return to these points in the next section when formally investigating the underlying sources of the superior performance of serial entrepreneur firms. However, not all differences between the two groups of firms need to be accounted for by initial conditions.

An alternative possibility is that serial entrepreneur firms find it easier to grow, either because of superior growth potential or weaker impediments to growth (for example due to better access to external funding from their first businesses). The right panel of Figure 6 speaks to the growth potential of regular and serial entrepreneur firms by visualizing how the respective firm size distributions fan out with firm age. In particular, the panel displays the size growth in the respective quartiles of the size distributions between startup and age ten. For example, the grey bar in the fourth quartile indicates that the largest 25% of SE firms at age 10 are about 150% bigger than the largest 25% of SE startups. In contrast, the same measure is "only" about 100% for R businesses. The lowest quartile of the size distribution is the only exception, with regular businesses expanding somewhat more with age compared to SE firms. Taken together, the figures suggests that SE firms both start larger and exhibit stronger growth potential compared to regular businesses.

4 Potential Driving Forces

Section 3 documents the macroeconomic importance of serial entrepreneur firms. We now offer an analysis of a range of potential sources underlying the superior performance of SE businesses and, in turn, their disproportionate aggregate contribution.

In particular, we focus on learning (see for example Lazaer, 2005; Lafontaine and Shaw, 2016) and selection (see for example Sedláček and Sterk, 2017; Shaw and Sørensen, 2022) as two broad channels driving firm performance. In the latter case, we consider a range of aspects on which serial entrepreneurs (and their firms) may be selecting – entrepreneur characteristics or ability, characteristics of the workforce employed in their firms and financial factors. The results below, therefore, provide a guide for theories attempting to model and understand serial entrepreneurship as well as shed light on the sources of firm success more generally.

4.1 Learning

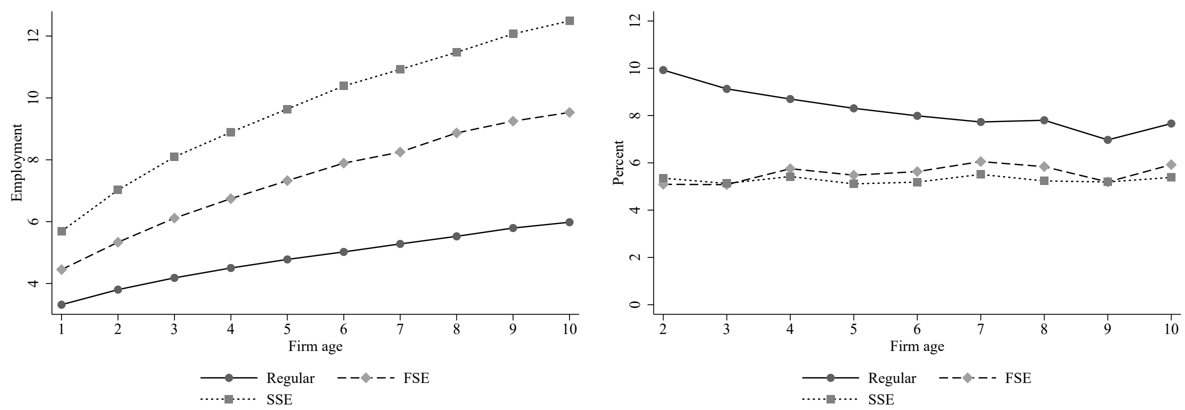
As a first potential driver of the serial entrepreneur premia, we consider learning by business owners.

First and Subsequent Businesses of Serial Entrepreneurs: Definition. Our data offers a natural way to disentangle ex-ante factors from ex-post developments by separately analyzing the performance of "first" (FSE) and "subsequent" (SSE) businesses of serial entrepreneurs. Intuitively, FSE firms are those businesses which entrepreneurs owned *before* they could be classified as serial entrepreneurs. In contrast, SSE businesses are the cause of the serial entrepreneur classification and constitute the second and further firms of serial entrepreneurs. Under the presumption of learning by business owners, subsequent firms of serial owners should be characterized by superior performance over and above the "first" business of serial owners.[25]

[25]In the data, it takes – on average – owners almost 6 years to get involved in their subsequent business (and therefore qualify to be categorized as a serial owners). There is, however, a large degree of heterogeneity in this regard. While the "fastest" 10% of serial entrepreneurs start their subsequent businesses within a year, the "slowest" 10% do so after about 12 years.

Figure 7: Size and exit profiles by age: Regular, First SE and Subsequent SE firms

(a) Firm size (b) Firm exit



Notes: The left panel shows average firm size by firm age, while the right panel shows average exit rates by firm age. Both subpanels depict regular and serial entrepreneur businesses, where the latter are split into first and subsequent businesses of serial entrepreneurs.

First and Subsequent Businesses of Serial Entrepreneurs: Estimated Premia. Figure 7 depicts the life-cycle profiles of firm sizes (left panel) and exit rates (right panel) for regular and serial entrepreneur firms. This time, however, the latter is split into the group of first and subsequent businesses of serial entrepreneurs. The figure paints a clear picture – both first and subsequent firms of serial entrepreneurs display noticably superior life-cycle patterns compared to those of regular businesses.

To formally test these patterns, we re-estimate our serial entrepreneur premia for the three groups of firms. Specifically, we consider the following regression

$$y_{i,s,t} = \alpha + \beta \mathbb{1}_{\text{s,s\_comp}} + \delta F_{i,s,t} + \epsilon_{i,s,t}, \tag{9}$$

where $y_{i,s,t}$ is again a given outcome variable of interest (log employment, exit rates, net employment growth and log labor productivity) for firm i in year t and in a given group of firms $s \in \{\text{R}, \text{FSE}, \text{SSE}\}$. In a given regression, however, we always restrict the sample to only two mutually exclusive groups – a base group s and a comparison group s_{comp}. Finally, the variable $\mathbb{1}_{\text{s,s\_comp}}$ is an indicator function, which depends on the given base and comparison groups. This indicator function is equal to one when firm i belongs to group s, and it is zero otherwise.

In our estimation, we consider the following possibilities: (i) $\mathbb{1}_{\text{R,FSE}}$ is equal to one if

Table 7: FSE and SSE premia

	Regular	FSE	SSE	Premia FSE-R	Premia SSE-R	Premia SSE-FSE
Size (workers)	5.4	9.3	11.9	0.37***	0.54***	0.24***
Exit (in %)	8.0	5.6	5.4	−1.56***	−2.11***	0.16***
Growth (in %)	8.9	10.0	9.7	2.02***	1.68 ***	−0.46***
Productivity (agg.=1)	0.82	1.13	1.19	0.19***	0.24***	0.04

Notes: The first three columns show, respectively, the averages of regular, first and subsequent serial entrepreneur firms. Columns 4 to 6 show, respectively, premia estimated from (9): "FSE-R" is the premium of first serial entrepreneur businesses over regular firms, "SSE-R" is the premium of subsequent serial entrepreneur businesses over regular firms and "SSE-FSE" is the premium of subsequent over first serial entrepreneur firms. The rows depict, respectively, average size (employment), exit rates, (employment-weighted) size growth and firm-level labor productivity scaled by labor productivity of all businesses. Ordinary Least Squares estimates with robust standard errors clustered at the firm level in parentheses. *** stands for statistical significance at the 1% level.

the firm is an FSE business (while all other firms in the sample are regular businesses) and zero otherwise, (ii) $\mathbb{1}_{\text{R,SSE}}$ is equal to one if the firm is an SSE business (while all other firms in the sample are regular businesses) and zero otherwise and (iii) $\mathbb{1}_{\text{FSE,SSE}}$ is equal to one if the firm is an SSE business (while all other firms in the sample are FSE businesses) and zero otherwise. Finally, in regression (9) we again control for age, industry and year fixed effects ($F_{i,s,t}$).

Table 7 shows the results where columns 1 to 3 depict average values of size, exit, growth rates and labor productivity in the three groups of firms. Columns 4 to 6 then report the coefficients β in the various versions of regression (9). The results document that both FSE and SSE firms are larger, exit less frequently, grow faster and are more productive relative to regular businesses (columns 4 and 5). In addition, in case of firm size, subsequent firms for serial entrepreneurs even outperform first SE business (column 6). This, therefore, suggests that learning may play a role in the success of serial entrepreneurs.[26]

[26]Recent evidence from Denmark also suggests that sales of second businesses of serial entrepreneurs are larger than those of their first firms, see Shaw and Sørensen (2022). Similarly, using Texas retail firms, Lafontaine and Shaw (2016) show that – after controlling for individual fixed effects – experience of serial entrepreneurs matters for the success of their businesses.

4.2 Selection

While the previous paragraphs suggest that learning may be an important driver of serial entrepreneur premia – especially when it comes to firm size – they does not explain why already the first businesses of serial entrepreneurs exhibit superior performance over regular firms. Therefore, we now turn to analyzing selection as an additional source of SE premia. The idea behind selection potentially driving the documented SE premia is based on the premise that only certain individual characteristics or specific conditions are conducive to successfully running a business.[27]

Data. In this analysis, we consider three groups of variables that plausibly explain the serial entrepreneur premia we find: (1) entrepreneur characteristics, (2) firm workforce characteristics, and (3) firm financial condition.

First, we include five entrepreneur characteristics, three of which are defined at the time of startup of their first business (FSE): gender, education, and past wages. Past wages refer to the individual's log hourly wage in their job prior to becoming an entrepreneur and closest to the start of their first business. As we also control for education, we consider past wages to proxy for entrepreneur's ability.[28] The last two entrepreneur characteristics we consider are age at first affiliation with the firm, and whether the owner is also a manager of the firm. To determine the latter, we make use of information in the QP which classifies individuals into one of eight levels of job hierarchy based on tasks performed in their job and the skills required to do so. Specifically, we consider an owner to be also a manager if the owner is classified as one in the top level of hierarchy: "top executives (top management)".[29]

Second, we summarize the composition of the workforce by averaging the following three characteristics across employees in R and SE firms. Age of workers, the proportion of females, and the average number of years of education. All these are readily observed in the QP.

Finally, motivated by a large literature studying the effect of financial frictions on

[27] See also Sedláček and Sterk (2017) for evidence that startup conditions matter for firms' growth potential, as well as aggregate outcomes.

[28] Note that using entrepreneurs' past wages restricts the sample to those business owners for whom we observe a transition from employment to entrepreneurship. The Appendix shows that results for the remaining explanatory factors are very similar when using the full sample, ignoring entrepreneurs' past wages. In addition, the Appendix also provides robustness exercises with regards to our wage proxy.

