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The analyses, opinions and findings of these papers represent the views of the authors, they are not necessarily those of the Banco de Portugal or the Eurosystem

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Lisboa, 2021 • www.bportugal.pt

Working Papers | Lisboa 2021 • Banco de Portugal Av. Almirante Reis, 71 | 1150-012 Lisboa • www.bportugal.pt •
Edition Economics and Research Department • ISBN (online) 978-989-678-794-3 • ISSN (online) 2182-0422

Serial Entrepreneurs, the Macroeconomy and Top Income Inequality

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October 2021

Abstract
Are serial entrepreneurs – owners of multiple firms – important for understanding the sources and aggregate consequences of business dynamism? Using unique administrative data, we show that – compared to other businesses – firms of serial entrepreneurs are larger, more productive, grow faster, exit less often and disproportionately contribute to aggregate job creation and productivity growth. Moreover, even the very first firms of serial entrepreneurs feature these "premia", suggesting an important role of innate abilities, rather than luck or learning. Finally, we show theoretically and quantitatively that serial entrepreneurship is also important for understanding and modelling of top income inequality.

JEL: D22, E24, L1

Keywords: Serial entrepreneurs, Income Inequality, Firm Dynamics.

Acknowledgements: The views expressed are those of the authors and not necessarily those of the Bank of Portugal, the Eurosystem, the Bank of England or any of its policy committees. First version February 2021. Sedláček gratefully acknowledges the financial support of the European Commission: this project has received funding from the European Research Council [grant number 802145].

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1. Introduction

Elon Musk is a serial entrepreneur. He is the (co-)founder of Tesla, SpaceX, Neuralink and The Boring Company and was previously involved in other firms, including Zip2, PayPal or OpenAI. Musk's current businesses have created an estimated $110,000$ jobs and – at the time of writing of this paper – Forbes ranked Musk as the richest person on the planet.[1] Are serial entrepreneurs such as Elon Musk, Oprah Winfrey or Sir Richard Branson only rare, albeit well-known, occurrences or is serial entrepreneurship widespread? And does the large-scale nature of serial entrepreneurship make it important also for *aggregate* outcomes, such as economic growth and inequality?

In this paper, we show that serial entrepreneurs are indeed crucial for understanding business dynamism, which has long been recognized to be important for aggregate outcomes (see e.g. Haltiwanger 2012), including income inequality (see e.g. Jones and Kim 2018). As such, our results serve two distinct purposes. First, we provide new empirical evidence which can be used to assess, develop and calibrate structural (macroeconomic) models with firm heterogeneity which have gained on popularity and importance, but which typically ignore serial entrepreneurship. Second, we show theoretically and quantitatively that serial entrepreneurship is important for understanding and modelling of top income inequality. This illustrates that studying serial entrepreneurs, a minority among business owners, can still help further our understanding of key economic issues.

Throughout our analysis, we make use of unique administrative employer-employee matched data from Portugal, the Quadros de Pessoal (QP). A key advantage of the QP is that it explicitly identifies business owners and can track 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, which runs from 1986 to 2017. Note that we define serial entrepreneurship as a permanent characteristic, a "fixed effect", of business owners.[2] For example, if an entrepreneur founds a first business in 1995 and a second firm in 2000, we classify such an individual as a serial entrepreneur for the *entire* sample. We then categorize firms accordingly: serial entrepreneur (SE) firms are owned by serial entrepreneurs, while regular (R) firms are all other businesses.

Using our dataset, we begin by documenting new facts about serial entrepreneurs and their businesses. First, we show that serial entrepreneurship is not a unique feature pertaining to particular industries, but instead it occurs throughout the entire economy. In particular, about 18 percent of all businesses

1. Employment estimate of Musk's businesses is based on his twitter feed from August 30, 2021.

2. The Appendix shows that our results are robust to an alternative, "year-by-year", definition which makes serial entrepreneurship a time-varying characteristic of business owners.

are owned by serial entrepreneurs and the sectoral composition closely mimics that of the economy as a whole.

Second, we show that businesses of serial entrepreneurs perform considerably better compared to other firms. To formalize these patterns at the firm level, we estimate "serial entrepreneur premia" – the average difference in a particular variable of interest between SE and R firms. In doing so, we also condition on a range of control variables. Our results suggest that firms of serial entrepreneurs are about 60 percent larger, roughly 25 percent less likely to shut down, grow by about 35 percent faster and are 34 percent more productive compared to regular businesses.

As a final step in our firm-level analysis, we document that these serial entrepreneur premia are present throughout firms' life-cycles. Moreover, they are also present among the select group of high-growth firms, so called "gazelles".[3] The latter have been shown to be crucial for aggregate job creation and productivity growth in the U.S., despite accounting for only a relatively small fraction of businesses (see e.g. Haltiwanger *et al.* 2017). We show that these patterns also hold in the case of Portugal. In addition, we document that serial entrepreneurs are about three times as likely to own gazelles and such high-growth firms significantly outperform gazelles of regular business owners.

In the second part of our paper, we turn to analyzing the micro-level sources and macroeconomic consequences of serial entrepreneurship. We start by asking what lies behind the superior performance of serial entrepreneur firms. Towards this end, we explicitly distinguish "first" (FSE) and "subsequent" (SSE) businesses of serial entrepreneurs. In other words, SSE businesses are those firms which, in fact, lead us to classify business owners as serial entrepreneurs. Comparing the performance of FSE, SSE and R firms allows us to gauge the extent to which the superior performance of serial entrepreneur firms relative to regular businesses is present from the onset (i.e. also for FSE firms), or develops only gradually over time (i.e. only for SSE firms). This distinction between the importance of "ex-ante" characteristics versus "ex-post" luck or learning has been recently highlighted as crucial for the understanding of firm growth and aggregate dynamics (see Sterk *et al.* 2021).

Our results clearly show that FSE and SSE businesses have very similar dynamics, substantially outperforming those of regular businesses. These patterns, therefore, point to (selection on) ex-ante heterogeneity as a key source of success of serial entrepreneurs, rather than learning or favorable ex-post shocks. Making use of observable characteristics of business owners, we further estimate that age

3. We define gazelles according to the Eurostat-OECD definition (see European Commission 2007) as young businesses which report average annual growth rates above 20 percent for at least three consecutive years.

and education of serial entrepreneurs can explain up to 22 percent of the estimated premia.[4]

Next, we document that serial entrepreneur firms disproportionately contribute to *aggregate* job creation and productivity growth. In particular, while on average about 18 percent of all businesses are owned by serial entrepreneurs, this group of businesses alone accounts for more than $1/3$ of aggregate job creation and productivity growth. Therefore, understanding the drivers of serial entrepreneurship and what sets the businesses of serial entrepreneurs apart from regular firms is of macroeconomic importance.

In the last part of our analysis, we investigate the role serial entrepreneurs play for (top) income inequality. Towards this end, we borrow a simple model of entrepreneurship and inequality from Jones and Kim (2018) and extend it for the presence of serial entrepreneurs. Within this framework, we show analytically that the prevalence of serial entrepreneurs increases income inequality. The intuition is simple – because serial entrepreneurship enables the diversification of business risk, serial entrepreneurs enjoy longer periods during which their (multiple) businesses remain in operation. This, in turn, provides them with an opportunity to grow their income for longer.

In order to quantify these effects, we generalize the simple model and estimate it on our data using a simulated method of moments. The results show that serial entrepreneurs are not only theoretically, but also quantitatively, important for top income inequality. Specifically, despite the fact that fewer than 3 percent of entrepreneurs simultaneously own multiple businesses, this group alone accounts for $10-20$ percent of top income inequality. Therefore, ignoring serial entrepreneurship – as is common in existing studies – skews our understanding of the sources of top income inequality.

The remainder of the paper is structured as follows. The next section lays out conceptual underpinnings of our analysis and relates them to existing studies. Section 3 describes our data and lays out our definitions. In Section 4, we provide our firm-level analysis, highlighting three new facts about serial entrepreneurs. Section 5 analyzes the macroeconomic implications of serial entrepreneurship and the final section concludes.

2. Conceptual Underpinnings

Although limited high-quality data makes studies of serial entrepreneurship relatively rare, the current paper is not the first to study the topic. For instance, earlier studies have found that serial entrepreneurs enjoy higher incomes (see e.g.

4. These findings are consistent with the results of e.g. Smith *et al.* (2019) and Choi *et al.* (2021), who document a positive relationship betweeen firm performance in the U.S. and the human capital of their owners or “founding teams”. Neither of these studies, however, focuses on serial entrepreneurship.

Chen 2013), stay in business longer (see e.g. Lafontaine and Shaw 2016), or that they report larger sales and are more productive (see e.g. Shaw and SÃ¸rensen 2019) than regular entrepreneurs.

To the best of our knowledge, however, we are the first to study the *macroeconomic impact* of serial entrepreneurship and its relation to average firm dynamics which have been embraced by modern macroeconomic models (see e.g. Acemoglu *et al.* 2018). In such models even relatively small changes to firm dynamics can have large macroeconomic impacts (see e.g. Clementi and Palazzo 2016). Therefore, we believe that our results provide several distinct contributions which we discuss briefly below.

2.1. Understanding the Sources of Firm Heterogeneity

This paper builds on and contributes to the literature on firm dynamics and the role of firm heterogeneity for aggregate outcomes. A series of influential papers have documented that young firms, and in particular a rare group of high-growth gazelles, contribute disproportionately to aggregate job creation and productivity growth (see e.g. Haltiwanger *et al.* 2017; Decker *et al.* 2017). While such firm heterogeneity has often been largely attributed to transitory post-entry productivity or demand differences (see e.g. Hopenhayn and Rogerson 1993, for a seminal contribution), there is growing evidence that also differences present at the entry phase (ex-ante heterogeneity) can have long-lasting effects on firms and, in turn, shape aggregate dynamics (see e.g. Jovanovic 1982; Melitz 2003; Sedláček and Sterk 2017; Sterk *et al.* 2021).

