Serial Entrepreneurs and the Macroeconomy*

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Abstract

Are serial entrepreneurs – owners of multiple firms – only rare occurrences or are they important for understanding the macroeconomy and aggregate business dynamism? Using unique administrative data, we document four new facts about firms of serial entrepreneurs: compared to other businesses, they (i) disproportionately contribute to aggregate job creation and productivity growth, (ii) are bigger and faster-growing, (iii) shape aggregate business dynamics and (iv) already the very first firms of serial entrepreneurs display superior performance. Finally, we discuss implications of our results for theoretical and quantitative macroeconomic models which – despite embracing firm heterogeneity – effectively ignore serial entrepreneurship.

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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?

In this paper, we use unique, economy-wide, administrative data to document that serial entrepreneurs are indeed important for the macroeconomy. The underlying reason is their crucial role for aggregate business dynamism, which has long been recognized to be important for macroeconomic outcomes (see e.g. Haltiwanger, 2012). In particular, our paper puts forward four new empirical facts about firms of serial entrepreneurs:

Fact 1: Important for the Macroeconomy
Serial entrepreneur firms disproportionately contribute to aggregate job creation and productivity growth.

Fact 2: Bigger and Faster-Growing
Compared to regular businesses, the firm size distribution of serial entrepreneur firms has a thicker right tail, and it fans out faster with firm age.

Fact 3: Drivers of Aggregate Business Dynamism
Compared to regular businesses, serial entrepreneur firms display lower exit rates and steeper life-cycle growth profiles (even among high-growth firms – "gazelles"), shaping aggregate business dynamism.

Fact 4: Better from the Beginning
Already the very first businesses of serial entrepreneurs are larger, grow faster, exit less often and are more productive than regular firms.

These results do not constitute "just" a set of new empirical facts about serial entrepreneur businesses. They also have important implications for *theoretical and quantitative* models of the macroeconomy which – despite embracing firm heterogeneity – effectively completely ignore serial entrepreneurship. In particular, our findings directly relate to a long-standing debate about the nature of firm growth and how it is impacted by micro-level frictions (see e.g. Gibrat, 1931; Axtell, 2001; Cabral and Mata, 2003; Kondo et al., 2021). In addition, this paper has immediate implications for macroeconomic mod-

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

els with firm dynamics, which have been successfully applied to study a wide range of questions.[2] Our results not only provide new empirical moments which can instill further discipline on these models, but they also offer guidance for the development of new frameworks which – given the aggregate importance documented in this paper – may aim to explicitly account for serial entrepreneurship.

In order to obtain our results, we make use of a unique administrative employer-employee matched panel dataset from Portugal, the Quadros de Pessoal (QP), which covers the universe of private sector firms (with at least one employee) and their workers. A key advantage of the QP – which runs from 1986 to 2017 – is that it explicitly identifies business owners and tracks them over time. This is true not only for sole proprietors and partnerships, but for all businesses in our dataset. We define serial entrepreneurs as business owners who simultaneously own at least two firms at some point within our sample. Note that under our definition, serial entrepreneurship is a permanent characteristic, a "fixed effect", of business owners.[3] 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.

At first glance, serial entrepreneurs and their businesses may not inspire great interest from a macroeconomic perspective. Only about 4 percent of all business owners are serial entrepreneurs and their firms represent less than 18 percent of all businesses. However, we show that serial entrepreneur firms considerably outperform regular businesses: they are larger, grow faster, exit less often and are more productive.[4] These "serial entrepreneur premia" – versions of which have been documented in other studies – provide a prelude to our key results concerning the aggregate importance of serial entrepreneur businesses.[5]

Fact 1 constitutes the headline result of this paper: while serial entrepreneur firms account for less than 18 percent of all businesses, they alone are responsible for more than 1/3 of aggregate job creation and productivity growth. This fact makes a strong case that further studying serial entrepreneurship should not be relegated to niche corners of the profession, but that it can even help us understand macroeconomic patterns. The remaining three facts dig deeper into the underlying sources of our headline result.

Specifically, Fact 2 documents two key features related to the firm size distributions of serial entrepreneur and regular firms. First, the size distribution of SE firms has a

[2]Heterogeneous firm models have been successfully applied to understand various topics including the impact of trade, monetary or fiscal policy, to study (financial) frictions and misallocation or to analyze growth and innovation (see e.g. Melitz, 2003; Midrigan and Xu, 2014; Sedláček and Sterk, 2019; Ottonello and Winberry, 2020; Acemoglu et al., 2018).

[3]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.

[4]These conclusions hold true even conditional on various control variables, such as firm age, industry and year fixed effects.

[5]Similar results can be found in e.g. Chen (2013); Lafontaine and Shaw (2016); Shaw and Sørensen (2019).

thicker right tail, i.e. it is skewed towards larger businesses. For instance, while less than 3 percent of all regular firms employ more than 20 workers, this threshold is surpassed by about 13 percent of serial entrepreneur firms. Second, the size distribution of SE firms fans out faster as businesses age. This points towards differences in life-cycle growth profiles between serial entrepreneur and regular firms. Therefore, while the aggregate importance of serial entrepreneur firms is partly due to their larger size (also evident at startup), a key role is also played by their stronger growth performance.

Therefore, Fact 3 zooms in on the respective patterns of business dynamism within our two types of firms. As other economies, Portugal is also characterized by so-called "up-or-out" dynamics by which young firms face high rates of exit, but surviving young businesses display strong growth. Our results show that serial entrepreneur businesses play a dominant role in shaping *aggregate* up-or-out dynamics.

Specifically, we document that, compared to regular businesses, the life-cycle growth profile of SE firms is considerably steeper. On the other hand, regular firms are characterized by higher exit rates. Therefore, while SE firms are largely responsible for the "up" part, R businesses make up much of the "out" part of aggregate up-or-out dynamics. Interestingly, these patterns hold even within the select group of high-growth firms – so called "gazelles".[6] In particular, serial entrepreneurs are not only about three times as likely to own high-growth firms, but the gazelles they own are larger, less likely to shut down, grow faster and are more productive compared to those owned by regular owners.