[29] This classification is defined by Portuguese law (Lima and Telhado Pereira, 2003; Caliendo et al., 2020). See also Queiró (2022) for a related study of managers in Portugal.

entrepreneurship and firm dynamics and the macroeconomy (see for example Cagetti and De Nardi, 2006; Jermann and Quadrini, 2012; Buera and Shin, 2013), we consider financial information of serial entrepreneur and regular firms. Towards this end, we merge the QP data with information in Sistema de Contas Integradas das Empresas (SCIE). The latter contains balance sheet and income statement information, available for all non-financial partnerships and corporations. We consider three summary measures of the financial condition of the firm: liquidity (ratio of liquid assets to total liabilities), solvency (ratio of total liabilities to total assets), and cash ratio (ratio of value of cash and cash equivalents to current liabilities).[30]

Estimation. To estimate the impact of the considered explanatory factors on firm performance, we revisit our serial entrepreneur premia regressions (6), but this time we include our explanatory variables, $G_{i,t}$, described above:

$$y_{i,t} = \alpha + \beta \mathbb{1}_{i \in SE} + \gamma F_{i,t} + \delta G_{i,t} + \epsilon_{i,t}. \tag{10}$$

Table 8 shows the results. Given our focus on business owners, the first four columns report estimates for the case when we consider entrepreneur characteristics as the only set of explanatory factors. The remaining columns show results for the case where we, in addition, consider characteristics of the workforce in serial entrepreneur firms and their financial condition.

The first row of Table 8 estimates "unconditional" serial entrepreneur premia, β^u, i.e. those estimated in (6) which ignore the explanatory variables. The second row reports "conditional" serial entrepreneur premia, β^c, estimated in (10) which take the explanatory factors, $G_{i,t}$, into account. The remaining rows report the contributions of individual explanatory factors to the estimated SE premia following the Gelbach (2016) decomposition which is invariant to the "order of elimination" of regressors. We group these factors into the three sets of factors discussed above: Entrepreneur characteristics (Panel A), Workforce characteristics (Panel B) and Financial Factors (Panel C). Within each panel, the first line reports the "total contribution" of the given set of factors. The second line shows the total contribution as a share of the unconditional SE premium, β^u. Finally, the remaining rows of each panel report contributions of the underlying

[30]While liquid assets include cash, they also include other liquid assets such as accounts receivable and short term investments. In addition, while current liabilities are a subset of total liabilities, the latter also contains long-term debt. The Appendix provides descriptive statistics for all explanatory variables.

individual factors.[31]

Entrepreneur Characteristics. The results in the first four columns of Panel A in Table 8 suggest that entrepreneur characteristics alone can explain between 20 and 40% of the estimated (unconditional) serial entrepreneur premia. Similar contributions can be found also when conditioning on other explanatory factors – in this case entrepreneur characteristics alone explain between 17 and 43% of the estimated serial entrepreneur premia (see last four columns of Panel A in Table 8).

The two most important contributors in this regard are the education of entrepreneurs and their past wages.[32] Specifically, compared to regular business owners, serial entrepreneurs are on average about 1.4 years more educated and command 25% higher hourly wages just before they start their first business.[33]

Overall, other entrepreneur characteristics do not provide quantitatively strong contributions to the estimated serial entrepreneur premia. Qualitatively, age contributes positively to the exit premium but negatively to the growth premium. With a certain degree of caution, this may be interpreted as older serial entrepreneurs tending to run more stable businesses with less upside potential. Finally, being an owner-manager (which is more common among serial entrepreneurs) can account for up to a third of the lower exit rates of SE firms. It does not, however, seem to be quantitatively important for the other estiamted SE premia.[34]

Workforce Characteristics. As a second set of explanatory factors, we consider characteristics of employees working in serial entrepreneur firms. The question we strive to answer is whether serial entrepreneurs are better at attracting workers which give them an edge over regular businesses. This is to some extent the case when it comes to firm growth and exit.

In particular, Panel B of Table 8 shows that workforce characteristics account for about 14% of the exit premium and 33% of the growth premium. Employee age – and to

[31] Note that as a result of rounding in each cell, the sum of individual factors does not always equal to total contribution.

[32] Note that past wages contribute negatively to the estimated exit premium. We interpret this as an indication of better outside options of entrepreneurs who previously earned high wages.

[33] These findings are consistent with Chen (2013) and Queiró (2022) who estimate selection on entrepreneurs' ability and education as being important for firm dynamics.

[34] Note that this does not imply that managerial input is not important for firm dynamics (see for example Akcigit et al., 2021). Rather, it suggests that serial entrepreneurs are not too different from regular businesses in this regard.

Table 8: Drivers of serial entrepreneur premia

	Entrepreneur characteristics only				Entrepreneur & other characteristics			
	Size	Exit	Growth	Productivity	Size	Exit	Growth	Productivity
Unconditional SE premium, β^u	0.46	−1.51	1.65	0.30	0.46	−0.40	0.52	0.28
Conditional SE premium, β^c	0.37	−0.97	1.12	0.18	0.35	−0.01	0.01	0.16
A: Entrepreneur characteristics								
Total contribution	0.09	−0.55	0.53	0.12	0.08	−0.12	0.23	0.09
Share of SE premium	21%	36%	32%	41%	18%	30%	43%	32%
Contributing factors:								
- *age*	−0.01	−0.06	−0.08	0.00	−0.00	−0.02	−0.06	−0.00
- *gender*	0.00	−0.04	0.04	0.01	−0.00	−0.03	0.04	0.01
- *education*	0.03	−0.27	0.29	0.05	0.02	−0.18	0.12	0.03
- *owner/manager*	0.01	−0.21	0.03	0.00	−0.00	−0.02	0.03	0.00
- *past wages*	0.07	0.04	0.24	0.05	0.06	0.14	0.09	0.05
B: Workforce characteristics								
Total contribution					0.00	−0.05	0.18	0.01
Share of SE premium					0%	14%	33%	3%
Contributing factors:								
- *age*					0.01	−0.06	0.14	0.00
- *gender*					0.00	−0.00	−0.00	0.00
- *education*					−0.01	0.03	0.03	0.01
C: Financial factors								
Total contribution					0.02	−0.21	0.12	0.02
Share of SE premium					5%	53%	23%	7%
Contributing factors:								
- *liquidity*					0.00	−0.01	0.02	0.00
- *solvency*					0.01	−0.23	0.10	0.01
- *cash ratio*					0.01	0.03	−0.00	0.00

Notes: The table reports results from estimating (10). The first row reports "unconditional" serial entrepreneur premia, β^u, which ignore explanatory factors, $G_{i,t}$. The second row shows conditional serial entrepreneur premia, β^c, which control for $G_{i,t}$. The remainder of the table reports individual contributions of explanatory factors, grouped into "Entrepreneur characteristics" (Panel A), "Workforce quality" (Panel B) and "Financial factors" (Panel C). Each panel reports the "Total contribution" of the set of factors, "Share of SE premia" defined as (Total contribution)/β^u and the contributions of the underlying individual factors. The table reports results for a decomposition using only entrepreneur characteristics (first 4 columns) and all considered factors (last 4 columns).

a lesser extent education – play an important role in this regard. These results suggest that serial entrepreneurs may be better at attracting more experienced workers. In contrast, workforce characteristics do not seem to have any bite when it comes to firm size and productivity premia.

Financial Factors. Finally, Panel C of Table 8 reports the contributions of financial factors to the estimated serial entrepreneur premia. While financial factors contribute only modestly to size and productivity premia of serial entrepreneurs (explaining between 4 and 7%), they play an important role in understanding the advantage of serial entrepreneurs when it comes to firm exit and growth.

In particular, financial factors account for between 20 and 51% of the estimated growth and exit premia, respectively. These effects are dominantly driven by differences in solvency between serial and regular entrepreneur firms. In particular, businesses of serial entrepreneurs enjoy a liability-to-assets ratio which is about 1/4 lower than that of regular businesses. In other words, considerably lower indebtedness of serial entrepreneur firms goes a long way in explaining their superior performance. This points to the importance of financial constraints as key determinants of firm exit and growth.

Next, we consider the same analysis but focus on first serial entrepreneur businesses only. This allows us to gauge whether serial business owners transition into entrepreneurship with a healthier balance sheet from the get-go, or whether the initial success of their first business provides a financial cushion for their subsequent firms, allowing them to thrive.

The results (presented in the Appendix) suggest that while entrepreneur and workforce characteristics display largely similar contributions to the estimated serial entrepreneur premia of FSE firms, the positive effect of financial factors is dampened. In particular, while solvency remains the dominant contributor, it explains "only" between 13 and 28% of the FSE premia.

Therefore, serial business owners indeed seem to enter entrepreneurship with a stronger financial position compared to regular entrepreneurs. At the same time, however, this financial edge gets only stronger for their subsequent firms, suggesting that SSE firms also benefit from the initial success of their FSE predecessors.

Summary. The results presented above suggest that entrepreneur characteristics (especially education and ability) and financial factors (especially solvency) are key drivers of estimated serial entrepreneur premia. These three factors alone explain up to $2/3$ of the estimated serial entrepreneur premia. To a lesser extent, the ability of serial entrepreneurs to attract more experienced workers also contributes to explaining their superior performance.

4.3 Discussion

This paper provides novel facts about the macroeconomic importance of serial entrepreneur firms *and* about the potential drivers of their superior performance. These results, however, do not "only" provide new facts about a particular group of firms, they also relate to existing theoretical and quantitative macroeconomic models. In this section, we discuss the implications of our results for such models. In addition, the Appendix sketches how accounting for serial entrepreneurship can change our understanding and modeling of other key economic questions such as (top) income inequality.

Disciplining macroeconomic models with heterogeneous firms. Macroeconomic models with firm heterogeneity embrace the constant business churn observed in the data. Firm-level heterogeneity in these models ultimately shapes the model's *aggregate* dynamics, including responses to policy interventions. Such models have increasingly gained on popularity and have now been successfully used to study a broad range of important questions including financial frictions (see for example Cooley and Quadrini, 2001; Cabral and Mata, 2003; Cagetti and De Nardi, 2006), misallocation (see for example Hsieh and Klenow, 2014; Eslava and Haltiwanger, 2021), size-dependent policies (see for example Gourio and Roys, 2014), pro-growth interventions (see for example Acemoglu et al., 2018; Ignaszak and Sedláček, 2022), market power (see for example Peters, 2020), selection and managerial delegation (see for example Akcigit et al., 2021), informality (see for example Ulyssea, 2021) or demographic change (see for example Hopenhayn et al., 2022).

However, heterogeneity across firms generated within these models is determined by *unobserved* firm-specific driving forces, such as productivity or demand. In order to discipline these firm-level drivers, researchers typically require their model to match salient features of the data related to firm dynamics, such as observed up-or-out patterns, the firm size (growth) distribution or job creation and destruction shares for different groups of firms.

In this context, the empirical facts presented in Section 3 constitute a set of new moments to which macroeconomic models with firm heterogeneity can be parameterized and evaluated against. Accounting for serial entrepreneurship may be important for the quantitative conclusions of such models as well as for uncovering new mechanisms or policy implications.

Sources of firm heterogeneity and theories of firm survival and growth. Striving to pinpoint the underlying reasons for the vast differences in firm performance has an strong tradition in the literature on (serial) entrepreneurship (see for example Schoar, 2010; Hombert et al., 2017; Shaw and Sørensen, 2019; Azoulay et al., 2020; Shaw and Sørensen, 2022; Azoulay et al., 2022). Closely related to the key topic of this paper, studies have also analyzed the macroeconomic impact of various groups of firms (see for example Haltiwanger et al., 2013, 2017). Understanding the sources of firm heterogeneity also has important implications for theoretical macroeconomic models. This is because, as explained above, firm heterogeneity in these models shapes their aggregate predictions.