Our results, therefore, constitute a further step towards a better understanding of the micro-level sources and macroeconomic impact of firm-level heterogeneity. In particular, while Sterk *et al.* (2021) recently document that ex-ante firm heterogeneity is crucial for understanding aggregate dynamics, our results from Sections 5.2 and 5.1 document that serial entrepreneurship is one such ex-ante characteristic.

This paper, therefore, points to entrepreneurs themselves as one such ex-ante characteristic of businesses which is related to their success. Empirically studying these patterns further, or linking heterogeneity among entrepreneurs to that of firms in structural models, may be a fruitful direction for future research.

2.2. Macroeconomic Impact of Firm Success

Our paper is also linked to studies of entrepreneurship and the determinants of post-entry growth heterogeneity. A range of factors have been identified as being related to firm growth, e.g. the age of workers (see e.g. Ouimet and Zarutskie 2014), the location of incorporation (see e.g. Guzman and Stern 2015), the name of the company (see e.g. Belenzon *et al.* 2017), the human capital of founders and founding teams (see e.g. Smith *et al.* 2019; Choi *et al.* 2021; Queiró forthcoming) or the founder's age (see e.g. Azoulay *et al.* 2020). We also relate to a strand of research focusing on venture capital projects, which suggests that both more experienced capital providers and entrepreneurs tend to start more successful businesses (see e.g. Kaplan and Schoar 2007; Gompers *et al.* 2010).

Our paper contributes to the above by using a dataset covering essentially the entire economy and highlighting serial entrepreneurship as a strong source of heterogeneity in firm performance along several dimensions. Moreover, we document that serial entrepreneur firms on their own contribute disproportionately to aggregate outcomes. As such, the empirical firm-level patterns documented in Section 4 can help further discipline the structural macroeconomic models with heterogeneous firms mentioned above.[5]

2.3. Entrepreneurship and Top Income Inequality

Finally, our paper relates to studies which focus on the importance of entrepreneurship in shaping income and wealth inequality (see e.g. Cagetti and De Nardi 2006). This holds both empirically, since a large share of income of top earners is derived from business owners (see e.g. Piketty *et al.* 2018), and theoretically, since the presence of "superstar entrepreneurs" can help reconcile the fast changes in inequality observed in the data with existing models (see Gabaix *et al.* 2016).

In the last part of this paper, we provide additional insights into this debate. In particular, Section 5.3 shows analytically and quantitatively how the presence of serial entrepreneurship affects top income inequality. Our results, therefore, suggest that accounting for serial entrepreneurship may be a promising direction of research focusing on (changes in) inequality.

3. Data and Definitions

The main purpose of this paper is to document the importance of serial entrepreneurs and their businesses for the macroeconomy. Towards this end, we begin by describing our primary data source and laying out the definitions of key variables.

3.1. Data

Our main data source is Quadros de Pessoal (QP), a census of private sector employees conducted each October by the Portuguese Ministry of Employment, Solidarity and Social Security (MESSS). It is an extremely rich administrative

5. See Hopenhayn and Rogerson (1993) for a seminal contribution on the role of firm dynamics in shaping aggregate outcomes and for instance Sterk *et al.* (2021) for a recent contribution highlighting the role of ex-ante firm heterogeneity in this regard.

employer-employee matched dataset with information at the firm, establishment and individual levels.

The survey covers almost the entirety of the economy's employment, with the exception of civil servants, self-employed and domestic servants.[6] 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.

Therefore, the unique advantage of the QP is its comprehensive information on both businesses (firms and establishments) and individuals, including business owners. We are able to link firm-level characteristics with an individual business owner and track both owners and their businesses over time.[7] This, in turn, allows us to track firm dynamics separately for business owners with different characteristics. In our analysis, we focus on the distinction between "serial" entrepreneurs – owners of multiple businesses – and all other "regular" business owners.

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. Additional checks are carried to make sure that the units which have previously reported in the database are not assigned a different identification number.

In the case of mergers and acquisitions, the identification numbers of the firms involved in the operation are transmitted to the resulting firm, while the others disappear, and are thus counted as exits in the data. However, mergers and acquisitions play a marginal role in Portugal, with Mata and Portugal (2004) estimating that they account for less than 1% of the total number of liquidations.

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

At the worker level, the QP has information on age, gender, education, occupation, date of hire, salary, job title and hours of work. We also have a unique

6. For our analysis, we also drop businesses from the agricultural sector, where coverage is low.

7. 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 S and C corporations) can only be proxied by employees who obtain wages in the first quarter of a firm's operation and who are among the top three earners in the firm. Their data, however, does not allow for the tracking of entrepreneurs over time and therefore cannot speak to serial entrepreneurship, the key focus of the current paper.

variable – "professional status" – which identifies an individual as either an owner of a business, a salaried worker, or both.

3.2. Definitions

The key concept of this paper is serial entrepreneurship. We use it to categorize businesses into those owned by serial entrepreneurs and all other, regular, businesses. Ultimately, therefore, 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 rate of exit. Below, we explicitly define all our key concepts.

Serial entrepreneurs. For every individual in every year, we count the number of businesses in which he or she is recorded as an owner.[8] We define an individual to be a serial entrepreneur if he or she simultaneously owns more than one business in a given year. All other business owners are classified as regular entrepreneurs.[9] Therefore, under this definition serial entrepreneurship is a time-varying characteristic of business owners.

Regular and serial entrepreneur firms. While the QP has information on both firms and establishments, our primary units of observation are firms.[10] In what follows, we will use the term business and firm interchangeably.

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 a serial entrepreneur.[11] All other businesses are classified as "regular (R) firms".

Firm size, growth, productivity and rate of exit. 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 also consistent with a range of existing studies (see e.g. Moscarini and Postel-Vinay 2012; Haltiwanger *et al.* 2013).

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

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

8. As is typical in the literature, when measuring worker characteristics we restrict our sample to individuals aged 16 to 70. Fewer than 1 percent of all entrepreneurs fall outside these bounds.

9. In the Appendix, we make an explicit distinction between regular (R) entrepreneurs and "return" (RE) entrepreneurs who closed their first business, but started another one with at least one year without business ownership in between. The results suggest that RE and R firms are very similar.

10. Note also that in the Portuguese economy, the vast majority (93 percent) of firms are single-establishment businesses (see Félix and Maggi 2019).

11. Note that 65.5% of firms have a single owner in the Portuguese economy.

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. Our analysis primarily focuses on the distinction between SE and R firms. The average growth rate of a group of firms pertaining to a group s can then be written as

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

where $X_t = \sum_s X_{st} = \sum_s \sum_{i \in s} X_{it}$.

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

Finally, we define the average exit rate of a group of firms s in period t as

$$D_{s,t} = \frac{(\#\text{ of exiting firms})_{s,t}}{(\#\text{ of firms})_{s,t}}. \tag{3}$$

When analyzing firm exit at the firm level, we make use of an indicator function. In particular, the indicator function is equal to 1 in period t if that period is the last during which we observe the given firm in the data, and it is equal to zero in all other periods.

High-growth firms. 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 percent per year, over a three year period.[12]

Note, however, that as with the definition of serial entrepreneurship, 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 gazelle, we continue to refer to such businesses as high-growth firms even beyond the age of 5. This allows us to gauge how high-growth firms differ from other businesses throughout their life-cycles, not just in the first five years of their existence or when they exhibit fast growth.

4. Three Facts About Serial Entrepreneurs

In this section we use our unique data to put forward three novel facts about serial entrepreneurs and their businesses. First, serial entrepreneurship is prevalent and not confined to particular industries. Second, on average, firms of serial

12. Practices differ in this case with the OECD using the term gazelle only for *young* (less than 5 years old) high-growth firms. In the Appendix, we show that our results are robust to alternative definitions of high-growth firms, such as those used in e.g. Haltiwanger *et al.* (2017).

entrepreneurs outperform those of regular business owners along several dimensions. Third, these "serial entrepreneur premia" exist throughout firms' life-cycles and hold also within the group of high-growth firms.

4.1. Prevalence of Serial Entrepreneurs

In our dataset, about 17.6 percent of all businesses are serial entrepreneur firms.[13] Recall that our definition of serial entrepreneurship is one of entrepreneurial "fixed effects". That is, almost a fifth of all businesses are owned by individuals who – at some point in the sample – owned multiple firms.

To gauge whether serial entrepreneurship is a trait of only some industries or whether it prevails in the economy as a whole, Table 1 shows firm shares by major industries which cover almost 90 percent of the Portuguese economy. The first column simply depicts the sectoral composition of the economy. The second and third columns report, respectively, the sectoral shares of regular and serial entrepreneur firms.

The values in Table 1 suggest that, by and large, serial entrepreneurship is not a feature specific to a particular industry. Instead, the sectoral composition of serial entrepreneur firms closely matches that of the economy as a whole. The only slight exception is the "real estate and other" sector which is characterized by a noticeably larger share of SE firms, relative to regular businesses.

	All	Regular	Serial
Wholesale and retail trade	33.1	33.1	32.7
Manufacturing	17.2	17.3	17.2
Construction	13.8	14.2	11.9
Accommodation and food services	11.3	11.9	8.7
Real estate and other activities	11.2	10.1	16.7

Table 1. Sectoral composition of regular and serial entrepreneur firms

Notes: The columns show, respectively, "all", "regular" 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.

4.2. The Serial Entrepreneur Premium

Let us now describe how, on average, firms of serial entrepreneurs differ from those of regular business owners.

13. The share of serial entrepreneurs, i.e. the number of business owners with multiple businesses relative to all business owners, is about 4 percent in our data.

Estimation. In particular, to formalize the differences between regular and serial entrepreneur firms, we estimate the following regression

$$y_{i,t} = \alpha + \beta \mathbb{1}_{i \in SE} + \gamma F_{i,t} + \varepsilon_{i,t}, \tag{4}$$

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, $F_{i,t}$.