The final Fact 4 answers the question of *when* SE firms realize their strong potential. In particular, it analyzes whether serial entrepreneurs found businesses with superior performance from the beginning, or whether they succeed only gradually as they open their subsequent firms. Towards this end, we explicitly distinguish between "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. Our results show that even FSE firms significantly outperform regular businesses. While SSE firms also outperform regular businesses, their performance is not significantly different from that of FSE firms.

As mentioned earlier, our results not only provide novel empirical insights into the importance of certain firms for the macroeconomy, they also directly relate to *theoretical and quantitative* macroeconomic models with firm dynamics. In these models, firm-level heterogeneity is what ultimately shapes aggregate responses to shocks and policies (see Sterk ⓡ al., 2021). However, the heterogeneity generated by these models is determined by *unobserved* firm-specific drivers, such as productivity or demand shocks. In order to discipline these firm-level forces – and in turn to discipline the model-predicted aggregate

[6] 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.

responses – researchers typically require the model to match salient features of the data related to firm dynamics. In this context, our results constitute a novel set of empirical moments to which such models can be parameterized, as well as providing new insight into the channels which may be responsible for the observed patterns.

For instance, the firm size distribution and up-or-out dynamics play a central role in analyzing cross-country differences in misallocation (see e.g. Hsieh and Klenow, 2014) or the impact of financial frictions (see e.g. Midrigan and Xu, 2014). Similarly, Fact 4 – showing that already the very first businesses of serial entrepreneurs display superior performance – points towards (selection on) ex-ante characteristics or persistent effects of initial conditions as potentially key driving forces of firm growth (see e.g. Luttmer, 2007; Sedláček and Sterk, 2017; Akcigit et al., 2021). In contrast, relatively less support is given to other mechanisms such as entrepreneurial learning or transitory ex-post shocks (see e.g. Lazaer, 2005; Lafontaine and Shaw, 2016; Shaw and Sørensen, 2021).

Finally, while empirical studies of serial entrepreneurship exist – we provide a brief review of the still relatively rare literature below – serial entrepreneurs are effectively completely missing from theoretical and quantitative work. Given the aggregate importance of serial entrepreneurs documented in this paper, our results also point out an important gap in the current literature. Therefore, we believe that our paper opens the door to future research on this – largely ignored, but quantitatively important – phenomenon.[7]

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, defines key variables and provides basic descriptive statistics from our dataset. Section 4 documents our four new empirical findings, and also provides a discussion of their implications for theoretical and quantitative models. Finally, Section 5 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 (see e.g. Chen, 2013; Lafontaine and Shaw, 2016; Shaw and Sørensen, 2019). To the best of our knowledge, however, we are the first to study the *macroeconomic* impact of serial entrepreneurship. We do so both by directly quantifying their macroeconomic footprint, but also by analyzing the impact they have on average *firm dynamics* which have been empirically and theoretically linked to productivity-enhancing reallocation and aggregate growth (see e.g. Haltiwanger et al., 2013; Acemoglu et al., 2018).

Below, we briefly describe how our paper relates to the existing literature on the

[7]As an additional example, in the Appendix we sketch how the presence of serial entrepreneurship can be important for other key economic questions, such as income inequality.

borders of firm dynamics and macroeconomics. Section 4.5 discusses in more detail the implications of our results for theoretical and quantitative macroeconomic models. In addition, the Appendix sketches how allowing for serial entrepreneurship can change our understanding and modeling of (top) income inequality. This strengthens the case that serial entrepreneurship is not of niche interest, but can help us understand key economic questions.

2.1 Macroeconomic Impact of Firm Success

First and foremost, 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 businesses (so called gazelles), contribute disproportionately to aggregate job creation and productivity growth (see e.g. Haltiwanger et al., 2017; Decker et al., 2017).

Our results in Section 4 – which document that firms of serial entrepreneurs disproportionately impact aggregate outcomes – contribute to the hunt for groups of firms most important for shaping aggregate dynamics. As will become clear below, serial entrepreneur firms display superior performance, even within the highly select group of high-growth gazelles. Therefore, our results suggest that the prevalence of serial entrepreneurs and the superior performance of their businesses are important for the understanding of the macroeconomy.

2.2 Understanding the Sources of Firm Heterogeneity

Our paper is also linked to studies of entrepreneurship and the determinants of post-entry growth heterogeneity across businesses. 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.

However, our results should not be viewed as "just" novel facts about a particular group of firms. They also constitute new empirical moments which can be used in future research to discipline the underlying sources of firm heterogeneity in structural macroeconomic models (see Jovanovic, 1982; Hopenhayn, 1992, for a seminal contributions). In these models, the specific degree and form of firm heterogeneity impacts aggregate dynamics and, in particular, the macroeconomic effects of policies and firm-level frictions (see Sterk ⓡ al., 2021). We discuss theses issues further in Section 4.5. Therefore, our results provide new insights into the sources of firm heterogeneity.

3 Data, Definitions and Basic Descriptive Statistics

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. Before presenting our key results in the next section, we show basic descriptive statistics concerning serial entrepreneurship.

3.1 Data

Our main data source is Quadros de Pessoal (QP), a Portuguese census of private sector employees conducted each October by the Ministry of Employment, Solidarity and Social Security (MESSS). It is an extremely rich administrative employer-employee matched panel dataset with information at the firm, establishment and individual levels.

The survey covers the universe of firms with at least one employee and their workers.[8] 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.

The unique advantage of the QP is that it not only has comprehensive information on businesses (firms and establishments) and their employees, but also on *business owners*. Moreover, thanks to the longitudinal linkages inherent to the database, we are able to connect firm-level characteristics with an individual business owner and track both owners and their businesses over time.[9] This, in turn, allows us to separately characterize firm dynamics of businesses with different owners. In our analysis, we focus on the distinction between "serial" entrepreneurs – owners of multiple businesses – and all other "regular" business owners.