One strand of the literature attributes differences across firms largely to transitory shocks (see for example Hopenhayn, 1992, for a seminal contribution). In these frameworks, firms are often faced with various frictions preventing them to immediately adjust and exacerbating the impact of firm-level disturbances (see for example Cooley and Quadrini, 2001; Cagetti and De Nardi, 2006; Buera and Shin, 2013; Kaas and Kircher, 2015; Sedláček, 2020; Bilal et al., 2022, for examples of entrepreneurship and firm dynamics models with financial or labor market frictions). Within this context, our results in Section 4 point towards learning, financial and labor market frictions as promising theories for understanding firm dynamics and serial entrepreneurship in particular.

Finally, in addition to the impact of transitory shocks and frictions, growing empirical evidence suggests that, so called "ex-ante", differences in growth potential are needed to match salient features of the micro-data (see for example Decker et al., 2014; Schoar, 2010; Sterk ⓡ al., 2021). In addition, there are theoretical contributions arguing that models lacking such ex-ante heterogeneity cannot explain certain empirical features related to firm growth (see for example Luttmer, 2011; Gabaix et al., 2016; Akcigit et al., 2021; Sterk ⓡ al., 2021). The results presented in Section 4, therefore, suggest that entrepreneurial education and ability may be some of the most important ex-ante factors driving differences in firm performance.

5 Concluding Remarks

In this paper we study why some firms are more successful than others and how this impacts aggregate outcomes. We make use of a unique administrative dataset from Portugal, exploiting information on serial entrepreneurs – impersonations of business success. We document that serial entrepreneur firms contribute disproportionately to aggregate job creation and productivity growth and that they shape overall business dynamism. The latter occurs largely because serial entrepreneurs are much more likely to own high-growth firms. In addition, we provide new evidence on the sources of such superior performance. Our results point towards learning and selection on entrepreneur education, ability and financial conditions as the key determinants of success.

Our results contribute to the existing literature in two distinct ways. First, they make a strong case for the analysis of serial entrepreneurs from a *macroeconomic* perspective – a topic that is not well understood. This is true not only for empirical work, which has been held back by a lack of available data sources, but especially for theoretical and quantitative macroeconomic research from which serial entrepreneurs are effectively completely missing. Second, they shed light on the reasons behind firm success, guiding the development of new theories and providing a means to discipline existing macroeconomic models of business dynamism.

Our results also open the door to further empirical questions which are, however, beyond the scope of this paper. How do firms of serial entrepreneurs respond to policy changes or what is the impact of existing institutional arrangements on the incentives to pursue serial entrepreneurship? Answering these and other questions will further our understanding of not only entrepreneurship and firm growth, but also of how the macroeconomy operates. Therefore, while Elon Musk enjoys the attention of more than 72 million followers on X (formally known as Twitter), we believe that he and other serial entrepreneurs deserve more attention still.

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Internet Appendix

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A Additional Empirical Results

This Appendix provides a range of robustness checks for our key empirical findings.

A.1 Alternative measurement of serial entrepreneurs

The results in Section 3, use the "fixed effect" definition of serial entrepreneurship where we treat any business owner who simultaneously owns multiple businesses as a serial entrepreneur *throughout the entire sample*. In this Appendix, we document that very similar results are obtained using the alternative, "year-by-year" definition, where we count as serial entrepreneurs only those business owners who own multiple businesses in a given year. This is intuitive, since in Section 4 we show that first and subsequent firms of serial entrepreneurs have similar characteristics.

Specifically, Table A1 and A2 document that even under the year-by-year definition serial entrepreneur firms still enjoy a significant premium over regular businesses and that they disproportionately contribute to aggregate job creation and productivity growth. In addition, the following Figures show that under the alternative definition serial entrepreneur firms still have a wider size distribution which fans out faster with firm age (Figure A1), they shape average up-or-out dynamics (Figure A2) and that even the very first businesses of serial entrepreneurs outperform regular businesses (Figure A3).[1]

Table A1: Serial entrepreneur premium: year-by-year definition

	Regular	Serial	SE Premium
Size (workers)	5.2	11.0	0.52***
Exit (in %)	7.8	6.9	-0.45***
Growth (in %)	9.6	10.6	2.13***
Productivity (agg. = 1)	0.88	1.26	0.31***

Notes: The columns show, respectively, the unconditional averages of regular and serial entrepreneur firms and the SE premium estimated from regression (6). The rows depict, respectively, average size (employment), exit rates, (employment-weighted) net employment growth and average labor productivity scaled by labor productivity of all firms. Ordinary Least Squares estimates with robust standard errors clustered at the firm level in parentheses. *** stands for statistical significance at the 1% level. Serial entrepreneur businesses are defined using the year-by-year definition.

[1] Note that exit rates of SE and R firms are much closer to each other, *unconditionally*. Nevertheless, estimating the SE exit premium still reveals that even year-on-year serial entrepreneur firms exit less frequently than regular businesses.

Table A2: Contributions to aggregates (in %): year-by-year definition

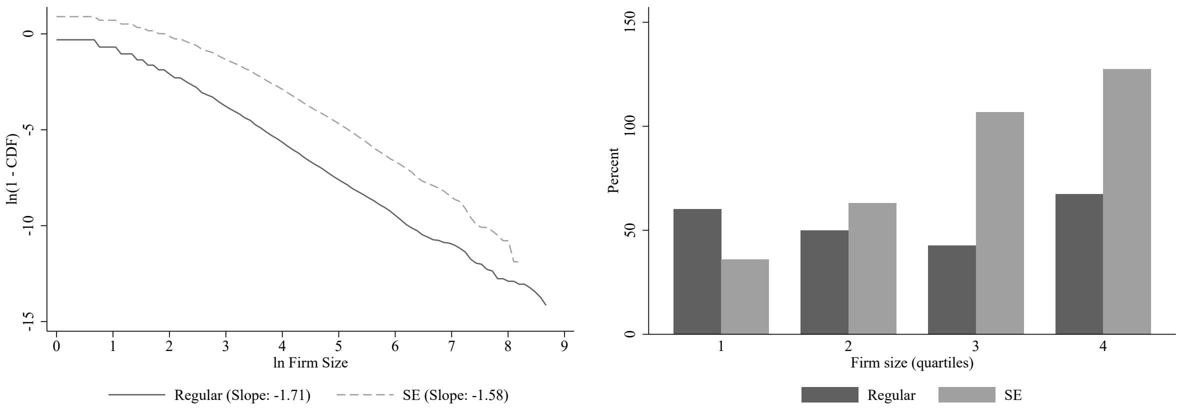
	Firms	Employment	Job creation	Job destruction	Productivity growth
Regular	95.3	90.6	91.2	92.2	95.2
Serial	4.7	9.4	8.8	7.8	4.8

Notes: The table shows, respectively, the contributions (in %) of "regular" and "serial entrepreneur" businesses to the aggregate number of firms, employment, job creation, job destruction and productivity growth. Serial entrepreneur businesses are defined using the year-by-year definition.

Figure A1: Firm size distribution and evolution: year-by-year definition

(a) Overall firm size distribution

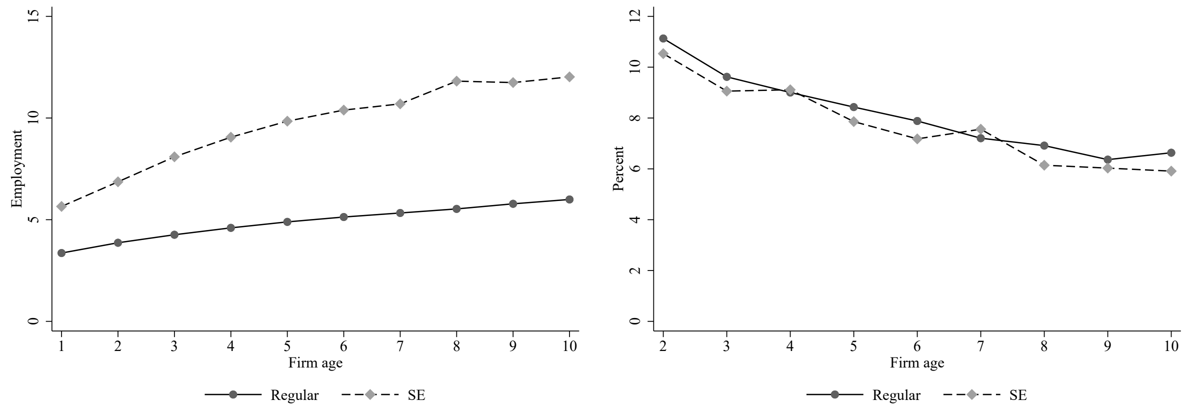
(b) Evolution of firm size distribution



Notes: Panel (a) of the figure shows the firm size distribution of regular and serial entrepreneur firms and Panel (b) visualizes the respective evolution by plotting the size growth (between startups and 10 year old firms) in the quartiles of the respective distributions. Serial entrepreneur businesses are defined using the year-by-year definition.

Figure A2: Size and exit profiles by age: year-by-year definition

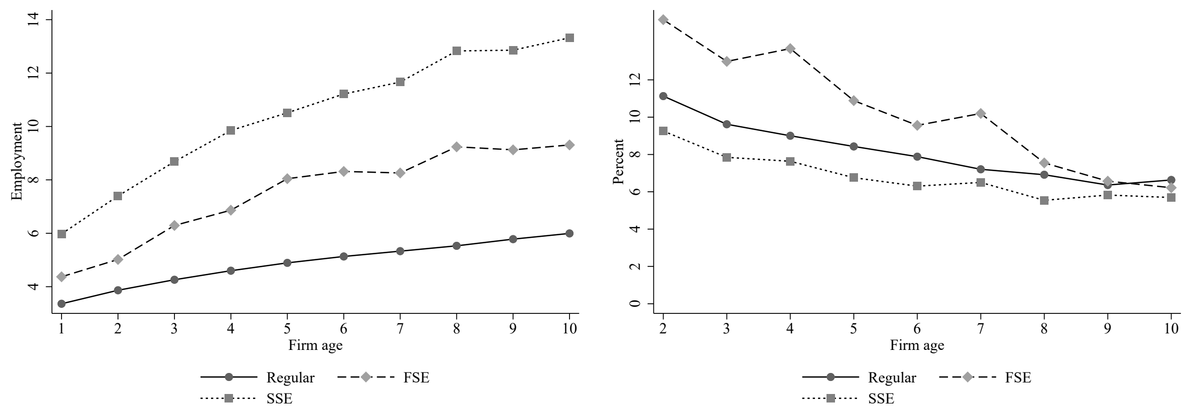
(a) Firm size (b) Exit rates



Notes: The left panel shows average firm size by age, while the right panel shows average exit rates by age. Both subpanels depict regular and serial entrepreneur businesses. Serial entrepreneur businesses are defined using the year-by-year definition.