	Regular	Serial	SE Premium
Size (workers)	4.7	14.7	0.57^{***}
Exit (in %)	8.4	5.6	-2.17^{***}
Growth (in %)	8.9	10.3	3.14^{***}
Productivity (aggregate = 1)	0.83	1.22	0.34^{***}

Table 2. Serial entrepreneur premium

Notes: The columns show, respectively, the unconditional averages of regular and serial entrepreneur firms and the SE premium estimated from regression (4). 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 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.

Serial entrepreneur premia. 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, grow faster and are more productive.

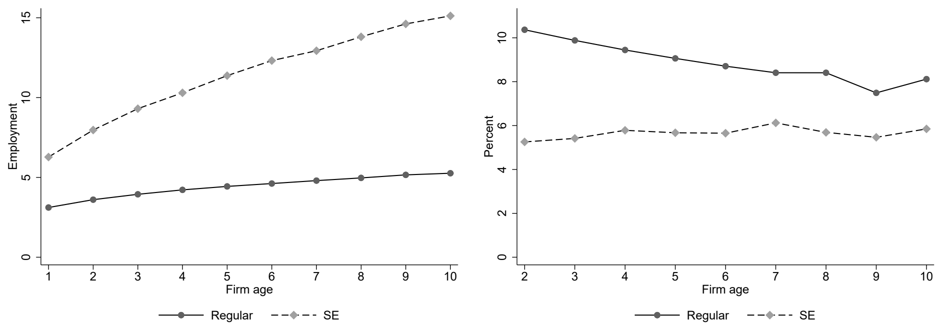
The third column then reports estimates of the respective serial entrepreneur premia, β. The estimates show that, even conditional on other control variables, serial entrepreneur firms outperform regular businesses. Importantly, the estimated premia are not only statistically significant, but they are also quantitatively large. In particular, our results suggest that on average SE businesses are almost 60 percent larger, their exit rates are about 27 percent lower, they grow at a pace which is

35 percent faster and they are 34 percent more productive compared to regular businesses.[14]

4.3. Life-cycle Dynamics of Serial Entrepreneur Firms

Having shown that firms of serial entrepreneurs are prevalent and, on average, substantially outperform regular businesses, we now turn to their life-cycle dynamics. Specifically, this subsection documents that there are marked differences between serial entrepreneur and regular firms throughout their life-cycles and that these differences are present even for the rare, but very important, sub-group of high-growth firms.

Life-cycle profiles of firm size and exit. Figure 1 shows average life-cycle patterns of firm size (left panel) and exit rates (right panel) for regular and serial entrepreneur firms. There is a dramatic difference between the two types of businesses, consistent with the estimated serial entrepreneur premia in Table 2.



(a) Firm size (b) Exit rates

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 subpanels depict regular and serial entrepreneur businesses.

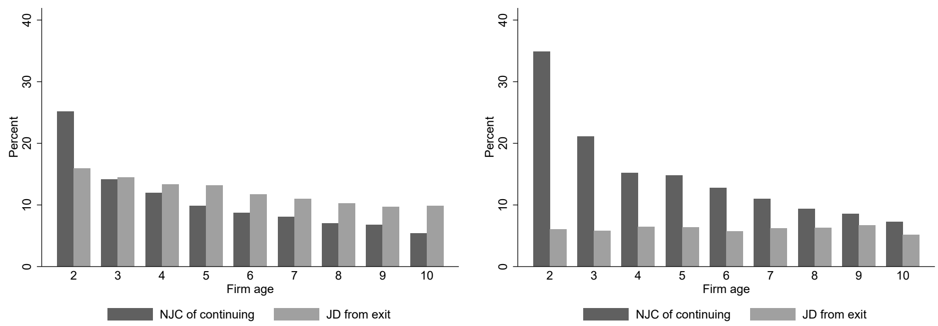
In particular, SE firms not only start up being twice as large as regular businesses, they also more than double in size (on average) within ten years of their existence. In contrast, regular businesses on average grow from about 3 employees at startup to only about 5 workers at the age of 10.

14. In regards the firm exit, the serial entrepreneur premium is estimated at about 2 percentage points. This is about 27 percent of the unconditional average exit rate of 7.4 percent among regular businesses. Similarly in the case of firm growth, the serial entrepreneur premium is estimated at 3.1 percentage points which is about 35 percent of the unconditional average growth rate of 8.9 percent among regular firms.

An even more apparent difference can be observed when comparing the exit rates of regular and SE firms. The rate at which SE firms shut down is not only considerably lower on average, it is also essentially flat over the course of their life-cycle. This contrasts starkly with the strong negative relationship between age and exit rates among regular firms – a known feature in many firm-level datasets around the world (see e.g. Calvino *et al.* 2015).

These results, therefore, suggest that serial entrepreneur firms are characterized by a very different firm selection process compared to regular businesses. Empirical evidence for the average firm points to a strong "up-or-out" process, often linked to productivity-enhancing reallocation at the aggregate level (see Haltiwanger *et al.* 2013). A better understanding of firm dynamics among serial entrepreneurs could, therefore, shed new light on the driving forces behind aggregate growth.

Job creation and destruction over the life-cycle. Consistent with the size and exit patterns in Figure 1, there is a clear difference in the rates of job creation and destruction between regular and serial entrepreneur firms. Figure 2 provides information on net job creation of continuing businesses together with job destruction from exit, by firm age. The left panel depicts regular businesses, while the right panel shows serial entrepreneur firms.



(a) Regular Firms (b) Serial Entrepreneur Firms

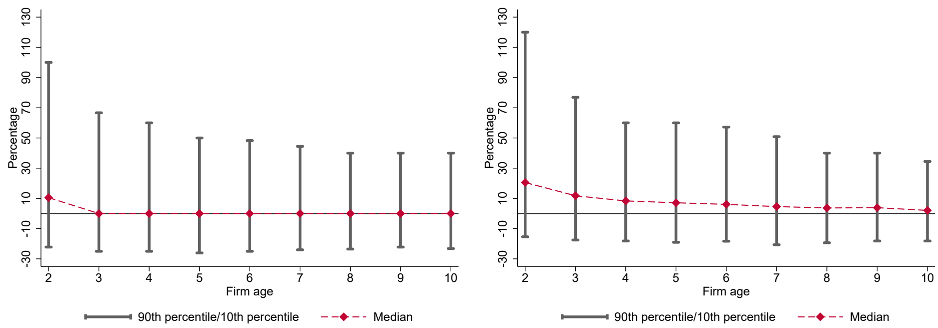
Figure 2: Up-or-out dynamics

Notes: The figure shows net job creation (NJC) rates of continuing businesses, together with job destruction (JD) rates from exit. Both as a function of business age. The left panel depicts regular firms, while the right panel shows serial entrepreneur businesses.

Two patterns stand out. First, net job creation by continuing regular businesses is almost a third lower compared to that by serial entrepreneurs. This holds true across the entire firm life cycle. Second, consistent with the exit patterns discussed above, while job destruction from exit falls with age among regular businesses, it is essentially flat among SE firms. These patterns, therefore, closely mimic those of exit rates in Figure 1.

Life-cycle distributions of firm size growth. Before moving on to the group of high-growth firms, we zoom in on growth dynamics over the life-cycle. Figure 3 shows the distribution of growth rates among regular (left panel) and serial entrepreneur firms (right panel). While the lower end (10th percentile) of the growth distributions is roughly similar across both types of businesses, the upper end (90th percentile) is much higher for serial entrepreneur firms.

Therefore, the higher median (net) growth rate of serial entrepreneurs is driven predominantly by the upper tail, whereby SE firms enjoy more extreme positive growth rates compared to regular businesses. This pattern holds essentially throughout their life-cycles, resulting in positive median growth rates even at the age of 10. On the other hand, the median regular firm stops growing at the age of about 3. These patterns naturally beg the question of the relationship between high-growth firms (gazelles) and serial entrepreneurship to which we turn next.



(a) Regular Firms

(b) Serial Entrepreneur Firms

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.

Serial entrepreneurs and "gazelles". We now turn our attention to an important sub-group of businesses – high-growth firms, so called "gazelles". These firms have been shown to be crucial in explaining the prominent role of startups and young businesses for aggregate job creation (see Haltiwanger *et al.* 2017). The following paragraphs document that even within this highly select group of firms, there are large differences between gazelles of regular and serial entrepreneurs.

To begin with, Table 3 confirms the findings in Haltiwanger *et al.* (2017) that gazelles contribute disproportionately to aggregate employment and job creation. In particular, the first column of Table 3 shows that while only about 9 percent of all firms can be classified as gazelles, they alone account for almost a third of employment and newly created jobs in the entire economy.

	All	Regular	Serial
Firms	8.9	61.0	39.0
Employment	31.1	42.1	57.9
Job creation	30.3	45.9	54.1

Table 3. Contribution of high-growth firms to aggregates (in $\%$)

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%).

The second and third columns of Table 3 then show the contributions of regular and serial entrepreneur gazelles to the overall patterns of high-growth firms. In particular, the table documents that about 40 percent of all high-growth firms are owned by serial entrepreneurs. Given that among all businesses serial entrepreneur firms account for about 18 percent, this means that serial entrepreneurs are about three times as likely to own a gazelle compared to regular business owners.[15]

Finally, we once again estimate our serial entrepreneur premia (4) for the rare sub-group of high-growth firms. Table (4) documents that even in this select group of firms, gazelles of serial entrepreneurs are considerably larger, exit less often, grow faster and are more productive compared to high-growth firms of regular business owners.[16]

	Regular	Serial	SE Premium
Size (workers)	16.4	38.1	0.33^{***}
Exit (in $\%$)	5.5	3.9	-1.36^{***}
Growth (in $\%$)	15.5	13.7	2.42^{***}
Productivity (agg.$=$1)	82.3	116.1	0.27^{***}

Table 4. Serial entrepreneur premium: High-growth firms

Notes: The columns show, respectively, the averages of regular and serial entrepreneur high-growth firms and the SE premium estimated from regression (4). 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.