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

[9]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 are not directly observable (though they can be proxied). Therefore, owners cannot be tracked over time, preventing the study of serial entrepreneurship.

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

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. Crucial to our study is a unique 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.[10] Below, we explicitly define all our key concepts.

Serial entrepreneurship. As is typical in the literature, we define an individual business owner as a serial entrepreneur if they own more than one firm within our sample. The group of serial entrepreneurs can be further categorized into (i) sequential and (ii) portfolio entrepreneurs. The former are serial entrepreneurs who experience gaps of non-entrepreneurship between business ownership. The latter are serial entrepreneurs who own multiple businesses at the same time. For our baseline analysis, we focus on portfolio serial entrepreneurs. Therefore – unless explicitly stated otherwise – in what follows we use the term "serial entrepreneur" to indicate a portfolio serial entrepreneur.

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

To identify serial entrepreneurs in our data, we count the number of businesses for which an individual is recorded as an owner in every year of our sample.[11] Next, we define an individual to be a (portfolio) serial entrepreneur if he or she simultaneously owns more than one business at *any* moment within our sample. Note that under this definition, serial entrepreneurship is viewed as a "permanent characteristic" (fixed effect) of individuals. The Appendix shows that our results are similar when we use a time-varying definition that categorizes individuals as serial entrepreneurs only for those years in which they own multiple firms.

For our baseline analysis, we categorize as "regular" entrepreneurs those business owners who are not classified as (portfolio) serial entrepreneurs. Therefore, as explained above, this definition of regular business owners also includes sequential serial entrepreneurs. The Appendix documents that the business performance of sequential entrepreneurs is indeed very close to that of firms owned by entrepreneurs who only ever own one business. This, therefore, explains our primary focus on portfolio entrepreneurs only.

Finally, note that – as is typical for the study of serial entrepreneurship – our definition may lead to potentially biased estimates because of right censoring. Specifically, entrepreneurs may be classified as "regular", despite the fact that they will start a second business in the future, *outside* our sample period. While this feature only likely creates a downward bias on estimates of the importance of serial entrepreneurs (i.e. our results may be viewed as lower bounds), we provide an explicit robustness check using a truncated sample in the Appendix.

Regular and serial entrepreneur firms. While the QP has information on both firms and establishments, our primary units of observation are firms.[12] 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. All other businesses are classified as "regular (R) firms". Note that 65.5% of firms have a single owner in the Portuguese economy. Nevertheless, the Appendix shows that our results are similar when we restrict our definition to firms which are *solely* owned by serial entrepreneurs. At the end of this section, we also provide more details on the ownership structure of serial entrepreneur 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

[11] 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.

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

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

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

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 $q_{i,t} = Z_{i,t}/E_{i,t}$, where $Z_{i,t}$ 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 ("gazelles"). Part of our analysis focuses on high-growth firms, so called gazelles. We follow the Eurostat-OECD (see European Commission, 2007) definition of gazelles as businesses up to 5 years old, with a minimum of 10 employees (at some point in the firm's existence), and with average annualised growth of at least 20 percent per year, over a three year period. Practices differ when it comes to definitions of gazelles and, therefore, 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).

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 high-growth firm, we continue to refer to such businesses as gazelles even beyond the age of 5 and even if their subsequent growth slows. This allows us to gauge how high-growth firms differ from other businesses throughout their life-cycles.

3.3 Basic Descriptive Statistics

Before moving to our central results, we first provide basic descriptive statistics of firm dynamics and serial entrepreneurship in the Portuguese economy. We return to these patterns in more detail in Section 4.

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

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

That said, given their superior growth performance, this group of firms alone accounts for almost a third of aggregate job creation and employment. Therefore, also in Portugal the relatively rare group of gazelles plays an influential role in determining aggregate patterns.

Prevalence of Serial Entrepreneurship. Let us turn to the core aspect of our analysis – serial entrepreneurship. Using our (once-and-for-all) definition of (portfolio) serial entrepreneurship, we find that only 4 percent of all business owners can be classified as serial entrepreneurs. The average number of businesses a serial entrepreneur owns is 1.7 and SE firms account for 17.6 percent of all businesses.[13]

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

Basic Characteristics of Serial Entrepreneur Firms and their Owners. Having shown that serial entrepreneurship is prevalent in the Portuguese economy, we now describe several characteristics of serial entrepreneurs and their businesses.

[13] Under the year-on-year definition of serial entrepreneurship, SE firms account for 5.3 percent of all businesses.

Table 1: Sectoral composition of serial entrepreneur firms

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

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

Table 2: Average characteristics of entrepreneurs and their businesses

	SE Firms			Entrepreneurs	
	First	Subsequent		Regular	Serial
Number of owners (#)	1.5	1.6	Age (years)	38.8	43.4
Share of SE owners (%)	84.2	83.8	Schooling (years)	8.9	10.4
Share of founders (%)	84.5	84.4	Female share (%)	32.6	19.3
Same sector share (%)		48.3	Same sector share (%)	53.3	53.3

Notes: The table reports average descriptive statistics for "first" and "subsequent" serial entrepreneur firms (left panel) and for "regular" and "serial" entrepreneurs (right panel). Among SE firms, the left panel reports average "number of owners", the "share of SE owners" among all owners, the share of SE owners who are present from startup ("share of founders") and the share of subsequent SE firms started in the same 2-digit industry as the first SE business ("same sector share"). Among entrepreneurs, the right panel reports "schooling", "age", the share of female entrepreneurs ("female share") and those starting a business in the "same sector" (at the 2-digit level) as their prior employment.

The left panel of Table 2 shows characteristics of SE firms, distinguishing first and subsequent (second, third and so on) businesses. On average, it takes serial entrepreneurs about 7 years to start their second business. In addition, both first and subsequent businesses of a given serial entrepreneur display roughly the same number of owners and the same share of owners who are serial entrepreneurs. Importantly, in the vast majority of SE firms (84 percent), serial entrepreneurs are present from startup indicating that they are likely "true" founders, rather than "just" investors. Finally, there is strong diversification of activity between first and subsequent businesses of serial entrepreneurs. In particular, only about half of all subsequent firms are started within the same 2-digit industry as the first business a serial entrepreneur owns.