Figure A3: Size and exit profiles by age: Regular, First SE and Subsequent SE firms: year-by-year definition

(a) Firm size (b) Firm exit

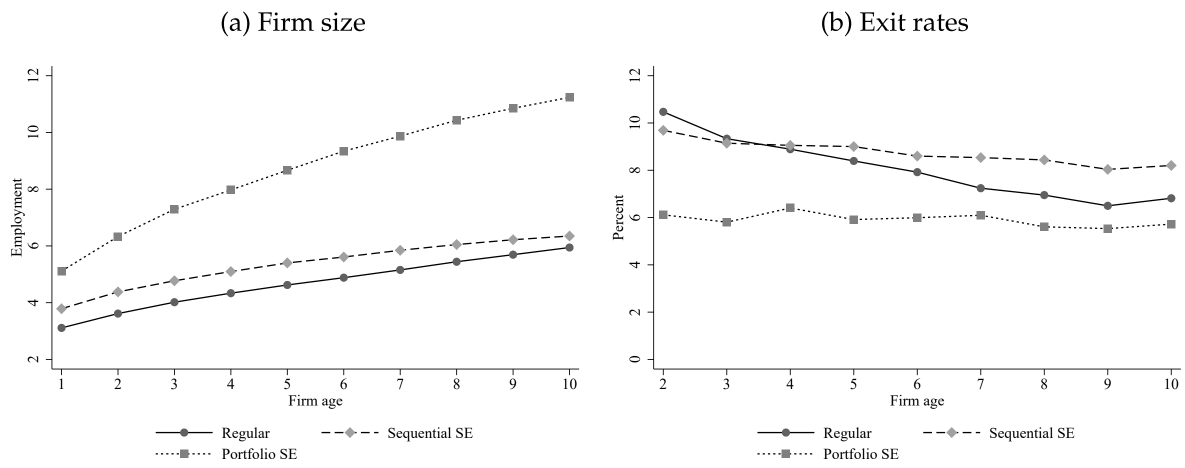


Notes: The left panel shows average firm size by firm age, while the right panel shows average exit rates by firm age. Both subpanels depict regular and serial entrepreneur businesses, where the latter are split into first and subsequent businesses of serial entrepreneurs. Serial entrepreneur businesses are defined using the year-by-year definition.

A.2 Sequential vs Portfolio Entrepreneurs

The main text defines serial entrepreneurs as business owners who *simultaneously* own multiple firms. These entrepreneurs have been dubbed "portfolio" serial entrepreneurs in the literature. In this Appendix, we show that businesses of "sequential" serial entrepreneurs, those who own multiple businesses with a non-entrepreneur spell in between (i.e. their first business shuts down before they start another), are more similar to regular firms than to those of portfolio serial entrepreneurs. Precisely for this reason we focus on portfolio serial entrepreneurs in the main text.

Figure A4: Size and exit profiles by age: Regular, portfolio and sequential businesses



Notes: The left panel shows average firm size by age, while the right panel shows average exit rates by age. Both subpanels depict regular, portfolio and sequential serial entrepreneur businesses.

Specifically, Figure A4 shows that firm performance of sequential serial entrepreneurs is very close to that of the group of true regular entrepreneurs. The only noticeable difference seems to be that firms of sequential entrepreneurs start (and remain) larger on average, compared to those of true regular business owners.

Table A3 presents estimates of premia associated with sequential serial entrepreneurs. The table confirms that sequential serial entrepreneurs own larger businesses compared to true regular entrepreneurs. However, neither of the other characteristics (exit rates, growth or productivity) display a superior premium.

Table A3: SE premia over regular, portfolio and sequential entrepreneurs

				Premia	
	Regular	Seq. SE	Portf. SE	Seq.-R	Portf.-Seq.
Size (workers)	5.3	5.8	10.9	0.19***	0.35***
Exit (in %)	7.9	8.2	5.4	0.64***	-2.49***
Growth (in %)	8.9	8.8	9.8	-0.35*	2.18***
Productivity (agg.=1)	0.79	0.88	1.17	0.00	0.26***

Notes: The first three columns show, respectively, the averages of regular, portfolio and sequential serial entrepreneur firms. Columns 4 and 5 show, respectively, premia estimated from (9): "Seq.-R" is the premium of sequential entrepreneur businesses over regular firms and "Portf.-Seq." is the premium of portfolio over sequential serial entrepreneur firms. The rows depict, respectively, average size (employment), exit rates, (employment-weighted) size growth and firm-level labor productivity scaled by labor productivity of all businesses. Ordinary Least Squares estimates with robust standard errors clustered at the firm level in parentheses. *** and * stand for, respectively, statistical significance at the 1% and 10% levels.

A.3 Analysis on a truncated sample period

As is typical in studies of serial entrepreneurship, also our analysis suffers from a right censoring bias. In particular, we categorize as regular entrepreneurs even those business owners who will become serial entrepreneurs in the future, *outside our sample*. While this bias likely leads to our results being a lower bound (since some of our regular entrepreneurs are in fact future serial entrepreneurs which – as our results suggest – own businesses with superior performance), this Appendix provides results where we explicitly address the bias.

Towards this end, we redo our analysis on a truncated sample. Specifically, we truncate the end of our sample in 2009 instead of letting it end in 2017. This truncation closely mimics the average number of years it takes a serial entrepreneur to start their second business. The truncation results in "reclassifying" 12.6% of serial entrepreneurs in our baseline specification as regular entrepreneurs because they start their subsequent businesses after 2009. Nevertheless, Table A4 and Figures A7 to A6 show that are key results remain to hold even for this truncated sample.[2]

Table A4: Contributions to aggregates (in %): truncated sample

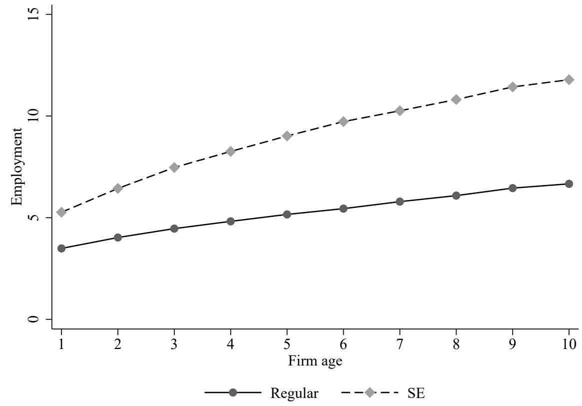
	Firms	Employment	Job creation	Job destruction	Productivity growth
Regular	87.1	78.9	79.9	83.2	80.8
Serial	12.9	21.1	20.1	16.8	19.2

Notes: The table shows, respectively, the contributions (in %) of "regular" and "serial entrepreneur" businesses to the aggregate number of firms, employment, job creation, job destruction and productivity growth. Estimates are based on a truncated sample, ending in 2009 instead of 2017.

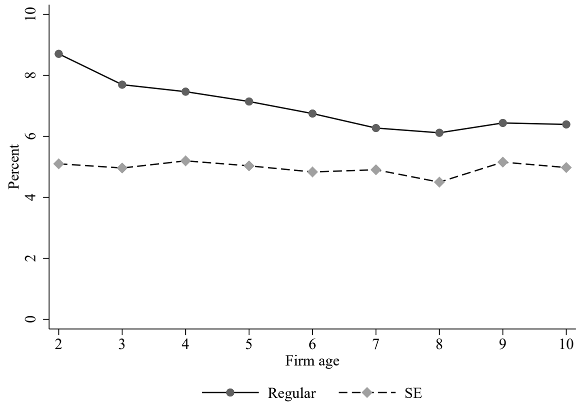
[2]The firm size distribution seems to fan out slightly less quickly, compared to the full sample. Nevertheless, average firm size of SE firms still grows faster on average, compared to R firms even in the truncated sample.

Figure A5: Size and exit profiles by age: truncated sample

(a) Firm size



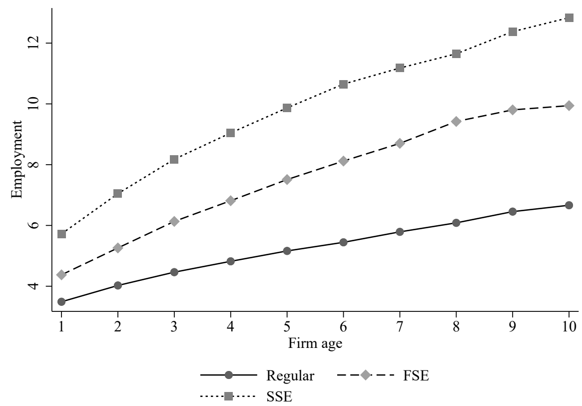
(b) Exit rates



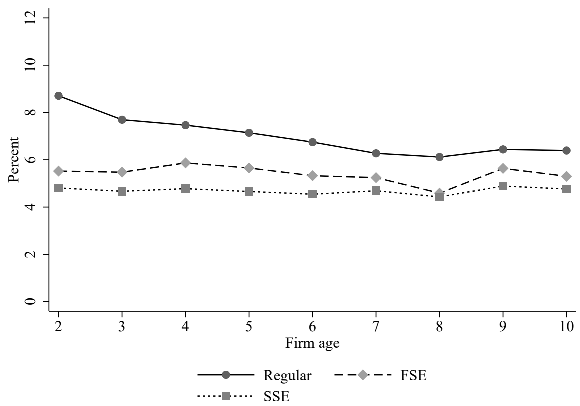
Notes: The left panel shows average firm size by age, while the right panel shows average exit rates by age. Both subpanels depict regular and serial entrepreneur businesses. Estimates are based on a truncated sample, ending in 2009 instead of 2017.

Figure A6: Size and exit profiles by age: Regular, First SE and Subsequent SE firms: truncated sample

(a) Firm size



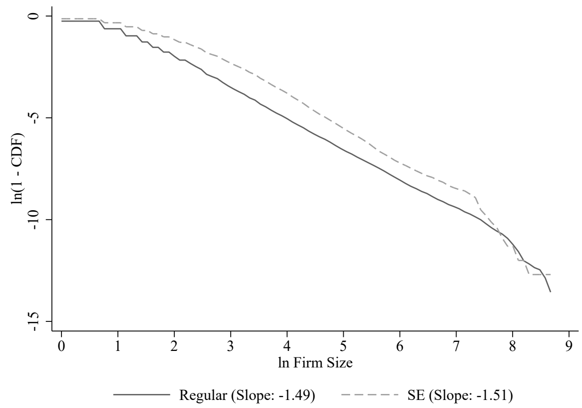
(b) Firm exit



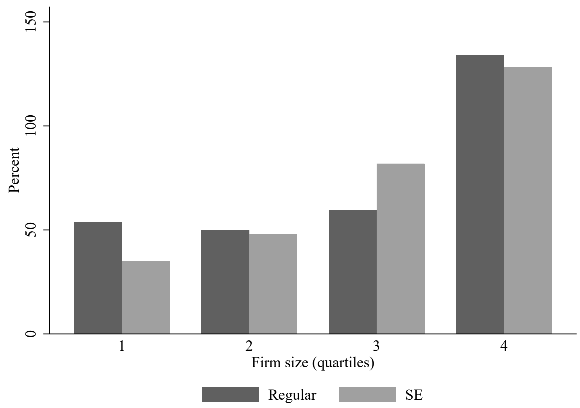
Notes: The left panel shows average firm size by firm age, while the right panel shows average exit rates by firm age. Both subpanels depict regular and serial entrepreneur businesses, where the latter are split into first and subsequent businesses of serial entrepreneurs. Estimates are based on a truncated sample, ending in 2009 instead of 2017.