15. 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, $Pr(\text{gazelle}|R) = 0.09 \times 0.61/0.82 \approx 0.07$ and $Pr(\text{gazelle}|SE) = 0.09 \times 0.39/0.18 \approx 0.20$.

16. The Appendix documents that, as with all firms, these premia are also present over gazelles' life-cycles.

Therefore, our results show that serial entrepreneurs are more likely to own gazelles. This is consistent with findings in Figure 3 which show that the growth distribution of serial entrepreneur firms differs from that of regular businesses mainly in the upper, high-growth, tail. Moreover, even within the group of high-growth firms those owned by serial entrepreneurs do better. In fact, the Appendix shows that serial entrepreneur gazelles tend to grow fast throughout their life-cycles. This contrasts with regular gazelles, for which growth slows after the age of about 6. Serial entrepreneurship, therefore, seems to be a particularly strong predictive characteristic of firm-level success.

5. Micro Origins and Macro Consequences of Serial Entrepreneurship

The previous section provided novel empirical facts about serial entrepreneurs: (i) serial entrepreneurship is prevalent, (ii) serial entrepreneur firms outperform those of regular business owners and (iii) these serial entrepreneur premia exist throughout firms' life-cycles and even among high-growth firms.

In this section, we turn to analyzing the micro-level origins of the serial entrepreneurship premium and their macroeconomic implications. In doing so, we first ask what serial entrepreneurship can tell us about the sources of firm heterogeneity. In particular, we investigate whether the serial entrepreneur premium is an innate, "ex-ante", feature or whether it develops over the course of an entrepreneur's life-time.

Next, we document the extent to which the relatively small share of serial entrepreneur businesses impacts the macroeconomy. As will become clear, serial entrepreneur firms contribute disproportionately to aggregate job creation and productivity growth.

Finally, we illustrate that serial entrepreneurship also has implications for other, widely-debated, questions. In particular, we show theoretically and quantitatively that accounting for serial entrepreneurship is important for our understanding of top income inequality.

5.1. Origins of the Serial Entrepreneur Premium

Studies have shown that micro-level distortions and seemingly small changes to firms' life-cycle patterns can have profound macroeconomic effects (see e.g. Hopenhayn and Rogerson 1993; Clementi and Palazzo 2016). Therefore, the sources of firm-level heterogeneity have been the subject of various empirical, theoretical and quantitative studies.

One view is that firms are subject to ex-post shocks to productivity or demand, which shape their life-cycle patterns (see e.g. Hopenhayn and Rogerson 1993). An alternative view is that there are innate, ex-ante, differences across firms with some businesses simply poised for growth (see e.g. Jovanovic 1982). Recent evidence suggests that firm heterogeneity is, in fact, to a large extent driven by ex-ante characteristics. Moreover, carefully accounting for the importance of ex-ante heterogeneity at the firm level can dramatically change our understanding of *aggregate* dynamics (Sterk *et al.* 2021).

In this subsection, we document that serial entrepreneurship is one such ex-ante characteristic which is associated with superior firm performance. In this sense, we provide new evidence for the debate whether entrepreneurial success is the result of (selection on) ex-ante characteristics or whether it is instead the result of learning or favorable supply or demand shocks (see e.g. Lazaer 2005; Lafontaine and Shaw 2016).

Ex-ante heterogeneity or ex-post evolution? To address the question of the sources of the serial entrepreneur premium, we explicitly distinguish "first" (FSE) and "subsequent" (SSE) businesses of serial entrepreneurs. While FSE firms are those which entrepreneurs owned *before* they became serial entrepreneurs, SSE businesses are the cause of their serial entrepreneur classification.

In what follows we analyze separately the performance of FSE, SSE and R businesses. Their comparison enables us to gauge to what extent the performance of serial entrepreneur firms develops over time in response to ex-post shocks and to what extent it reflects ex-ante heterogeneity.

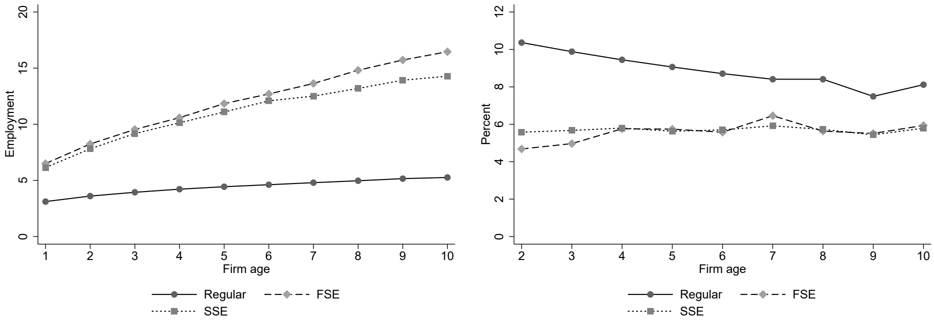
First vs subsequent vs regular businesses. On average, it takes entrepreneurs almost 7 years to found their subsequent business. There is, however, a large degree of heterogeneity in this regard. While the "fastest" 10 percent of serial entrepreneurs start their subsequent businesses within two years, the "slowest" 10 percent do so after about 14 years.

Figure 4 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 essentially the same life-cycle patterns, noticeably superior to those of regular businesses.

These patterns are reinforced by Figure 5 which shows job creation of continuing firms and job destruction from exiting businesses for the three groups of firms. Instead of plotting the levels, however, we directly visualize the *differences* between these respective groups of firms. Specifically, the left panel shows the difference between first businesses of serial entrepreneurs and regular firms. The right panel then shows the difference between subsequent and first firms of serial entrepreneurs.

The left panel confirms that continuing FSE firms create more and exiting FSE businesses destroy fewer jobs compared to their regular firm counterparts. In contrast, the right panel does not show a clear pattern in the job creation and destruction differences between first and subsequent serial entrepreneur firms.

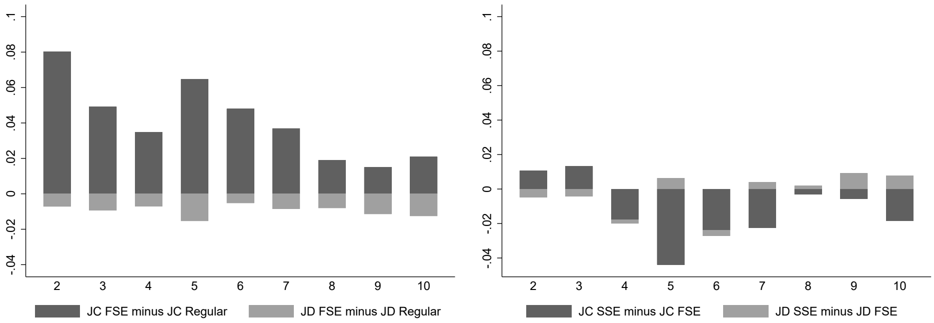
Serial entrepreneur premia for first and subsequent businesses. Finally, to formally test the above patterns, we re-estimate our serial entrepreneur premia



(a) Firm size (b) Firm exit

Figure 4: Size and exit profiles by age: Regular, First SE and Subsequent SE firms

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.



(a) FSE minus Regular (b) SSE minus FSE

Figure 5: Job creation of continuing firms and job destruction from exit: Regular, FSE and SSE

Notes: The left panel plots the differences between regular and first serial entrepreneur firms by firm age, while the right panel shows the differences between subsequent and first serial entrepreneur firms.

for the three groups of firms. Specifically, we consider the following regression

$$y_{i,s,t} = \alpha + \beta \mathbb{1}_{\mathsf{s,s\_comp}} + \delta F_{i,s,t} + \varepsilon_{i,s,t}, \tag{5}$$

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 $s \in \{\mathsf{R}, \mathsf{FSE}, \mathsf{SSE}\}$. 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 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 (5) we again control for age, industry and year fixed effects ($F_{i,g,t}$).

Table 5 shows the results where columns 1 to 3 depict average values of size, exit, growth rates and labor productivity. Columns 4 to 6 show the coefficients β in the various versions of regression (5). While FSE firms are substantially larger, exit less frequently, grow faster and are more productive on average compared to regular businesses (column 4), these premia are somewhat smaller for SSE firms (column 5). Importantly, the premia are comparably negligible or even overturn in sign when comparing subsequent and first serial entrepreneur firms (column 6).

				Premia		
	Regular	FSE	SSE	FSE-R	SSE-R	SSE-FSE
Size (workers)	4.7	16.4	13.7	0.60^{***}	0.41^{***}	0.06^{***}
Exit (in %)	8.4	5.5	5.6	-1.99^{***}	-2.26^{***}	-0.22^{***}
Growth (in %)	8.9	10.5	10.2	3.76^{***}	2.76^{***}	-1.16^{**}
Productivity (agg.=1)	0.83	1.19	1.23	0.37^{***}	0.29^{***}	-0.03

Table 5. FSE and SSE premia

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 (5): "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. *** and ** stand for, respectively, statistical significance at the 1% and 5% levels.

Serial entrepreneur premia and individual business owner characteristics. While the paragraphs above suggest that ex-ante characteristics are the key source of serial entrepreneur premia, they do not pinpoint what such ex-ante characteristics are. We now make a step forward in understanding these patterns by analyzing the relationship between the estimated serial entrepreneur premia and observed individual characteristics of the respective business owners.

Towards this end, we revisit our serial entrepreneur premia regressions (4), but this time we also include a range of observable characteristics of business owners

	Size	Exit	Growth	Productivity
Unconditional	0.572	-2.170	3.143	0.315
Conditional on $G_{i,t}$	0.527	-1.979	2.716	0.245
Contributions of individual entrepreneurial characteristics				
Total contribution	0.045	-0.191	0.427	0.070
- age	0.018	-0.063	0.417	-0.005
- gender	-0.001	-0.029	-0.019	0.009
- education	0.028	-0.099	0.029	0.066

Table 6. Serial entrepreneur premia and owner characteristics

Notes: The table reports results from estimating (6). The first row reporst "unconditional" serial entrepreneur premia, β, which ignore entrepreneur characteristics, $G_{i,t}$. The second row shows serial entrepreneur premia "conditional" on entrepreneur characteristics. The bottom four rows provide the decomposition of the difference between the first and second rows into the individual entrepreneurial characteristics following the procedure in Gelbach (2016). All estimates are statistically significant at the 1% level, with the exception of education in the grwoth regression which is insignificant.