The right panel of Table 2 documents observable characteristics of business owners – both regular and serial entrepreneurs. For direct comparability, we measure the latter at the time of starting the first business.[14] The panel shows that serial entrepreneurs are somewhat older, more educated and more likely to be male, relative to regular business owners. Both types of entrepreneurs, however, display the same tendency for sectoral

[14]Results are very similar without conditioning on startup of first SE businesses.

"diversification". In particular, only just over one half of business owners start their firm in the same 2-digit industry as they were last employed in.

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

To formalize such differences, we estimate the following regression

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

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, $F_{i,t}$.

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

Table 3 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 25 percent lower, they grow at a pace which is 35 percent faster and they are 34 percent more productive compared to regular businesses.[15]

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

[15] In regards the firm exit, the serial entrepreneur premium is estimated at about 2.2 percentage points. This is about 25 percent of the unconditional average exit rate of 8.8 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.

Table 3: Serial entrepreneur premium

	Regular	Serial	SE Premium
Size (workers)	4.7	14.7	0.57^{***}
Exit (in %)	8.8	5.8	-2.24^{***}
Growth (in %)	8.9	10.3	3.14^{***}
Productivity (aggregate = 1)	0.83	1.22	0.34^{***}

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.

4 Four Facts and Implications for Theory

This section lays out our main empirical findings. In particular, using our unique data we put forward four novel facts about firms of serial entrepreneurs. We begin with the headline fact concerning the macroeconomic impact of SE firms. Each of the remaining three facts then digs deeper into the underlying sources of this headline result. Specifically, in this section we show that serial entrepreneur firms are:

Fact 1: Important for the Macroeconomy
Serial entrepreneur firms disproportionately contribute to aggregate job creation and productivity growth.

Fact 2: Bigger and Faster-Growing
Compared to regular businesses, the firm size distribution of serial entrepreneur firms has a thicker right tail, and it fans out faster with firm age.

Fact 3: Drivers of Aggregate Business Dynamism
Compared to regular businesses, serial entrepreneur firms display lower exit rates and steeper life-cycle growth profiles (even among high-growth firms – "gazelles"), shaping aggregate business dynamism.

Fact 4: Better from the Beginning
Already the very first businesses of serial entrepreneurs are larger, grow faster, exit less often and are more productive than regular firms.

In what follows, we describe each of our four facts in more detail. We close this Section with a discussion of what our results imply for theoretical macroeconomic models.

4.1 Aggregate Importance of Serial Entrepreneur Firms

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

Contributions to aggregate employment, job creation and destruction. We start by documenting that serial entrepreneur firms contribute disproportionately to *aggregate* employment and job creation.

Specifically, Table 4 shows that while SE businesses represent only about 18 percent of all firms, they alone 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. The Appendix shows that this disproportionate employment contribution holds also at entry and exit. Table 4 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.

Contributions to aggregate productivity growth. Next, we turn our attention to the contribution of serial entrepreneur firms to *aggregate* productivity growth. Towards this end, let us define industry-specific productivity by

$$Q_{jt} = \sum_{g} \sum_{i \in s} \omega_{it} q_{it} \tag{5}$$

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 the logarithm of labor productivity at the firm level. We follow Foster et al. (2001) and decompose the change in industry-level productivity as

$$\Delta Q_{jt} = \sum_{s} \left[\underbrace{\sum_{i \in s} \omega_{i,t-1} \Delta q_{it}}_{\text{within}} + \underbrace{\sum_{i \in s} (q_{i,t-1} - Q_{j,t-1}) \Delta \omega_{it}}_{\text{between}} + \underbrace{\sum_{i \in s} \Delta q_{it} \Delta \omega_{it}}_{\text{cross}} \right]. \tag{6}$$

Focusing on continuing businesses only (as in e.g. Haltiwanger et al., 2016), we compute the above decomposition for every industry-year pair in our data. Finally, to aggregate up to the entire economy, we use average gross output weights, following the

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

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

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.

Table 5: Aggregate productivity growth decomposition

	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

Notes: The table reports values (in %) from the productivity growth decomposition in (6). 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.

approach of Foster et al. (2001) and Baily et al. (1992).

In our productivity decomposition in Equation (6), 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 shares from (on average) relatively less to relatively more productive businesses. The third, cross, term encompasses the combination of the previous two, whereby a reallocation of market shares towards businesses which display increases in firm-level productivity contributes positively to aggregate productivity growth.

The first row of Table 4 reports average aggregate productivity growth over our sample period and the contributions of the within, between and cross components from the decomposition in (6). The second and third rows show the contributions of serial entrepreneurs – to each of the elements – in levels and as a share of the three components of aggregate productivity growth. Consistent with other studies (see e.g. Dias and Robalo Marques, 2021; Reis, 2013), 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.

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 that only about 18 percent of all businesses are owned by serial entrepreneurs. Therefore, the above results lead us to our first fact:

Fact 1: Important for the Macroeconomy
Serial entrepreneur firms disproportionately contribute to aggregate job creation and productivity growth.

4.2 Serial Entrepreneurs and the Firm Size Distribution

Let us now turn to investigating the underlying sources of Fact 1. In particular, in this subsection we analyze the firm size distributions of serial and regular entrepreneurs. A key question that this subsection answers is the extent to which the aggregate impact of SE firms is driven by "just" a few very large businesses or by an overall stronger growth potential of SE firms.

Firm size distributions. Panel (a) of Figure 1 shows the firm size distributions of regular and SE firms.[16] As is well known, Portugal (as well as other advanced economies), display a size distribution which is skewed towards small firms (see e.g. Haltiwanger et al., 2013; Cabral and Mata, 2003). This pattern holds also within the groups of regular and SE firms. However, the extent is much weaker for firms of serial entrepreneurs. In particular, while only 3 percent of regular firms employ more than 20 workers, this fraction is 13 percent among SE businesses. Note that only 1.6 percent of SE firms employ more than 100 workers. This suggests that while the size distribution of SE firms is tilted towards larger businesses, the aggregate importance of serial entrepreneur firms is not driven by "just a few" very large firms.