Figure A7: Firm size distribution and evolution: truncated sample

(a) Overall firm size distribution



(b) Evolution of firm size distribution



Notes: Panel (a) of the figure shows the firm size distribution of regular and serial entrepreneur firms and Panel (b) visualizes the respective evolution by plotting the size growth (between startups and 10 year old firms) in the quartiles of the respective distributions. Estimates are based on a truncated sample, ending in 2009 instead of 2017.

A.4 Sole ownership only

In the main text, we classify serial entrepreneur firms as any business for which at least one owner is a serial entrepreneur. In this Appendix, we refine this definition to focus only on those businesses which have only a *single* owner. Those with a single serial entrepreneur owner are classified as SE firms, while all other businesses (i.e. including firms with multiple owners – serial entrepreneurs or not) are classified as regular. Table A5 and Figures A8 to A10 show that our key results remain to hold, albeit to a smaller quantitative extent (especially the firm-size distribution is quite close between R and SE firms). This is not surprising as the superior performance of part-owned SE firms (which make up almost 60% of all, solely and partly-owned, SE firms) is counted towards R businesses. Nevertheless, even then, solely owned SE firms are larger, growth faster and disproportionately contribute to aggregate job creation and productivity growth.

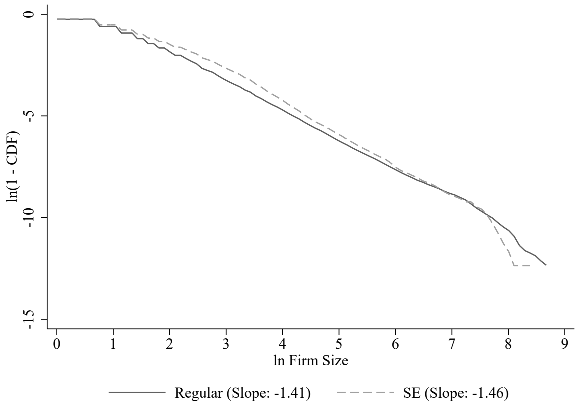
Table A5: Contributions to aggregates (in %): sole serial entrepreneurship

	Firms	Employment	Job creation	Job destruction	Productivity growth
Regular	94.1	92.6	92.4	93.0	90.1
Serial	5.9	7.4	7.6	7.0	9.9

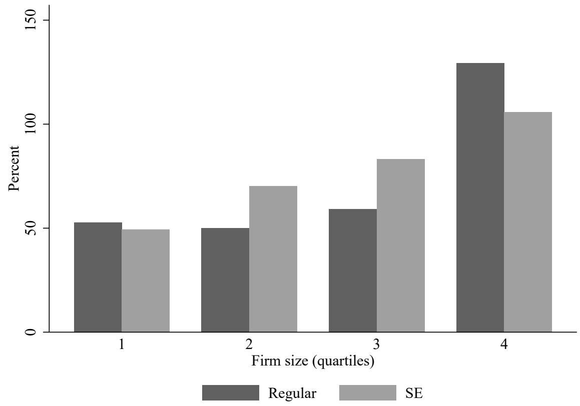
Notes: The table shows, respectively, the contributions (in %) of "regular" and "serial entrepreneur" businesses to the aggregate number of firms, employment, job creation, job destruction and productivity growth. In contrast to the main text, SE firms are restricted to have only a single owner.

Figure A8: Firm size distribution and evolution: sole serial entrepreneurship

(a) Overall firm size distribution



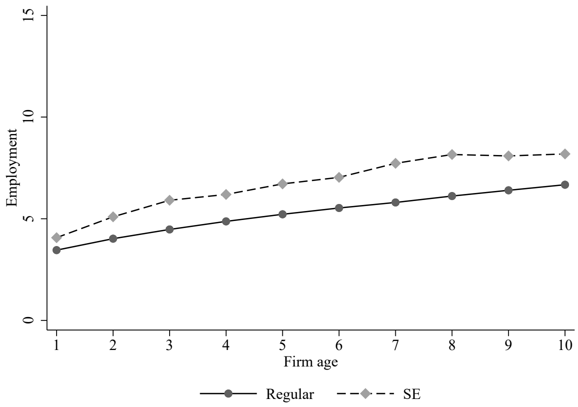
(b) Evolution of firm size distribution



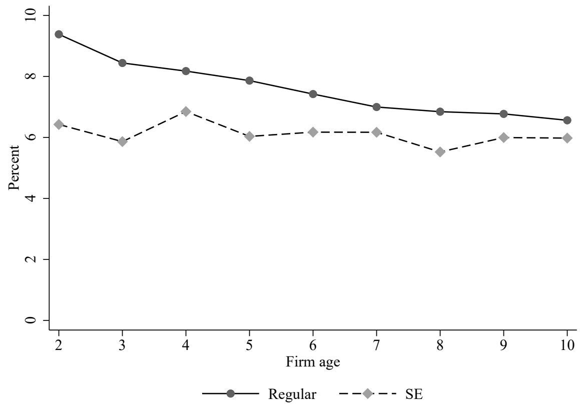
Notes: Panel (a) of the figure shows the firm size distribution of regular and serial entrepreneur firms and Panel (b) visualizes the respective evolution by plotting the size growth (between startups and 10 year old firms) in the quartiles of the respective distributions. In contrast to the main text, SE firms are restricted to have only a single owner..

Figure A9: Size and exit profiles by age: sole serial entrepreneurship

(a) Firm size

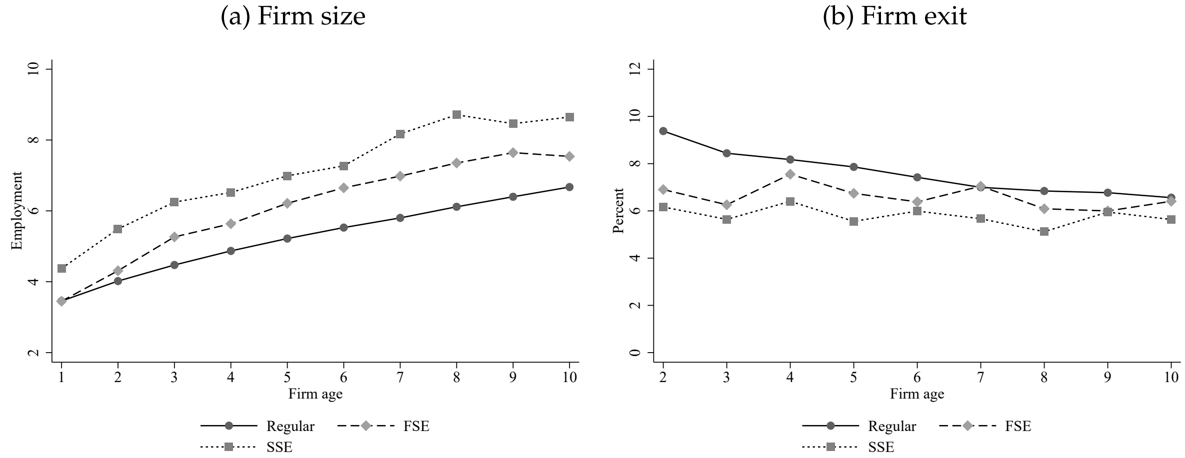


(b) Exit rates



Notes: The left panel shows average firm size by age, while the right panel shows average exit rates by age. Both subpanels depict regular and serial entrepreneur businesses. In contrast to the main text, SE firms are restricted to have only a single owner.

Figure A10: Size and exit profiles by age: Regular, First SE and Subsequent SE firms: sole serial entrepreneurship



Notes: The left panel shows average firm size by firm age, while the right panel shows average exit rates by firm age. Both subpanels depict regular and serial entrepreneur businesses, where the latter are split into first and subsequent businesses of serial entrepreneurs. In contrast to the main text, SE firms are restricted to have only a single owner.

A.5 Alternative definition of high-growth firms

The main text defined gazelles following the Eurostate-OECD definition (see European Commission, 2007). In this Appendix, we consider an alternative definition of gazelles. In particular, we follow Haltiwanger et al. (2017) and define gazelles as firms with annual growth rates higher than 25%. Note that this definition does not condition on firm age, nor does it consider gazelles to be a permanent characteristics as we is assumed in the main text.

Tables A6 and A7 replicate Table 5 and 6 in the main text. The results in this Appendix, therefore, suggest that even under an alternative definition of gazelles, high-growth firms still remain to be disproportionately important for aggregate employment and job creation and gazelles owned by serial entrepreneurs outperform regular high-growth firms.

Table A6: Contribution of high-growth firms to aggregates (in $\%$): alternative definition

	All gazelles	SE gazelles
Firms	19.3	15.4
Employment	22.2	24.3
Job creation	73.5	24.2

Notes: The table reports characteristics of all continuing high-growth firms (HW firm-year definition: employment growth above 25%) (first column) and those owned by serial entrepreneurs (second column). Shares are in % of all businesses in the first column, while they are a fraction of all high-growth firms in the second column.

Table A7: Serial Entrepreneur Premium for high-growth firms: alternative definition

	Regular	Serial	SE Premium
Size (workers)	6.8	12.3	0.361^{***}
Growth (in $\%$)	58.3	59.2	1.56^{*}
Productivity (aggregate = 1)	0.88	1.25	0.198^{***}

Notes: The columns show, respectively, the averages of regular and serial entrepreneur continuing high-growth firms and the SE premium estimated from regression (6). The rows depict, respectively, average size (employment), job creation rates. Ordinary Least Squares estimates with robust standard errors clustered at the firm level in parentheses. *** stands for statistical significance at 1%.

A.6 Productivity Decomposition Among Continuing Firms Only

While the main text considered a decomposition of aggregate productivity growth into the contributions of incumbent as well as entering and exiting firms, this Appendix focuses only on the former. In particular, even only within incumbent businesses, SE firms contribute disproportionately to aggregate productivity growth which is especially true for the "within" component of growth.

Table A8: Aggregate productivity growth decomposition

	Total	Within	Between	Cross
Aggregate	6.5	10.5	3.7	−7.7
Serial entrepreneur firms: level	1.1	2.5	0.4	−1.8
Serial entrepreneur firms: share of aggregate	16.9	23.8	10.8	23.4

Notes: The table reports values (in %) from the productivity growth decomposition in (8). The first row reports aggregates, the second and third rows reports the contribution of serial entrepreneur firms only in levels and as a share of the aggregate, respectively.

A.7 Controlling for Industry and Location

In the main text, we focus on "raw" averages when analyzing firms' life-cycle profiles. While our results suggest that serial entrepreneurship is not a feature of a few particular industries (see for example Table 1 in the main text), in this Appendix we control for industry and geographical location explicitly.