(averaged at the firm-level), $G_{i,t}$:

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

The characteristics of individual entrepreneurs which we consider include their age, gender and education, all measured at the time of startup of (FSE) firms. Similarly to our measurement of serial entrepreneurship, we consider owners' characteristics at the time of startup of their first businesses to be "fixed effects" and use these values also for subsequent firms of serial entrepreneurs.[17]

Table 6 shows the results. The first row estimates (6) while ignoring entrepreneurial characteristics, $G_{i,t}$. The second row reports serial entrepreneur premia conditional on observed owner characteristics and the third row reports the difference between the unconditional and conditional premia, i.e. the "total contribution" of entrepreneurial characteristics. The remaining rows then show the contributions of individual characteristics, following the Gelbach (2016) decomposition which is invariant to the "order of elimination" of regressors.

The results suggest that entrepreneurial characteristics alone can explain between 7 and 22 percent of the estimated (unconditional) serial entrepreneur premia. The single most important contributor to all serial entrepreneur premia is education, consistent with the results in Queiró (forthcoming). While entrepreneurial age seems to be a factor when it comes to the growth premium of serial entrepreneur firms, it does not have a clear overall effect on the estimated premia.

17. The Appendix shows that similar results are obtained when considering a "year-by-year" measurement of entrepreneurial characteristics.

Taking stock. All the results above suggest that the superior performance of serial entrepreneur firms is present from the onset. Therefore, the serial entrepreneur premium is likely the result of (selection on) ex-ante heterogeneity, rather than ex-post evolution, e.g. due to learning. While our results suggest that observable entrepreneur characteristics, especially education, can explain up to a quarter of the estimated premia, a large part of the premia remain unexplained.

In addition, recall that first firms of serial entrepreneurs are defined as the businesses which serial entrepreneurs own *before* starting their second and subsequent businesses which are the reason for their classification as serial entrepreneurs. Therefore, we are likely underestimating the true premia in our sample. This is because some of the entrepreneurs which we have classified as regular will found a subsequent business in the future. If these entrepreneurs also run businesses which are similar in performance to those of existing serial entrepreneurs, this pushes up the average performance of R firms. Despite this effect, we estimate a clear serial entrepreneur premium.

5.2. Aggregate Importance of Serial Entrepreneur Firms

As has been discussed earlier, economists have strived to identify various groups of firms which are most important for driving aggregate outcomes (see e.g. Birch 1981; Guzman and Stern 2015; Haltiwanger *et al.* 2017).

In this context – of striving to understand the firm-level sources of aggregate growth – we document that serial entrepreneur firms have a disproportionate impact on aggregate job creation and productivity growth. These results, therefore, pave a direction for future research into the under-studied group of serial entrepreneurs and their firms.

Contributions to aggregate employment, job creation and destruction. We begin by documenting that serial entrepreneur firms contribute disproportionately to *aggregate* employment and job creation. Specifically, Table 7 shows that while SE businesses represent about 18 percent of all firms, they employ almost 40 percent of the workforce. This is consistent with our estimated premia which show that serial entrepreneur firms are considerably larger compared to regular businesses. Note that this disproportionate employment contribution holds also at entry and exit.

Table 7 further reports that serial entrepreneur firms also create (and destroy) a disproportionate amount of jobs. In particular, firms of serial entrepreneurs are responsible for more than 34 percent of all job creation and almost 29 percent of all job destruction. Overall, serial entrepreneur businesses have a disproportionate impact on the aggregate economy.

Contributions to aggregate productivity growth. Section 4.2 documented that serial entrepreneur businesses are considerably more productive compared to regular

	Firms	Employment	Job creation	Job destruction
Regular	82.4	61.5	65.7	71.3
Serial	17.6	38.5	34.3	28.7

Table 7. Contributions to aggregates (in %): Regular and serial entrepreneur firms

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.

firms. This subsection shows that serial entrepreneur firms also drive a large share of *aggregate* productivity growth.

Towards this end, let us define an industry-specific productivity by

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

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 (the shares $\omega_{it} \geq 0$ sum to one), and q_{it} is again productivity at the firm level. We follow Foster *et al.* (2001) and decompose the change in industry-level productivity as

$$\Delta Q_{jt} = \sum_{s} \left[\underbrace{\sum_{i \in s} \omega_{i,t-1} \Delta q_{it}}_{\text{within}} + \underbrace{\sum_{i \in s} (q_{i,t-1} - Q_{j,t-1}) \Delta \omega_{it}}_{\text{between}} + \underbrace{\sum_{i \in s} \Delta q_{it} \Delta \omega_{it}}_{\text{cross}} \right]. \tag{8}$$

In (8), the first term is based on within-firm productivity changes, weighted by initial market shares in the industry. As such, this 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 share 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.

As a measure of firm-level productivity, $q_{i,t}$, we once again use the logarithm of sales per worker and we focus only on continuing businesses (see e.g. Haltiwanger *et al.* 2016). We compute the decomposition in (8) for every industry-year pair in our data. Finally, to aggregate up to the entire economy, we use average gross output weights, following the approach of Foster *et al.* (2001) and Baily *et al.* (1992).

The first row of Table 7 reports average aggregate productivity growth over our sample period and the contributions of the within, between and cross components

	Total	Within	Between	Cross
Aggregate	8.1	13.0	3.4	−8.3
Serial entrepreneur firms: level	2.9	5.5	0.5	−3.1
Serial entrepreneur firms: share of aggregate	35.8	42.2	14.7	37.3

Table 8. Aggregate productivity growth decomposition

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

from the decomposition in (8). The second and third rows show the contributions of serial entrepreneurs – to each of the elements – in levels and as a share of the aggregate contributions to productivity growth. Overall, our decomposition reveals that aggregate productivity growth is predominantly driven by within-firm growth, with reallocation contributing relatively little and with the cross-term being negative.[18]

Importantly for the focus of our paper, the results suggest that serial entrepreneur firms are crucial for aggregate productivity growth. In particular, they alone account for more than one third (36 percent) of aggregate productivity growth, despite the fact that only about 18 percent of all businesses are owned by serial entrepreneurs.

Taking stock. This subsection provided evidence that serial entrepreneur firms have a disproportionate impact on aggregate job creation and productivity growth. As such, these results contribute to existing studies by highlighting the group of serial entrepreneur businesses as particularly important for aggregate dynamics. Failing to account for such firms (empirically, or theoretically), may therefore skew our view of the macroeconomy.

5.3. Serial Entrepreneurship and 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

18. These results are consistent with Dias and Robalo Marques (2021) and Reis (2013).

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.[19] 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. $\text{Pr}[\text{age} > a] = e^{-\delta a}$.

In this setting, the fraction of top earners, $\text{Pr}[\text{income} > y]$, 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

$$\text{Pr}[\text{income} > y] = \text{Pr}[\text{age} > a(y)] = e^{-\delta a(y)} = \left(\frac{y_0}{y}\right)^{\mu/\delta}. \tag{9}$$

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, $\mu\zeta = \frac{1}{\delta} = \mu\mathbb{E}[A_b]$.

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

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

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.[20] 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.[21] 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.

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.[22] Finally, since longer expected business longevity allows entrepreneurs to accumulate more income, serial entrepreneurship raises top income inequality. Formally, using (9), we can write the income share of the top p percent of earners as

$$S(p) = \left(\frac{100}{p}\right)^{\mu\mathbb{E}[A_e]-1}. \tag{10}$$

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 diversification. We know from Section 4 that, in fact, serial entrepreneurship comes with a premium. Therefore, as a second quantitative

20. The Appendix provides analytical results for a case when this assumption is relaxed.

21. 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.

22. 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).

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 (10) 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 (10) to compute the implied top income shares in the absence of serial entrepreneurship. The results are shown in Table 9. 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.[23] Therefore, even when serial entrepreneurship is viewed as only a means of risk diversification, it has quantitatively important implications for top income inequality.

Generalized model: SE firms with empirical serial entrepreneur 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 $(\mu_i,\ y_{0,i})$, 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

23. 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).

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.

	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

Table 9. Top income inequality (in $\%$): data and model

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 4, third row. In both cases, we use the formula (10) to compute the implied top income shares.

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 10 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.

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		

Table 10. Model estimation: moments and parameters

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.

Generalized model: Results. The last row of Table 9 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 (10), 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 30.3 and 9.2. In other words, serial entrepreneurship – while accounting for the premia estimated in Section 4 – 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.

6. Discussion and Concluding Remarks

In this paper we use a unique administrative dataset from Portugal, which enables us to link firm characteristics to those of their owners. Our primary focus is on serial entrepreneurs – business owners who simultaneously own multiple firms. Using our dataset, we show three novel facts about serial entrepreneur firms: (i) they are prevalent and not confined to a particular sector, (ii) they outperform all other businesses along several dimensions and (iii) these serial entrepreneur premia are present throughout the life-cycles of firms and also within the select group of high-growth firms.

Next, our analysis focused on a better understanding of the micro-level sources and macroeconomic consequences of serial entrepreneurship. In particular, our results suggest that the superior performance of serial entrepreneur firms is driven by selection on ex-ante characteristics, rather than the result of favorable ex-post shocks or learning. Moreover, we documented that serial entrepreneur firms disproportionately contribute to aggregate job creation and productivity growth, as well as to top income inequality.