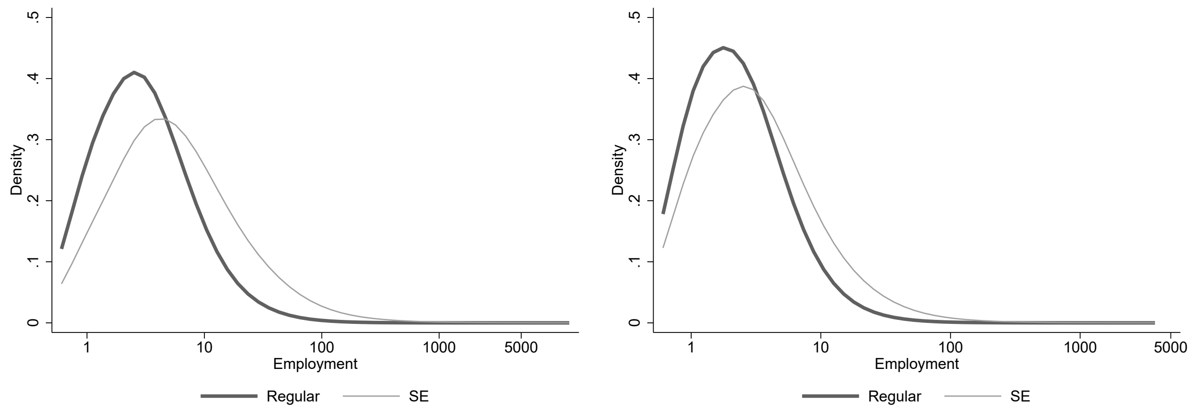
The apparent differences between regular and SE firms suggest different sources of – or impediments to – firm growth among the two types of businesses. One possibility is that SE firms are larger from the onset. To investigate this possibility, Panel (b) of Figure 1 plots the respective size distributions among R and SE startups. The panel confirms that size differences between regular and serial entrepreneur firms indeed exist already at startup. These results, therefore, suggest that SE businesses may enjoy superior innate performance ("ex-ante heterogeneity") or they may face more favorable initial conditions. We return to these points at the end of this section.

Evolution of the firm size distributions. The differences in size distributions of regular and serial entrepreneur firms (Panel (a) of Figure 1) need not be driven solely by initial conditions. An alternative possibility is that serial entrepreneur firms find it easier to grow, either because of superior growth potential or weaker impediments to growth (e.g. due to better access to external funding from their older businesses). Figure

[16]Similarly to Cabral and Mata (2003), we estimate the firm size distributions using a kernel density smoother with normal density and a bandwidth of 0.5.

Figure 1: Firm size distribution: SE and regular firms

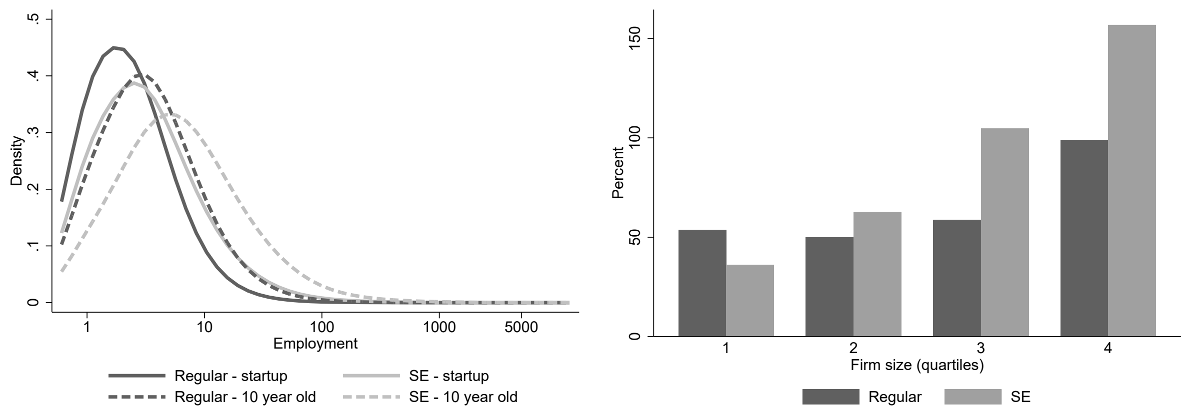
(a) All firms (b) Startups only



Notes: Panel (a) of the figure shows the firm size distribution of regular and serial entrepreneur firms. Panel (b) displays the same distributions for the group of startups.

Figure 2: Evolution of firm size distribution: SE and regular firms

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



Notes: Panel (a) of the figure shows the firm size distribution of regular and serial entrepreneur firms for the group of startups and ten year old businesses. Each for the group of regular and serial entrepreneur firms. Panel (b) visualizes the respective evolution by plotting the size growth (between startups and 10 year old firms) in the quartiles of the respective distributions.

2 speaks to the growth potential of R and SE firms by visualizing the evolution of the respective firm size distributions as firms age and grow.

Panel (a) shows the respective size distributions conditional on two age groups – startups and ten year old firms. As documented for all manufacturing businesses in Portugal Cabral and Mata (2003), the size distribution gradually fans out – becoming increasingly more symmetric – as firms age. This holds true for both regular and serial entrepreneur firms. However, the pattern is much stronger for SE businesses for which the size distribution of ten year old firms is considerably more symmetric. In fact, the size distribution of ten year old R firms remains very much skewed towards small businesses – closely resembling that of serial entrepreneur *startups*.

Finally, the superior growth potential of SE firms is confirmed in Panel (b) of Figure 2 which directly visualizes how the respective distributions fan out with firm age. In particular, the panel displays the size growth in the respective quartiles of the size distributions between startup and age ten. For example, the grey bar in the fourth quartile indicates that the largest 25 percent of SE firms at age 10 are about 150 percent bigger than the largest 25 percent of SE startups. In contrast, the same measure is "only" about 100 percent for R businesses.