In particular, we estimate the following regressions

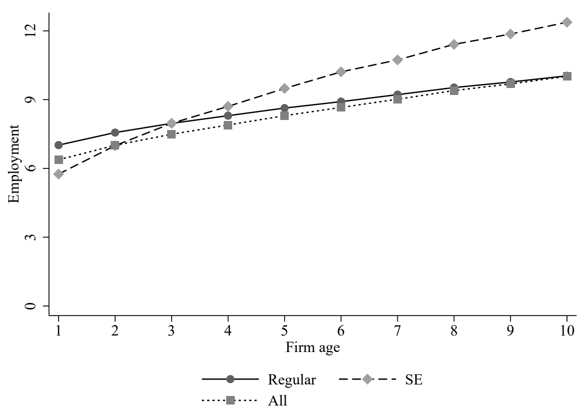
$$y_{j,t} = \alpha + \sum_a \delta_a \mathbb{1}(a) + \sum_i \delta_i \mathbb{1}(i) + \sum_g \delta_g \mathbb{1}(g) + \epsilon_{j,t}, \tag{A1}$$

where $y_{j,t}$ is a variable of interest (size or exit rates) of firm j in period t, a, i and g indicate, respectively firm age, industry and geographical location of operation, $\mathbb{1}$ are the associated indicator functions and the δ's are the respective estimated coefficients. We estimate the above for the three groups of firms (SE, R and all) separately.

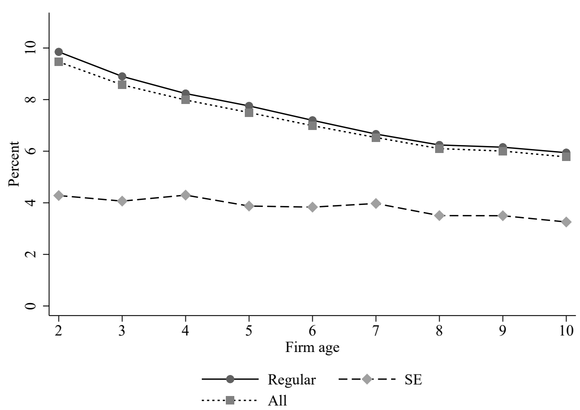
Figures A11 and A12 plot the estimated size and exit life-cycle profiles. For a given age a and particular firm type (SE, R or all), the latter is given by $\alpha + \delta_a$. The results suggest that controlling for industry and geographical location changes little on our results. The only exception is the initial size of SE firms which is now very similar to that of R businesses. However, the considerably stronger growth rate of SE firms remains apparent, even when controlling for industry and location effects.

Figure A11: Size and exit profiles by age

(a) Firm size



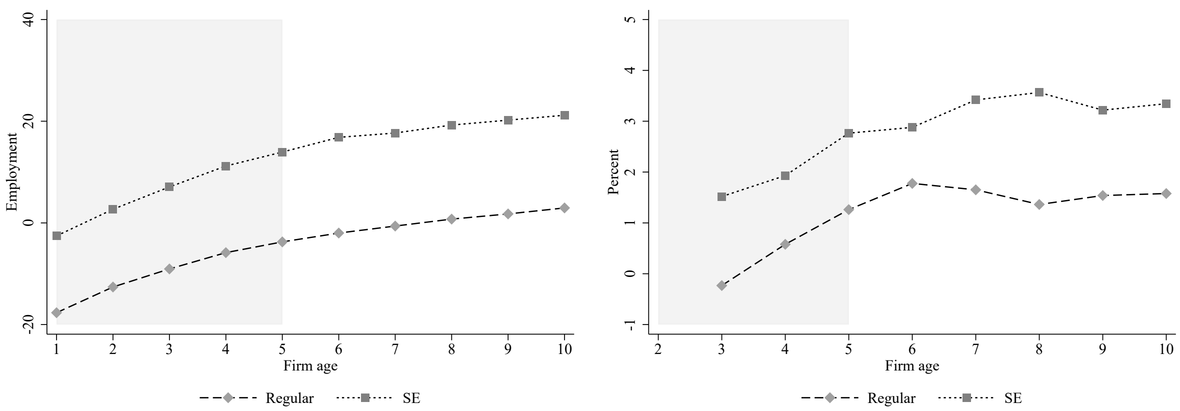
(b) Exit rates



Notes: The left panel shows average firm size by age, while the right panel shows average exit rates by age. Both panels depict all, regular and serial entrepreneur businesses.

Figure A12: High-growth firms: Size and exit profiles by age

(a) Firm size (b) Exit rates



Notes: The left panel shows average firm size by age, while the right panel shows average exit rates by age. Both panels depict regular and serial entrepreneur high-growth businesses. We define gazelles as businesses younger than five years which display an annual growth rate of at least 20 percent for at least 3 years and employ at least 10 workers at some point in their life-time (see European Commission, 2007). Shaded areas indicate the five year period used for defining high-growth firms.

A.8 Selection: Robustness Exercises

Section 4 investigates to what extent various observable characteristics can account for the estimated serial entrepreneur premia. In this Appendix, we provide various sensitivity checks of our baseline results.

Table A9: Summary statistics: Gelbach explanatory variables

	Entrepreneur char. only		Entrepreneur & other char.	
	Regular	Serial	Regular	Serial
A: Entrepreneur characteristics				
Age (years)	40.2	41.3	40.0	41.1
Female proportion (%)	30.9	23.7	30.7	23.6
Education (years)	9.2	10.6	10.4	11.4
Owner/manager (%)	93.2	98.0	94.5	98.7
Wages (log hourly rate)	0.232	0.482	0.313	0.537
B: Workforce characteristics				
Age (years)			39.7	39.7
Female proportion (%)			56.0	55.2
Education (years)			12.9	13.2
C: Financial factors				
Liquidity			2.15	2.18
Solvency			0.93	0.79
Cash ratio			0.93	0.68

Notes: The table reports average values for the explanatory variables considered in our SE premia regressions (10). All financial factors are ratios: Liquidity=liquid assets/total liabilities, solvency=total liabilities/total assets, cash ratio=cash and cash equivalents/current liabilities.

Explanatory variables. Table A9 provides average values for all the explanatory variables used in the our SE premia regressions, see equation (10). Recall that in the main text, entrepreneur characteristics and financial factors alone can explain up to 80% of the estimated SE premia. Within these, entrepreneur education, past wages and the solvency ratio are the most important factors (they alone can account for up to 2/3 of the estimated SE premia).

As can be seen from Table A9, serial entrepreneurs are more educated and command higher wages prior to starting a business. In particular, on average they have 1-1.4 years of extra education (depending on the sample being used) and earn about 25% more than regular entrepreneurs just before starting their first business. In terms of solvency, serial entrepreneur firms enjoy a liability-to-asset ratio which is 15% lower compare to regular businesses.

Not Controlling for Entrepreneur Ability. One of the key drivers of the estimated SE premia are past wages of serial entrepreneurs. We view these as proxies for underlying ability. In the main text, we use wages from the most recent year *prior to* moving into entrepreneurship. This, however, necessarily restricts our sample to only serial entrepreneurs for whom we observe the transition from paid work to entrepreneurship. Therefore, to check that our main results are not driven by this restricted sample, we re-estimate them while ignoring past wages.

Table A10 shows results for the case when we do not include wages as an explanatory variable. The results for the remaining explanatory factors remain relatively similar to those in the main text. In particular, entrepreneur characteristics alone explain between 14 and 34 percent of the estimated premia. Financial factors, and especially solvency, remain very important for exit and growth premia, accounting for 60 and 26, respectively. Finally, the age of workers also remains to play a role and explains between 15 and 41 percent of the exit and growth premia. Therefore, using the restricted sample in the main text – which allows us to control for entrepreneur ability – does not qualitativley affect our results.

Alternative Proxies for Entrepreneur Ability. Next, we re-estimate our results but instead of using wages from the most recent year prior to entrepreneurship, we consider average wages over (at most) three years prior to moving into entrepreneurship. The results are presented in Table A11. As can be seen, the estimated contributions change only very slightly. In fact, the contributions of entrepreneur characteristics to explaining the estimated SE premia increase somewhat when using this alternative measure.

First serial entrepreneur firms only. Financial factors were shown to play an important role in explaining the estimated SE premia. This is particularly true for solvency or, conversely, indebtedness. In this Appendix, we investigate the extent to which this is the case also for first serial entrepreneur (FSE) firms. The comparison between results from the main text and the ones in this Appendix then provide an indication of the extent to which subsequent serial entrepreneur firms can benefit from the (financial) success of their FSE predecessors.

Table A12 shows the results. All conclusions remain qualitatively the same as for our results in the main text. In particular, entrepreneur education, past wages, as well as solvency and to a lesser extent the age of workers in SE firms all explain sizeable fractions of the estimated SE premia.

Table A10: Drivers of serial entrepreneur premia: No past wages

	Entrepreneur characteristics only				Entrepreneur & other characteristics			
	Size	Exit	Growth	Productivity	Size	Exit	Growth	Productivity
Unconditional SE premium, β^u	0.48	−1.90	1.60	0.31	0.45	−0.36	0.45	0.27
Conditional SE premium, β^c	0.41	−1.25	1.19	0.21	0.38	0.07	0.01	0.19
A: Entrepreneur characteristics								
Total contribution	0.06	−0.65	0.41	0.10	0.04	−0.16	0.15	0.06
Share of SE premium	14%	34%	26%	31%	10%	46%	32%	21%
Contributing factors:								
- *age*	−0.00	−0.04	−0.06	0.00	−0.00	−0.01	−0.07	0.00
- *gender*	0.00	−0.04	0.05	0.01	0.00	−0.02	0.05	0.01
- *education*	0.05	−0.26	0.37	0.07	0.04	−0.11	0.15	0.04
- *owner/manager*	0.01	−0.32	0.05	0.01	−0.00	−0.02	0.02	0.00
B: Workforce characteristics								
Total contribution					0.00	−0.05	0.18	0.01
Share of SE premium					1%	15%	41%	3%
Contributing factors:								
- *age*					0.01	−0.07	0.14	0.00
- *gender*					−0.00	0.00	−0.00	0.00
- *education*					−0.01	0.01	0.04	0.01
C: Financial factors								
Total contribution					0.02	−0.21	0.12	0.02
Share of SE premium					5%	60%	26%	7%
Contributing factors:								
- *liquidity*					0.00	−0.01	0.02	0.00
- *solvency*					0.01	−0.23	0.10	0.02
- *cash ratio*					0.01	0.03	0.00	0.00

Notes: The table reports results from estimating (10). The first row reports "unconditional" serial entrepreneur premia, β^u, which ignore explanatory factors, $G_{i,t}$. The second row shows conditional serial entrepreneur premia, β^c, which control for $G_{i,t}$. The remainder of the table reports individual contributions of explanatory factors, grouped into "Entrepreneur characteristics" (Panel A), "Workforce quality" (Panel B) and "Financial factors" (Panel C). Each panel reports the "Total contribution" of the set of factors, "Share of SE premia" defined as (Total contribution)/β^u and the contributions of the underlying individual factors. The table reports results for a decomposition using only entrepreneur characteristics (first 4 columns) and all considered factors (last 4 columns).