We believe that individually our results may be used for various purposes, such as providing moments for the disciplining of heterogeneous firm macroeconomic models or as a guide for the introduction of serial entrepreneurship into existing models of firm dynamics. An important question which we have left for future research how serial entrepreneurship may impact policy. Our results open the door to investigating how existing institutional arrangements support or hinder the incentives to pursue serial entrepreneurship. Similarly, a key question is whether serial entrepreneurs respond differently to policy interventions, compared to other firms. Grasping such patterns may then help further our understanding of, for instance, the transmission of monetary policy in an environment with heterogeneous firms (see e.g. Ottonello and Winberry 2020).

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Appendix A: Robustness

This Appendix provides robustness checks for our key empirical findings. In particular, we focus on alternative definitions of serial entrepreneurship and of high-growth firms.

A.1. Alternative measurement of serial entrepreneurs

The results in Section 4, we use the "fixed effect" definition of serial entrepreneurship. In this Appendix, we document that very similar results are obtained using the alternative, "year-by-year" definition. This is intuitive, since in Section 5.1 we show that first and subsequent firms of serial entrepreneurs have very similar characteristics.

More concretely, Tables A.1 to A.4 below replicate Tables 1 to 4 in the main text. Similarly, Figures A.1 to A.4 replicate Figures 1 to 3 in the main text. All the results suggest that even under the "year-by-year" definition of serial entrepreneurship, our three facts remain to hold (i) serial entrepreneurship is prevalent and not confined to particular industries, (ii) on average, firms of serial entrepreneurs outperform those of regular business owners along several dimensions and (iii) these "serial entrepreneur premia" exist throughout firms' life-cycles and hold also within the group of high-growth firms.

	All	Regular	Serial
Wholesale and retail trade	33.2	33.1	34.1
Manufacturing	17.4	17.4	16.2
Construction	14.4	14.6	11.1
Accommodation and food services	11.1	11.3	7.4
Real estate and other activities	11.2	10.9	18.2

Table A.1. Sectoral composition of regular and serial entrepreneur firms: year-by-year definition

Notes: The columns show, respectively, "all", "regular" 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.

A.2. Alternative definition of high-growth firms

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 percent. 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.

	Regular	Serial	SE Premium
Size (workers)	5.9	12.8	0.53^{***}
Exit (in %)	8.0	6.8	-0.68^{***}
Growth (in %)	10.3	11.4	1.99^{***}
Productivity (agg. = 1)	0.87	1.24	0.31^{***}

Table A.2. Serial entrepreneur premium: year-by-year definition

Notes: The columns show, respectively, the unconditional averages of regular and serial entrepreneur firms and the SE premium estimated from regression (4). 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.

	All	Regular	Serial
Firms	8.6	88.8	11.2
Employment	21.3	84.7	15.3
Job creation	28.7	85.6	14.4

Table A.3. Contribution of high-growth firms to aggregates (in %): year-by-year definition

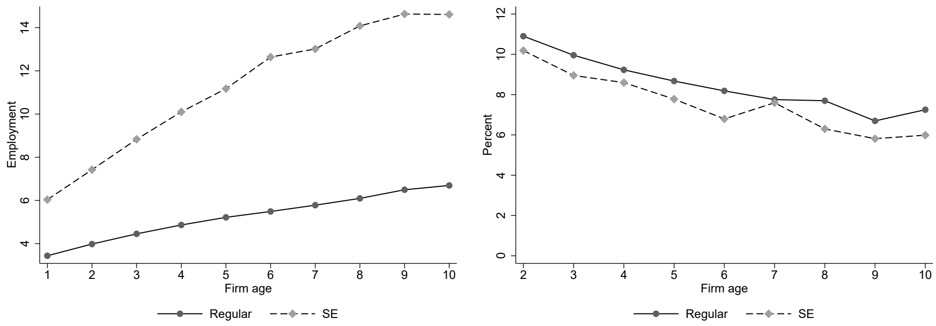
Notes: The table reports characteristics of all high-growth firms (first column) and those owned "regular" and "serial" entrepreneurs (second and third columns). Shares are in % of all businesses in the first column, while they are a fraction of all high-growth firms in the second and third columns (hence,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

	Regular	Serial	SE Premium
Size (workers)	22.8	32.3	0.27^{***}
Exit (in %)	4.6	3.6	-0.92^{***}
Growth (in %)	16.0	15.4	0.82
Productivity (agg.=1)	93.2	122.4	0.23^{***}

Table A.4. Serial entrepreneur premium: High-growth firms - year-by-year definition

Notes: The columns show, respectively, the averages of regular and serial entrepreneur high-growth firms and the SE premium estimated from regression (4). 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.

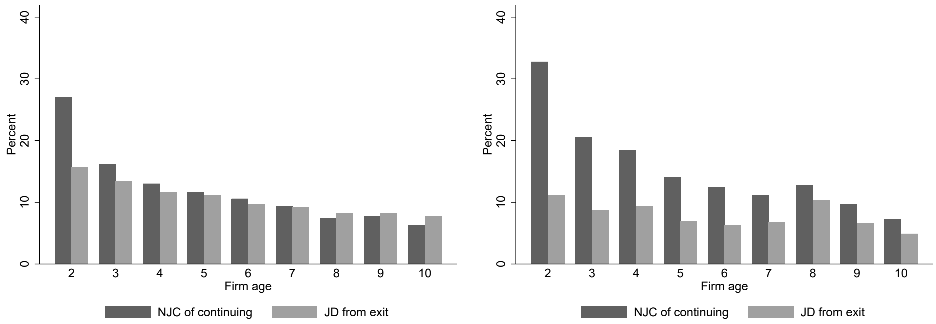
Tables A.5 and A.6 replicate Table 3 and 4 in the main text. The results in this Appendix, therefore, suggest that even under an alternative definition of gazelles, high-growth firms still remain to be disproportionately important for aggregate



(a) Firm size (b) Exit rates

Figure A.1: Size and exit profiles by age: year-by-year definition

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.



(a) Regular Firms (b) Serial Entrepreneur Firms

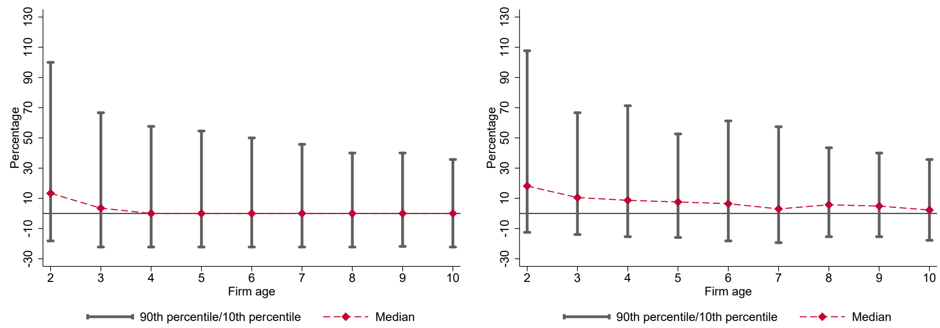
Figure A.2: Up-or-out dynamics: year-by-year definition

Notes: The figure shows net job creation rates of continuing businesses, together with job destruction rates from exit. Both as a function of business age. The left panel depicts regular firms, while the right panel shows serial entrepreneur businesses.

employment and job creation and gazelles owned by serial entrepreneurs outperform regular high-growth firms.

Appendix B: Additional empirical results

In this Appendix we provide a range of additional empirical results.

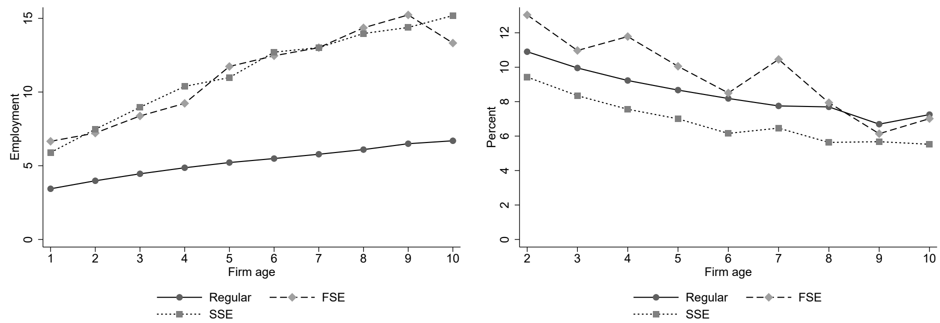


(a) Regular Firms

(b) Serial Entrepreneur Firms

Figure A.3: Employment growth distributions: year-by-year definition

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.



(a) Firm size

(b) Firm exit

Figure A.4: Size and exit profiles by age: Regular, First SE and Subsequent SE firms: year-by-year definition

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.

B.1. Business dynamics of all firms

Figure B.1 depicts the average life-cycle profiles of firm size and exit in the Portuguese economy. Comparing this figure with Figure 1 shows that, unsurprisingly, average life-cycle dynamics fall in between those of regular and serial entrepreneur businesses.

	All gazelles	SE gazelles
Firms	22.4	19.3
Employment	20.5	38.6
Job creation	74.1	39.9

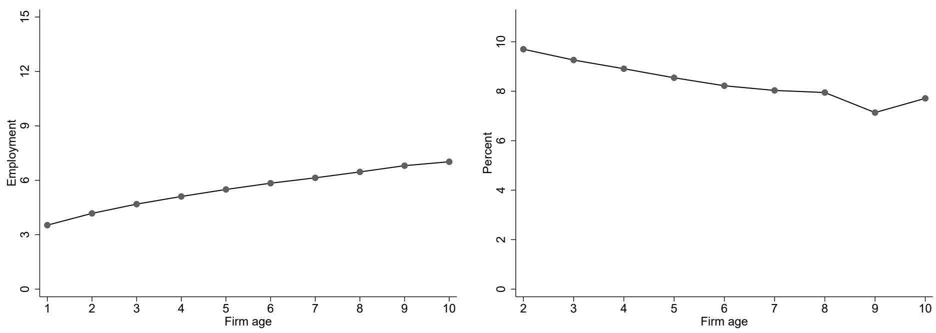
Table A.5. Contribution of high-growth firms to aggregates (in %): alternative definition

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.