Therefore, Panel (b) makes clear that compared to regular firms, businesses of serial entrepreneurs have stronger growth potential, especially at the top end of the size distribution. The lowest quartile of the size distribution is the only exception, with regular businesses expanding somewhat more with age compared to SE firms. These findings lead us to our second fact:

Fact 2: Bigger and Faster-Growing
Compared to regular businesses, the firm size distribution of serial entrepreneur firms has a thicker right tail, and it fans out faster with firm age.

The evolution of the firm size distribution has been used to identify the impact of financial frictions on firm growth (see e.g. Cabral and Mata, 2003). Therefore, our results shed new light on this issue and point to a sharp distinction between different groups of firms in either the sensitivity or exposure to financial frictions. We return to these points in more detail in Section 4.5.

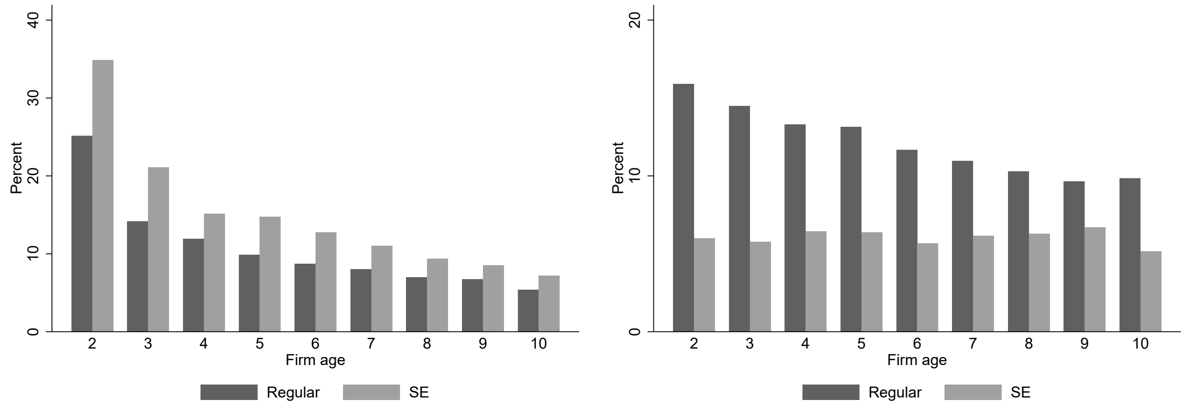
4.3 Aggregate Business Dynamism

Having shown that the firm size distribution of SE firms fans out faster, compared to regular businesses, we now zoom in on the underlying business dynamics. In particular, in this subsection we focus on indicators which measure firm and worker churn – so called up-or-out dynamics, job creation and destruction rates and the distribution of firm-level (net) growth rates. These variables not only underlie the evolution of the firm size distribution discussed above, but they are also of independent interest as they have been shown to be important indicators of *aggregate* productivity-enhancing factor reallocation (see Haltiwanger et al., 2013). Therefore, this subsection quantifies the extent to which SE businesses drive aggregate up-or-out dynamics.

Job creation and destruction over the life-cycle. As discussed in Section 3.3, existing empirical evidence points to strong "up-or-out" dynamics in developed economies.

Figure 3: Up-or-out dynamics

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



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

We, therefore, begin our analysis by investigating job creation of continuing firms and job destruction from exit, by firm age. These patterns are shown in Figure 3 with net job creation of continuing firms in the left panel and job destruction from exit in the right panel. In both panels, we separately depict the values for serial entrepreneur and regular businesses.

Two patterns stand out. First, net job creation by continuing regular businesses is almost a third lower compared to that by serial entrepreneurs. This holds true essentially across the entire firm life cycle. Second, while job destruction from exit falls with age among regular businesses, it is essentially flat among SE firms. The latter contrasts starkly with the strong negative relationship between age and job destruction from exit found in many firm-level datasets around the world (see e.g. Calvino et al., 2015).

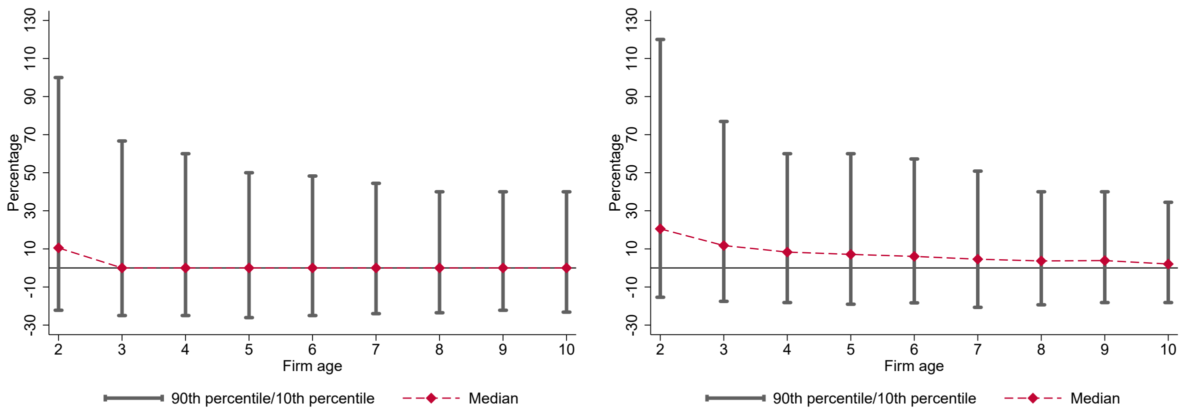
Figure 3, therefore, suggests that understanding aggregate up-or-out dynamics partly boils down to the prevalence and growth potential of serial entrepreneurs firms. Specifically, while the "up" part is largely driven by SE firms and their job creation prowess, R firms are responsible for much of the "out" part with their higher job destruction rates. We quantify these relative contributions to aggregate business dynamics at the end of this subsection.