Table A11: Drivers of serial entrepreneur premia: 3 years of past wages

	Entrepreneur characteristics only				Entrepreneur & other characteristics			
	Size	Exit	Growth	Productivity	Size	Exit	Growth	Productivity
Unconditional SE premium, β^u	0.46	−1.51	1.65	0.30	0.46	−0.40	0.52	0.28
Conditional SE premium, β^c	0.37	−0.97	1.12	0.18	0.35	−0.01	0.00	0.16
A: Entrepreneur characteristics								
Total contribution	0.09	−0.54	0.52	0.12	0.08	−0.12	0.23	0.09
Share of SE premium	20%	36%	32%	41%	17%	30%	44%	32%
Contributing factors:								
- *age*	−0.01	−0.06	−0.09	0.00	−0.00	−0.02	−0.06	−0.00
- *gender*	0.00	−0.04	0.04	0.01	−0.00	−0.03	0.04	0.01
- *education*	0.03	−0.28	0.28	0.05	0.02	−0.19	0.11	0.03
- *owner/manager*	0.01	−0.21	0.03	0.00	−0.00	−0.02	0.03	0.00
- *past wages*	0.07	0.06	0.26	0.06	0.06	0.14	0.11	0.05
B: Workforce characteristics								
Total contribution					0.00	−0.05	0.17	0.01
Share of SE premium					0%	14%	33%	3%
Contributing factors:								
- age					0.01	−0.06	0.14	0.00
- gender					0.00	−0.00	−0.00	0.00
- education					−0.01	0.01	0.03	0.01
C: Financial factors								
Total contribution					0.02	−0.27	0.12	0.02
Share of SE premium					5%	66%	22%	7%
Contributing factors:								
- liquidity					0.00	−0.01	0.02	0.00
- solvency					0.01	−0.23	0.10	0.01
- cash ratio					0.01	−0.03	−0.00	0.00

Notes: The table reports results from estimating (10). The first row reports "unconditional" serial entrepreneur premia, β^u, which ignore explanatory factors, $G_{i,t}$. The second row shows conditional serial entrepreneur premia, β^c, which control for $G_{i,t}$. The remainder of the table reports individual contributions of explanatory factors, grouped into "Entrepreneur characteristics" (Panel A), "Workforce quality" (Panel B) and "Financial factors" (Panel C). Each panel reports the "Total contribution" of the set of factors, "Share of SE premia" defined as (Total contribution)/β^u and the contributions of the underlying individual factors. The table reports results for a decomposition using only entrepreneur characteristics (first 4 columns) and all considered factors (last 4 columns).

However, the contribution of financial factors is noticably smaller when focusing on FSE firms only. Specifically, while for all firms, financial factors explain between 20 and 50 percent of the estimate exit and growth SE premia, these values are "only" 13 and 28 percent in the group of FSE firms. Therefore, it indeed seems to be the case that SSE firms partly benefit from the financial success of their FSE predecessors which allows them to operate with greater solvency ratios.

Table A12: Drivers of serial entrepreneur premia: no SSE firms

	Entrepreneur characteristics only				Entrepreneur & other characteristics			
	Size	Exit	Growth	Productivity	Size	Exit	Growth	Productivity
Unconditional SE premium, β^u	0.34	−1.18	1.55	0.26	0.36	−0.55	0.70	0.25
Conditional SE premium, β^c	0.25	−0.85	0.86	0.15	0.25	−0.25	−0.06	0.15
A: Entrepreneur characteristics								
Total contribution	0.09	−0.31	0.69	0.10	0.08	−0.03	0.36	0.08
Share of SE premium	27%	26%	45%	41%	23%	6%	52%	33%
Contributing factors:								
- *age*	0.01	0.12	0.17	−0.00	0.01	0.05	0.13	0.00
- *gender*	0.00	−0.03	0.03	0.01	−0.00	−0.02	0.03	0.00
- *education*	0.03	−0.26	0.27	0.05	0.02	−0.17	0.10	0.03
- *owner/manager*	0.00	−0.17	0.02	0.00	−0.00	−0.02	0.02	0.00
- *past wages*	0.05	0.04	0.20	0.05	0.05	0.13	0.09	0.05
B: Workforce characteristics								
Total contribution					0.01	−0.10	0.30	0.01
Share of SE premium					3%	19%	43%	3%
Contributing factors:								
- age					0.01	−0.12	0.26	0.00
- gender					−0.00	0.01	0.00	−0.00
- education					−0.01	0.01	0.04	0.01
C: Financial factors								
Total contribution					0.02	−0.16	0.09	0.02
Share of SE premium					5%	29%	13%	6%
Contributing factors:								
- liquidity					0.00	−0.01	0.01	0.00
- solvency					0.01	−0.17	0.08	0.01
- cash ratio					0.01	0.02	0.00	0.00

Notes: The table reports results from estimating (10). The first row reports "unconditional" serial entrepreneur premia, β^u, which ignore explanatory factors, $G_{i,t}$. The second row shows conditional serial entrepreneur premia, β^c, which control for $G_{i,t}$. The remainder of the table reports individual contributions of explanatory factors, grouped into "Entrepreneur characteristics" (Panel A), "Workforce quality" (Panel B) and "Financial factors" (Panel C). Each panel reports the "Total contribution" of the set of factors, "Share of SE premia" defined as (Total contribution)/β^u and the contributions of the underlying individual factors. The table reports results for a decomposition using only entrepreneur characteristics (first 4 columns) and all considered factors (last 4 columns).

B A Model of Serial Entrepreneurship and Income Inequality

The main text discusses what our results imply for quantitative macroeconomic models. In this Appendix we sketch how serial entrepreneurship can impact other key economic questions. In particular, we investigate their role for (the modeling of) top income inequality.

Entrepreneurship is long recognized to play a central role for understanding (top) income inequality (see e.g. Cagetti and De Nardi, 2006). This holds both empirically and theoretically (see e.g. Gabaix et al., 2016; Piketty et al., 2018).

In this section we highlight that ignoring serial entrepreneurship – as is common in existing studies – skews our understanding of top income inequality. Borrowing and extending a simple model of entrepreneurship and income inequality from Jones and Kim (2018), we first show analytically that serial entrepreneurship affects top income inequality. Next, we generalize the model and estimate its parameters using our data, showing that serial entrepreneurs are disproportionately important for income inequality in the Portuguese economy.

The results in this subsection serve two purposes. First, they illustrate the quantitative importance of serial entrepreneurship for the study of top income inequality. Second, they suggest how current models may be extended to account for serial entrepreneurship. We believe both directions to be promising avenues for future research.

Simple model of entrepreneurs and top income inequality. Jones and Kim (2018) provide a simple model linking entrepreneurship, business dynamism and top income inequality.[3] In particular, they assume that when an individual becomes an entrepreneur (a "top earner"), he or she earns y_0. As long as the entrepreneur remains in business, their income grows over time at a rate μ. Therefore, income per person after a years of operation is given by $y(a) = y_0 e^{\mu a}$.

Businesses, however, are subject to a constant (creative destruction) risk, δ, of shutting down. If this occurs, the exiting business is replaced by a new entrepreneur who starts again at a level of earnings y_0. As is well understood, and shown explicitly in Jones and Kim (2018), this Poisson replacement process gives rise to a firm age distribution which follows the exponential distribution, i.e. $\Pr[\text{age} > a] = e^{-\delta a}$.

[3]For more details, including a general equilibrium analysis of creative destruction and inequality, refer to Jones and Kim (2018).

In this setting, the fraction of top earners, $\Pr[\text{income} > y]$, can also be expressed analytically. In particular, noting that it takes $a(y) = \frac{1}{\mu} \log\left(\frac{y}{y_0}\right)$ years for entrepreneurs to reach a certain income level y, the fraction of top earners is given by

$$\Pr[\text{income} > y] = \Pr[\text{age} > a(y)] = e^{-\delta a(y)} = \left(\frac{y_0}{y}\right)^{\mu/\delta}. \tag{A2}$$

Therefore, this simple model implies that (top) income is distributed according to a Pareto distribution with tail coefficient $\zeta = \mu/\delta$. This simple model is appealing for at least two reasons. First, the Pareto distribution of income conforms well with empirical evidence. Second, the Pareto tail of the income distribution directly depends on the rate of income growth and creative destruction. In particular, the Pareto tail is simply equal to the rate of income growth multiplied by expected business longevity, $\mu\zeta = \frac{1}{\delta} = \mu\mathbb{E}[A_b]$.

B.1 Allowing for serial entrepreneurship

We now propose to adjust the model along two dimensions. First, we assume that entrepreneurial income is in fact proportional to firm size. Given the result above, this implies that the firm size distribution is also Pareto, consistent with the data (see e.g. Luttmer, 2007). Second, we entertain the possibility of serial entrepreneurship, i.e. of individuals who own more than just one business. As will become clear, this possibility drives a wedge between the firm size and entrepreneur income distributions. Below, we formalize how this wedge may affect top income inequality.

For tractability, let us assume that serial entrepreneurship is only a means of diversifying business risk. Specifically, we assume that every period – at a constant rate σ – each firm encounters a new "opportunity" enabling it to start an additional (spin-off) business. However, we assume that total per-period entrepreneurial income remains unchanged with the expansion of business operations. Instead, total income is diluted into the multiple businesses of serial entrepreneurs and continues to grow exponentially at a rate μ.[4] Hence, serial entrepreneurship only diversifies the risk of shutting down, but does not affect per-period income (growth). All other features of the model remain the same as before.

[4]The opposite also holds – if one business of a serial entrepreneur shuts down, total per-period income remains unchanged and the remaining businesses scale up proportionally. One way of micro-founding such a setup is to assume constant returns to a fixed time endowment of entrepreneurs.

Serial entrepreneurship and risk diversification: Analytical details. The model presented above is identical to features of the model presented in Klette and Kortum (2004). In particular, the distribution of "product lines among firms" in Klette and Kortum (2004) is identical to that of the distribution of firms among entrepreneurs in our model.

To see this, recall that in our model each business of a serial entrepreneur has a probability σ of expanding into an additional business and a probability δ of shutting down. This is isomorphic to Klette and Kortum (2004) where a given product line within a firm has an (endogenous) probability, λ, of innovating and acquiring an additional product line and the (endogenous) probability μ of being displaced by a competitor.

Therefore, in what follows we use some of the original results in Klette and Kortum (2004). In particular, let $f_n(t; n_0)$ denote the probability that an entrepreneur has n businesses in period t, having started with n_0 in period 0. The change in this probability is then given by

$$\dot{f}_n(t; n_0) = (n-1)\sigma f_{n-1}(t; n_0) + (n+1)\delta f_{n+1}(t; n_0) - n(\sigma+\delta) f_n(t; n_0). \tag{A3}$$

The above equation is the analogue of equation (5) in Klette and Kortum (2004). The reasoning for it is simple – if the entrepreneur had $n-1$ businesses, then with probability $\sigma(n-1)$ (i.e. σ per business) that entrepreneur becomes one with n businesses. Conversely, there is a $(n+1)\delta$ probability that an entrepreneur with exactly $n+1$ businesses looses one of them. Finally, with probability $n(\sigma+\delta)$ an entrepreneur with n businesses either looses or gains a business. The solution to the above equations described above is provided in Appendix C of Klette and Kortum (2004).