	Regular	Serial	SE Premium
Size (workers)	5.6	15.4	0.502^{***}
Growth (in %)	58.0	61.7	0.055^{***}
Productivity (aggregate = 1)	0.88	1.28	0.231^{***}

Table A.6. Serial Entrepreneur Premium for high-growth firms: alternative definition

Notes: The columns show, respectively, the averages of regular and serial entrepreneur continuing high-growth firms and the SE premium estimated from regression (4). The rows depict, respectively, average (employment) size, job creation rates. Ordinary Least Squares estimates with robust standard errors clustered at the firm level in parentheses. *** stands for statistical significance at 1%.

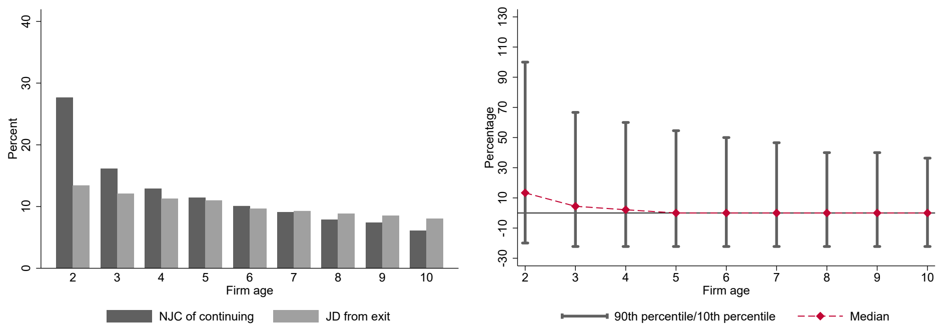


(a) Firm size (b) Exit rates

Figure B.1: Size and exit profiles by age of all firms

Notes: The left panel shows average firm size by age, while the right panel shows average exit rates by age.

Similarly, Figure B.2 depicts net job creation of continuing businesses and job destruction from exiting firms. Again, the patterns are for all businesses, rather than conditioning on regular or serial entrepreneurs. As is typical in other countries, both net job creation and job destruction from exit decline with age. These patterns are then reflected in the growth rate distribution which shows that effectively the median firm older than 4 years does not grow.



(a) Net job creation and destruction from exit (b) Growth rate distribution

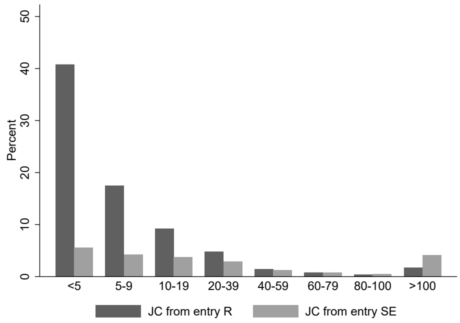
Figure B.2: Up-or-out dynamics

Notes: The left panel of the figure shows net job creation rates of continuing businesses, together with job destruction rates from exit. Both as a function of business age. The right panel shows the distribution of growth rates (10th and 90th percentiles, together with the median) as a function of firm age.

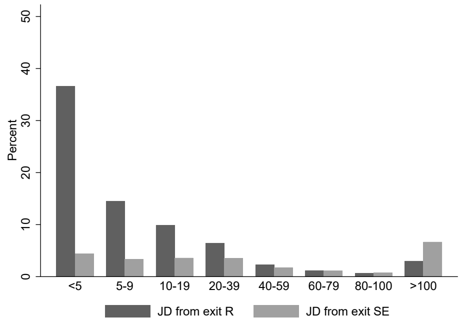
B.2. Size distribution of startups and exiting firms

Figure B.3 shows job creation from entry (left panel) and job destruction from exit (right panel) as a function of firm size. The figure confirms that new businesses of serial entrepreneurs are on average larger than their regular counterparts. In particular, the firm size distribution of SE startups is heavily skewed to the right with about 18 percent of all job creation among SE startups coming from new SE firms with more than 100 workers. In contrast, regular startups are rarely this large – the job creation share of regular businesses with more than 100 workers is only about 2 percent. Overall, SE businesses create about 23 percent of all jobs among startups, almost double of their firm share at startup (13 percent). This again points to the fact that SE businesses start up substantially larger than R firms.

The size distribution of exiting firms (right panel of Figure B.3) effectively mirrors that of entering businesses. While regular firms which shut down are predominantly small, large serial entrepreneur firms (with more than 100 workers) account for 26 percent of job destruction from exit among SE businesses. Interestingly, serial entrepreneur firms account for 25 percent of all job destruction from exit, despite the fact that out of all firms which shut down only 12 percent of them are SE businesses. This confirms that also exiting SE firms are on average considerably larger than regular businesses which shut down.



(a) Startups



(b) Exiting firms

Figure B.3: Job creation from entry and job destruction from exit

Notes: The figure shows job creation shares from entry and job destruction shares from exit by size categories for regular and serial entrepreneur firms.

		Gazelles	
	All firms	Regular	Serial
Wholesale and retail trade	33.1	18.6	25.0
Manufacturing	17.2	33.0	28.4
Construction	13.8	22.4	15.0
Accommodation and food services	11.3	6.4	7.0
Real estate and other activities	11.2	9.2	13.4

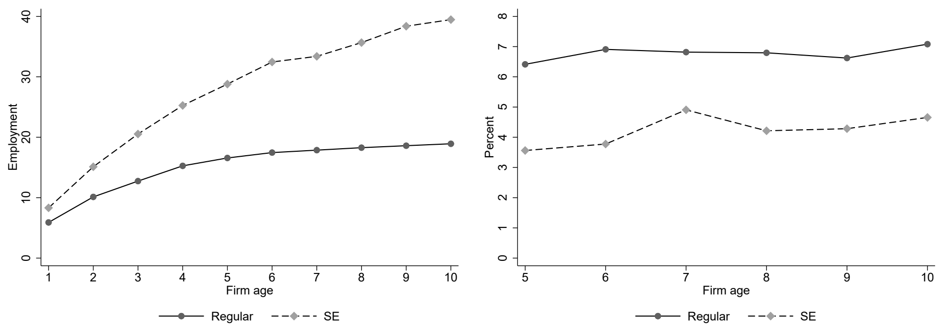
Table B.1. Sectoral composition of all and high-growth firms

Notes: The columns show, respectively, the sectoral shares of "all" firms, and "regular" and "serial" entrepreneur high-growth firms. The values report the shares (in %) of each group of businesses across five broad industries.

B.3. High-growth firms

In this Appendix we provide further details on high-growth firms (defined as in the main text). First, Table B.1 shows that gazelles are somewhat more likely to appear in Construction and Manufacturing (their sectoral shares are higher compared to those of all businesses), while they are somewhat less likely to be in Wholesale and Retail Trade, and in Accommodation and Food Services. Within the group of high-growth businesses, regular and SE gazelles have a similar sectoral composition with the exception of Construction and Wholesale and Retail Trade. While in the former SE gazelles are far less common, they are relatively more common in the latter compared to regular gazelles.

Second, Figure B.4 depicts the life-cycle profiles of firm size and exit rates of regular and serial entrepreneur gazelles. The figure makes clear that, as with all other businesses, also gazelles owned by serial entrepreneurs considerably outperform their regular counterparts.



(a) Firm size (b) Exit rates

Figure B.4: 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 subpanels depict regular and serial entrepreneur high-growth businesses.

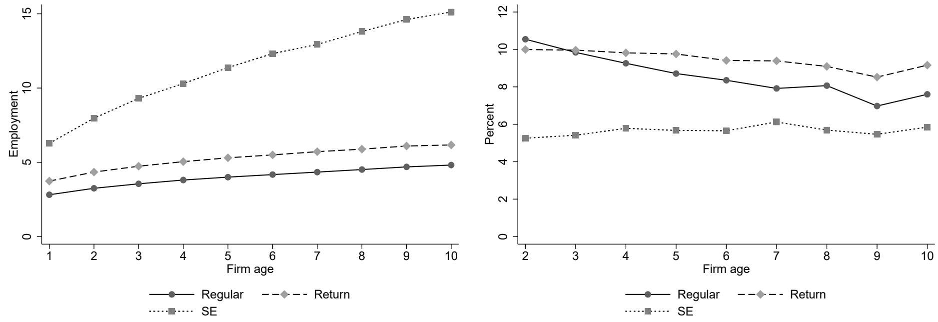
B.4. Return entrepreneurs

Within the group of regular entrepreneurs, we can define those who own multiple businesses, but never simultaneously – so called "return entrepreneurs". Figure B.5 and Table B.2 show that such return entrepreneurs are very close to the group of regular entrepreneurs. For this reason, we do not group them together with serial entrepreneurs in the main text.

B.5. Further details on entrepreneurial characteristics

Section 4.1 estimates serial entrepreneur premia conditional on observed entrepreneurial characteristics. In this Appendix, we provide further details and results.

Table B.3 shows average characteristics of entrepreneurs – regular and serial – for our sample period. The observed characteristics include age, education and gender. Education in our dataset is a categorical variable reporting the highest completed level of education from "no schooling" to "college degree". We convert this into number of years spent in schooling by assigning average number of years spent in each education level.



(a) Firm size

(b) Exit rates

Figure B.5: Size and exit profiles by age: Regular and return 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, return and serial entrepreneur businesses.

				Premia	
	Regular	Return	SSE	R-RE	SSE-RE
Size (workers)	4.3	5.6	14.7	0.20***	0.64***
Exit (in %)	8.1	8.9	5.6	-0.94***	-1.80***
Growth (in %)	8.9	9.5	10.3	-0.15	3.25***
Productivity (agg.=1)	0.79	0.89	1.22	-0.07***	0.37***

Table B.2. SE premia over regular and return entrepreneurs

Notes: The first three columns show, respectively, the averages of regular, first and subsequent serial entrepreneur firms. Columns 4 and 5 show, respectively, premia estimated from (5): "R-RE" is the premium of return entrepreneur businesses over regular firms and "SSE-RE" is the premium of serial entrepreneur businesses over return 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 5% levels.