Life-cycle distributions of firm size growth. Let us now zoom in on the up- part of business dynamism and analyze net job creation and its distribution by firm age. Figure 4 shows the distribution of employment 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

Figure 4: Employment growth distributions

(a) Regular Firms (b) Serial Entrepreneur Firms



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.

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. In contrast, the median regular firm stops growing at the age of about 3. These patterns are consistent with our results regarding the evolution of the respective firm size distributions discussed in the previous subsection.

Serial entrepreneurship and gazelles. Given that the difference between growth distributions of SE and R firms lies mainly in the high end (Figures 2 and 4), we now turn our attention to an important sub-group of businesses – high-growth firms, or so called gazelles. As we have discussed earlier, these firms have been shown to be crucial in explaining the prominent role of startups and young businesses for aggregate job creation, productivity and output growth (see Haltiwanger et al., 2017).

To begin with, Table 6 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 6 shows that while only about 9 percent of all firms in Portugal can be classified as gazelles according to the Eurostat-OECD definition, these firms alone account for almost a third of employment and newly created jobs in the entire economy.

The second and third columns of Table 6 then show the contributions of regular and serial entrepreneur gazelles to the overall patterns of high-growth firms. In particular,

Table 6: Contribution of high-growth firms to aggregates (in %)

	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

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%).

Table 7: Serial entrepreneur premium: High-growth firms

	Regular	Serial	SE Premium
Size (workers)	16.4	38.1	0.33***
Exit (in %)	5.7	4.1	-1.42***
Growth (in %)	15.5	13.7	2.42***
Productivity (agg.=1)	82.3	116.1	0.27***

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.

the table documents that about 40 percent of all high-growth firms are owned by serial entrepreneurs. Given that serial entrepreneur firms account for about 18 percent of all firms, this implies that serial entrepreneurs are about three times as likely to own a gazelle compared to regular business owners.[17]

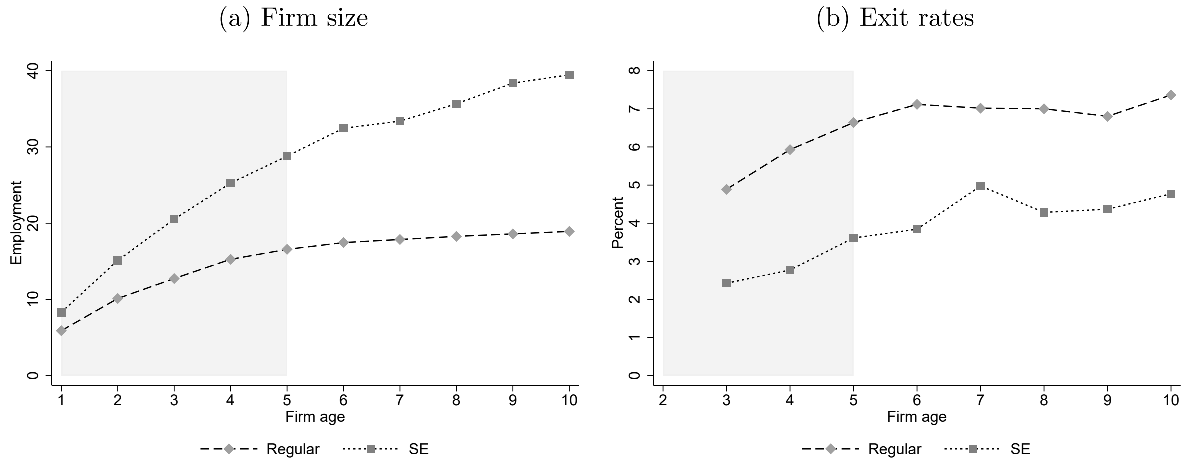
Serial entrepreneur premium and up-or-out dynamics among gazelles. Table (7) shows estimated serial entrepreneur premia (4), but this time for the rare sub-group of high-growth firms. The table documents that even in this select group of firms, gazelles of serial entrepreneurs are considerably larger, exit less often, grow faster and are more productive compared to high-growth firms of regular business owners.

Finally, Figure 5 plots average size and exit profiles for the groups of SE and R gazelles. The shaded areas in the figure indicate the five-year window used to define gazelles. Recall, however, that we follow high-growth firms even after that age and even if their growth slows.

Two patterns stand out. First, exit rates of regular gazelles are almost twice as high

[17]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 $Pr(\text{gazelle}|SE) = 0.09 \times 0.39/0.18 \approx 0.20$.

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



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

as those of serial entrepreneur gazelles.[18] Second, SE gazelles display strong growth throughout their life-cycles. In contrast, growth of regular gazelles peters out after the age of five years.

The fact that growth slows among regular gazelles after the age of five is not surprising, given that this is the cutoff age used in the definition of high-growth firms (i.e. businesses with sustained high growth in the first five years of their existence). Insofar as firm growth is partly driven by favorable – but transitory – shocks, average growth of gazelles will fade after the age of five as such "luck" runs out.

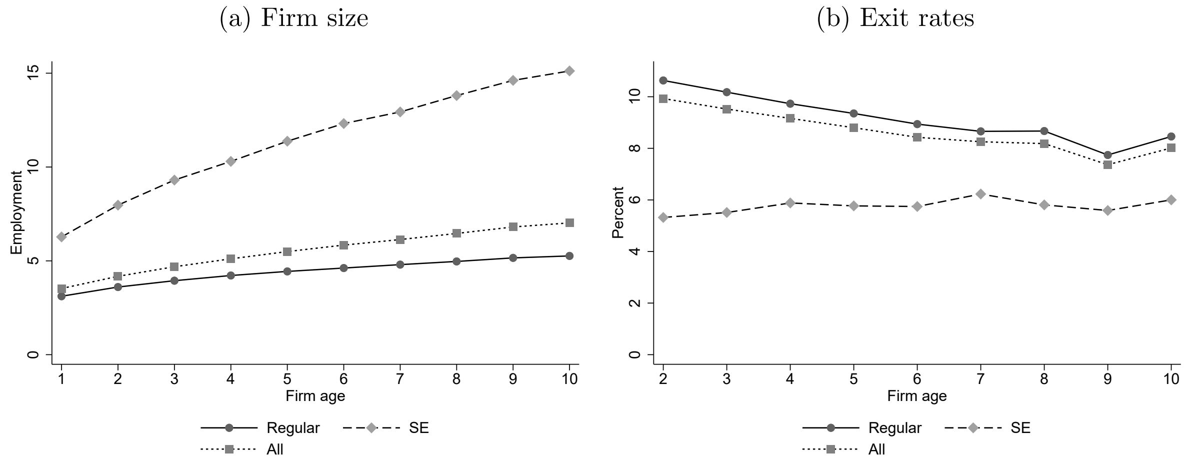
In stark contrast, SE gazelles continue their growth even after the cutoff age of five years. These patterns point towards different drivers of – or impediments to – growth, e.g. more persistent disturbances, stronger innate growth potential or better access to external financing. As such, our findings have important implications for models of firm growth to which we turn at the end of this Section.