Entrepreneurial exit (the shutting down of all businesses of an entrepreneur) can be described as $\dot{f}_0(t; n_0) = \delta f_1(t; n_0)$. Using (A3), we can express the expected number of years entrepreneurs remain in operation, having started with 1 business, as (see B.3 in Klette and Kortum, 2004)

$$\mathbb{E}[A] = \int_0^\infty (1 - f_0(a; 1)) da = \frac{\ln\left(\frac{\delta}{\delta-\sigma}\right)}{\sigma}.$$

Taking the above, one can express the (expected) entrepreneurial death rate as

$$\delta_E = 1/\mathbb{E}[A] = \frac{\sigma}{\ln\left(\frac{\delta}{\delta-\sigma}\right)}.$$

Finally, the share of entrepreneurs with exactly 1 business (i.e. regular entrepreneurs) is given by (see equations (17) and (18) in Klette and Kortum (2004))

$$F_1 = s_R = 1 - s_{SE} = \frac{\frac{\sigma}{\delta}}{\ln\left(\frac{\delta}{\delta-\sigma}\right)}.$$

Combining the above two equations shows that

$$\delta_E = \frac{\ln\left(\frac{\delta}{\delta-\sigma}\right)}{\sigma} = (1 - s_{SE})\delta.$$

Serial entrepreneurship and top income inequality. Therefore, even if serial entrepreneurship is only a means of risk diversification, it affects top income inequality. Intuitively, the possibility of serial entrepreneurship increases expected business longevity as it takes longer for *all* firms of serial entrepreneurs to shut down. Formally, the Appendix shows that the expected amount of years for which entrepreneurs remain in business, $\mathbb{E}[A_e]$, is higher than the expected lifetime of individual firms, $\mathbb{E}[A_b]$:

$$\mathbb{E}[A_e] = \frac{1}{\delta_E} = \frac{1}{\delta(1 - s_{SE})} = \frac{\mathbb{E}[A_b]}{1 - s_{SE}},$$

where s_{SE} is the share of serial entrepreneurs.[5] Finally, since longer expected business longevity allows entrepreneurs to accumulate more income, serial entrepreneurship raises top income inequality. Formally, using (A2), we can write the income share of the top p percent of earners as

$$S(p) = \left(\frac{100}{p}\right)^{\mu\mathbb{E}[A_e]-1}. \tag{A4}$$

The following paragraphs quantify the impact of serial entrepreneurs on top income inequality in Portugal. Towards this end, we proceed in two distinct ways. First, we use the above theoretical result and moments from our dataset to quantify the share of top income inequality driven by the presence of serial entrepreneurs. Recall, however, that this value is based on assuming that serial entrepreneurship is only a means of risk

[5] Our extension renders the distribution of firms across entrepreneurs isomorphic to the distribution of product lines across firms in the model of Klette and Kortum (2004). The Appendix describes how their original results can be reframed for our purposes to show that serial entrepreneurship raises business ownership longevity. With $\sigma = 0$ there are no serial entrepreneurs, $s_{SE} = 0$, and we recover the original setup of Jones and Kim (2018).

diversification. We know from Section 3 that, in fact, serial entrepreneurship comes with a premium. Therefore, as a second quantitative exercise, we generalize the simple model in order to account more appropriately for the presence of serial entrepreneur premia.

Quantitative results: SE firms as risk diversification only. In order to evaluate top income inequality in Portugal, we make use of equation (A4) and data from the World Inequality Database. In particular, using average values of top income shares, $S(p)$, in Portugal between 1989 and 2017 we recover the implied values for $\zeta = \mu\mathbb{E}[A_e]$ as

$$\zeta = \frac{\log(S(p))}{\log(100/p)} + 1.$$

Next, to quantify the impact of serial entrepreneurship on top income inequality, we first ask what Pareto shape parameter would prevail in its absence:

$$\zeta_b = \mu\mathbb{E}[A_b] = \mu\mathbb{E}[A_e](1 - s_{SE}) = \zeta(1 - s_{SE}).$$

Having obtained values for ζ_b, we then use (A4) to compute the implied top income shares in the absence of serial entrepreneurship. The results are shown in Table A13. The top row reports the inequality measures in the data. The second row shows what income inequality would look like in the absence of serial entrepreneurship, assuming that the latter serves only as a way to diversify risk.

These results show that ignoring serial entrepreneurship lowers top income inequality. In particular, top income shares decrease by $4 - 6$ percent (by 1.3 and 0.6 percentage points for the income shares of the top 10 and 1 percent, respectively). These values are, however, disproportionately large compared to the share of serial entrepreneurs who account for only 2.7 percent of all business owners.[6] Therefore, even when serial entrepreneurship is viewed as only a means of risk diversification, it has quantitatively important implications for top income inequality.

[6]Note that s_{SE} measures the (current period) share of entrepreneurs who own multiple businesses simultaneously in a given year. This is somewhat different from the "fixed effect" definition used in the remainder of the paper. The reason is that for computing entrepreneurial income it only matters whether entrepreneurs currently have multiple businesses, not whether they will at some point in the future. Therefore, this "year-by-year" value is somewhat lower than the "fixed effect" measure (2.7 vs 5 percent on average in our sample).

Table A13: Top income inequality (in %): data and model

	top 10%	top 1%
Data	37.2	10.2
Model predictions: no serial entrepreneurs		
SE firms as risk diversification only	35.9	9.6
SE firms with premia	30.3	9.2

Notes: The table shows top income inequality in the "data" and "model". The former is taken from the World Inequality Databse. The latter is based on assuming SE firms are only a means of risk diversification, second row, or assuming that SE firms are characterized by the premia estimated in Section 3, third row. In both cases, we use the formula (A4) to compute the implied top income shares.

B.2 Generalized model: SE firms with estimated premia

In order to account for the empirical serial entrepreneur premia, we generalize our simple model along several dimensions. In particular, we assume that the economy is populated by two types of entrepreneurs indexed by $i = \{H, L\}$. Each type of entrepreneurs faces a different income process (μ_i, $y_{0,i}$), risks of shutting down (δ_i) and of encountering additional business opportunities (σ_i).

Whenever a business shuts down it is replaced by a new firm – either owned by a serial entrepreneur or by a new business owner. In the latter case, we assume that "de novo" startups are of type H with probability α and of type L with probability $1 - \alpha$. In the former case, we assume that serial entrepreneurs give rise to additional businesses of the same type as their existing firms. Compared to our model thus far, however, we assume that each additional business starts at a level of income (size) $y_{0,i}$ (and leaves the income (size) of all the other incumbent businesses of the serial entrepreneur unchanged). In other words, serial entrepreneurship is no longer only a means of business risk diversification, but it also raises entrepreneurial income.

Generalized model: Estimation. We normalize $y_{0,L} = 1$ and estimate the remaining 8 parameters using a simulated method of moments (SMM) and the following 9 moments from our dataset: (i-ii) average growth and exit rates of all firms, (iii-iv) average growth rates of R and SE firms, (v-vi) average exit rates of R and SE, (vii-viii) share of SE firms in all businesses and the average number of businesses per serial entrepreneur and (ix) size of young SE firms relative to young R businesses. In our estimation we minimize the following loss function

$$L = \min \frac{1}{9} \sum_{j=1}^{9} \frac{|\text{data}_j - \text{model}_j|}{\text{data}_j},$$

where we index each individual moment discussed above with j. In our estimation, we define young firms as those younger than six years. While all individual parameters typically affect all the model's results, average growth and exit rates of R and SE businesses are most closely related to the growth and exit rates of high- and low-type firms. Similarly, the size of young SE firms relative to young R businesses helps pin down $y_{0,H}$. The remaining four moments – share of SE businesses, the average number of SE firms per serial entrepreneur and the average growth and exit rates of all firms – jointly discipline the unconditional share of high-type startups (α) and the rate of additional business opportunities by type (σ_H and σ_L). Moreover, requiring the model to closely match overall averages of firm growth and exit rates is key for our quantitative results which depend on the Pareto shape parameter $\zeta = \mu/\delta$.

Table A14 shows the results of our estimation. The first two columns report the moments in the data and those implied by our estimation, showing that the model fit is very good. The third and fourth columns then show the parameter estimates. High-type firms are estimated to grow more than twice as fast and exit by about 10 percent less frequently than low-type firms. At the same time, high-type entrepreneurs are estimated to encounter additional business opportunities four times as frequently. However, the absolute level of these encounters is relatively low (2 percent per year). Finally, the unconditional share of high-type firms among startups is about 15 percent.

Generalized model: Results. The last row of Table A13 shows the impact of serial entrepreneurship on top income inequality. These values are based on a counterfactual exercise in which we "switch off" serial entrepreneurship in our generalized model by assuming that $\sigma_H = \sigma_L = 0$. Leaving all other parameters at their estimated values, we then simulate the model to obtain new values for average firm growth and exit rates, and therefore also of the Pareto tail coefficient $\zeta_{\text{no SE}} = \mu_{\text{no SE}}/\delta_{\text{no SE}}$. Finally, using the latter in (A4), we compute the implied top income inequality which would prevail in the absence of serial entrepreneurship.

Without serial entrepreneurs top income inequality lessens considerably. In particular, the share of income going to the top 10 and 1 percent, respectively, drops to

Table A14: Model estimation: moments and parameters

moments	data	model	parameter	estimate
size growth, all firms	4.4%	4.5%	μ_H	7.7%
size growth, SE firms	6.9%	7.0%	μ_L	3.5%
size growth, R firms	4.1%	4.2%	α	15.1%
exit rate, all firms	8.0%	8.0%	δ_H	7.9%
exit rate, SE firms	5.6%	5.6%	δ_L	8.8%
exit rate, R firms	8.3%	8.3%	σ_H	2.0%
SE share, firms	17.2%	10.9%	σ_L	0.5%
(size young SE)/(size young R)	2.1	2.1	$y_{0,H}$	3.8
average # of firms per SE	2.2	2.3		

Notes: The table shows, in columns 1 and 2, the moments in the "data" and those implied by our "model" estimation, respectively. The table also reports the estimates of the model parameters in columns 3 and 4.

30.3 and 9.2. In other words, serial entrepreneurship – while accounting for the premia estimated in Section 3 – is responsible for $11 - 22$ percent of top income inequality. Recall once more that this is despite the fact that only about 2.7 percent of all business owners simultaneously own multiple businesses.

Taking stock. This final step of our analysis documented both theoretically and quantitatively that taking into account serial entrepreneurship is important for our understanding of top income inequality. This is because the possibility of serial entrepreneurship drives a wedge between the firm size and the entrepreneur income distributions. Incorporating the possibility of serial entrepreneurship into existing models studying income inequality may, therefore, be a fruitful avenue for future research.