Panel A of Table B.3 shows entrepreneurial characteristics across all business owners. Panel B then reports these characteristics measured at the time of the start of (FSE) firms.

The values suggest that serial entrepreneurs are about 3 years older, have about 1.5 years of more education and are about half as likely to be women, compared to regular business owners. In our sample we observe that 42% of all workers are women. Therefore females are under-represented among regular, but especially among serial entrepreneurs.

Finally, Table B.4 shows the contributions of different entrepreneurial characteristics to the estimated serial entrepreneur premia, but where such

	Regular	Serial
A: Across all entrepreneurs		
Age (years)	42.3	45.8
Schooling (years)	8.2	9.7
Female share (%)	30.0	17.7
B: At start of first business		
Age (years)	38.8	43.4
Schooling (years)	8.9	10.4
Female share (%)	32.6	19.3

Table B.3. Average descriptive statistics of entrepreneurs

Notes: The table reports average descriptive statistics for "regular" and "serial" entrepreneurs. Panel A computes these values for all entrepreneurs in our sample, panel B does the same but only for those where we observe the very first business. Schooling and age are measured in years. The share of female entrepreneurs is reported in %.

	Size	Exit	Growth	Productivity
Unconditional	0.512^{***}	-2.346^{***}	2.961^{***}	0.314^{***}
Conditional on $G_{i,t}$	0.484^{***}	-2.301^{***}	2.751^{***}	0.246^{***}
Contributions of individual entrepreneurial characteristics				
Total contribution	0.028	-0.044	0.210	0.068
- age	0.000^{a}	-0.002^{b}	-0.045^{b}	-0.001
- gender	0.001	-0.052	0.102	0.010
- education	0.027	0.010^{a}	0.153	0.059

Table B.4. Serial entrepreneur premia and owner characteristics measured year-by-year

Notes: The table reports results from estimating (6). The first row reporst "unconditional" serial entrepreneur premia, β, which ignore entrepreneur characteristics, $G_{i,t}$. The second row shows serial entrepreneur premia "conditional" on entrepreneur characteristics. The bottom four rows provide the decomposition of the difference between the first and second rows into the individual entrepreneurial characteristics following the procedure in Gelbach (2016). a stands for no statistical significance at 10% significance level and b stands for statistical significance at 5% significance level.

characteristics are measured on a "year-by-year" basis. The results are similar to those in the main text – education is a key driver of entrepreneurial success.

Appendix C: Details about analytical results

In this Appendix we provide the provide details on our analytical results in the main text.

C.1. Serial entrepreneurship and risk diversification

The model presented in Section 5.3 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

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

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 (C.1), 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

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

C.2. Serial entrepreneurship as more than just diversification

An alternative view – though still simplified – is that serial entrepreneurship enables business owners to expand their venture over and above to what would be allowed by owning one firm only. One way to think about this is to assume that firms have a natural, "optimal", firm size. Serial entrepreneurship is then a means of scaling business operations that overcomes such decreasing returns.

Assume the following environment. As before, businesses start with productivity q_0 which grows over time at rate μ. Each business is subject to an exogenous destruction rate of δ. Finally, business owners also face a probability σ of obtaining an additional business opportunity.

In contrast to our previous setting, however, we assume that taking up the additional business opportunity does not mean that entrepreneurial effort is diversified. Instead, we assume that the original business continues as before while the new business starts from scratch, i.e. with productivity q_0.

Let us formalize what our setting means for the evolution of income (productivity). For tractability, we assume that business owners can have at most 2 firms (i.e. a conservative assumption). Expected income is then a combination of income from the first and the second firm. The latter, however, can be started at any period after the founding of the first business. Therefore, there is heterogeneity in incomes, depending on the age of the second business and this needs to be taken into account. In particular, expected entrepreneurial income (for $a > 0$) can be written as

$$y(a) = \underbrace{y_0 e^{\mu a}}_{\text{1st firm}} + \underbrace{\sum_{j=0}^{a-1} (1-\sigma)^j \sigma y_0 e^{\mu(a-1-j)}}_{\text{2nd firm}}, \tag{C.2}$$

where the second term takes into account the different possibilities of when the 2nd business could have been started. For instance, at age 1, i.e. in the first year after starting the original business, only a fraction σ of entrepreneurs start a 2nd business. The latter then delivers income of y_0, i.e. $y(1) = y_0 e^{\mu} + \sigma y_0$. At age 2, the fraction of entrepreneurs who started in year 1 see their income grow. In addition, another fraction σ (of those who still own only 1 business, i.e. $(1-\sigma)$) start a 2nd business, which brings income y_0. Therefore, expected income is $y(2) = y_0 e^{2\mu} + \sigma y_0 e^{\mu} + (1-\sigma)\sigma y_0$.

Let us define $\theta = (1-\sigma)e^{-\mu} < 1$ and write

$$y(a) = y_0 e^{\mu a} + \sigma y_0 e^{\mu(a-1)} \sum_{j=0}^{a-1} (1-\sigma)^j e^{-\mu j} = y_0 e^{\mu a} + \sigma y_0 e^{\mu(a-1)} \sum_{j=0}^{a-1} \theta^j \quad \text{(C.3)}$$

$$= y_0 e^{\mu a}(1 + e^{-\mu} \sum_{j=0}^{a-1} \theta^j)$$

$$= \underbrace{y_0 e^{\mu a}}_{\text{income without serial entrepreneurship}} \underbrace{\left(1 + e^{-\mu} \frac{1-\theta^{a-1}}{1-\theta}\right)}_{\text{serial entrepreneurship income correction factor}} . \quad \text{(C.4)}$$

As in the original exercise without serial entrepreneurship, we can use (C.3) to express the age necessary to achieve a certain income level, $a(y)$. This time, however, we take into account that on average entrepreneurs of a certain age potentially own 2 businesses which have been started at various points in the past.

Unfortunately, the above does not allow for closed form solutions. However, (C.3) can be readily solved with a non-linear solver for a grid of possible income values. Using again $\delta = 0.09$ and $\mu = 0.04$ and setting σ such that the share of serial entrepreneurs $SE_{\text{share}} = \sigma(1-\delta)/(1-(1-\delta)(1-\sigma))$ is about 17% as before we get the distributions visualized in Figure C.1.[24]

There are two takeaways. First, the serial entrepreneur income correction factor "fattens" the distribution (panel A). Second, the central Pareto property of the income distribution – that the conditional mean of the distribution above a certain threshold, relative to that threshold, is constant – changes somewhat (panel B). In particular, for lower incomes this Pareto property is higher than predicted by the "no serial entrepreneur" model. Interestingly, this type of pattern is also present in the data (see e.g. Figure 4 in Jones, Kim (2018)).

Therefore, considering serial entrepreneurship not only helps in explaining higher inequality (as with our previous way of modelling). It also helps in a better characterization of the full income distribution.

24. The share of serial entrepreneurs is given by $0 + (1-\delta)\sigma + (1-\delta)^2(1-\sigma)\sigma + ... = (1-\delta)\sigma(1 + (1-\delta)(1-\sigma) + (1-\delta)^2(1-\sigma)^2 + ... = (1-\delta)\sigma/(1-(1-\delta)(1-\sigma))$.

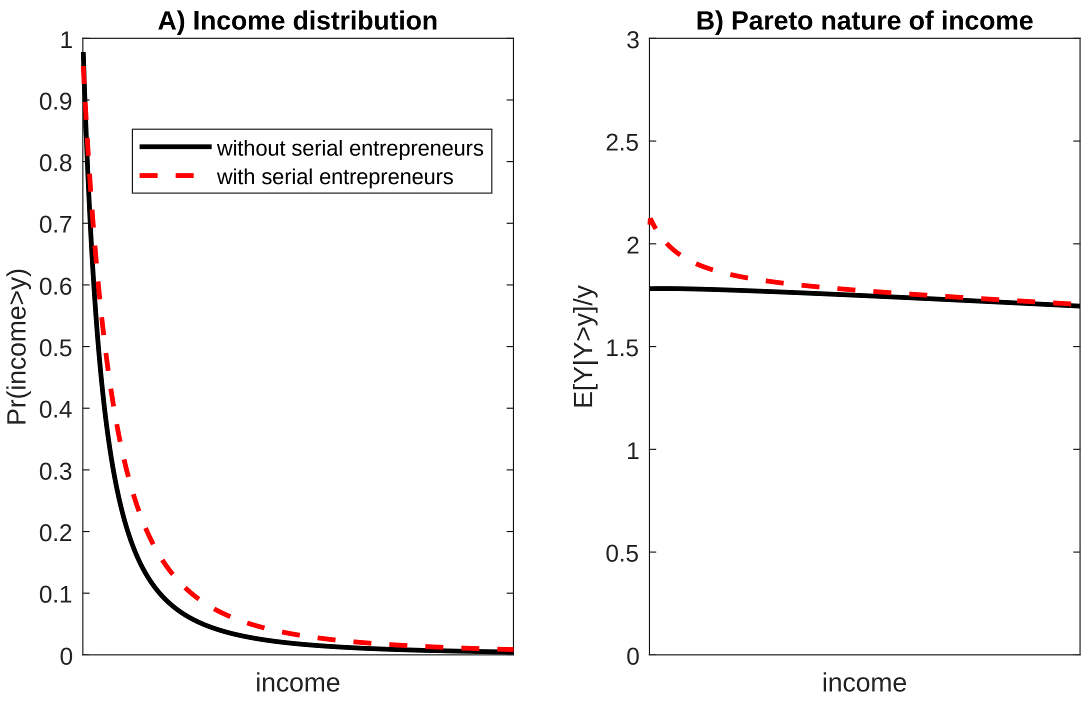


Figure C.1: Implied income distribution

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