Contribution to average up-or-out dynamics. Finally, we ask the question of how important are serial entrepreneur businesses for *average* up-or-out dynamics observed in the data. Figure 6 depicts life-cycle profiles for average firm size and exit rates by firm age. It does so separately for all, regular and serial entrepreneur firms.

As discussed in the previous section, *on average* young businesses exit more often, but surviving young firms almost double in size in the first ten years of their existence.These

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

Figure 6: 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.

average patterns, however, hide a dramatic difference between the life-cycle patterns of regular and serial entrepreneur firms, consistent with the serial entrepreneur premia estimated in Table 3, with the firm size evolution in Figure 2 and with the job creation and destruction patterns discussed above.

The left panel of Figure 6 shows that 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.

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 mimics the patterns of job destruction from exit in Figure 3.

Importantly, Figure 6 allows us to quantify the importance of SE firms for aggregate up-or-out dynamics. We do so by comparing life-cycle profiles of all firms to those of regular businesses, since the latter depicts how the aggregate patterns would look like in the absence of serial entrepreneur firms.

If it were not for SE firms, the average life-cycle profile of firm size would be much flatter – and progressively so as firms age. Specifically, while average startup size would fall by about 12% in the absence of SE firms, 10 year old firms would on average be more than 25% smaller. In contrast, average exit rates would increase by about 5% (0.5 percentage points) in the absence of SE firms, but they would retain their declining pattern with age. The patterns above lead us to our third fact:

Fact 3: Drivers of Aggregate Business Dynamism
Compared to regular businesses, serial entrepreneur firms display lower exit rates and steeper life-cycle growth profiles (even among high-growth firms – "gazelles"), shaping aggregate business dynamism.

These findings are important for research in which firms' life-cycle profiles play a crucial role for identifying economic mechanisms or frictions, such as studies of misallocation (see e.g. Hsieh and Klenow, 2014). We discuss these and other model implications in more detail in Section 4.5.

4.4 Ex-ante vs ex-post drivers of SE firm growth

Given the documented aggregate importance of SE firms driven by their superior growth potential, this subsection analyzes *when* that potential gets realized. In particular, we shed light on whether SE firms are "better from the the beginning" – an indication of "ex-ante" heterogeneity – or whether they "become better" over time – pointing towards stronger "ex-post" factors.

Our data offers a natural way to disentangle ex-ante factors from ex-post developments by separately analyzing the performance of "first" (FSE) and "subsequent" (SSE) businesses of serial entrepreneurs. Intuitively, FSE firms are those businesses which entrepreneurs owned *before* they could be classified as serial entrepreneurs. In contrast, SSE businesses are the cause of the serial entrepreneur classification and constitute the second and further firms of serial entrepreneurs.

First vs subsequent vs regular businesses. On average, it takes entrepreneurs almost 7 years to found their subsequent business (and therefore qualify to be categorized as a serial entrepreneur). 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.

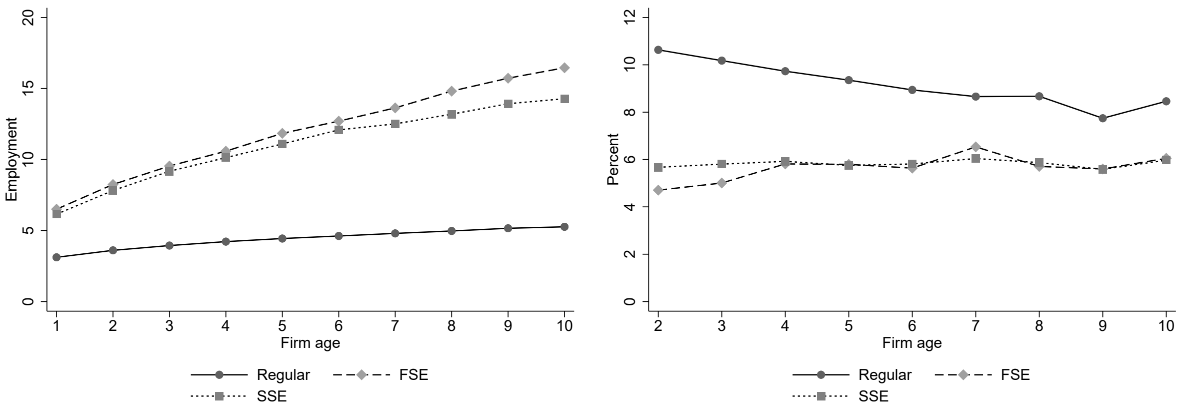
Figure 7 depicts the life-cycle profiles of firm sizes (left panel) and exit rates (right panel) for regular and serial entrepreneur firms. This time, however, the latter is split into the group of first and subsequent businesses of serial entrepreneurs. The figure paints a clear picture – both first and subsequent firms of serial entrepreneurs display essentially the same life-cycle patterns, noticeably superior to those of regular businesses.

These patterns are reinforced by Figure 8 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

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

(a) Firm size

(b) Firm exit

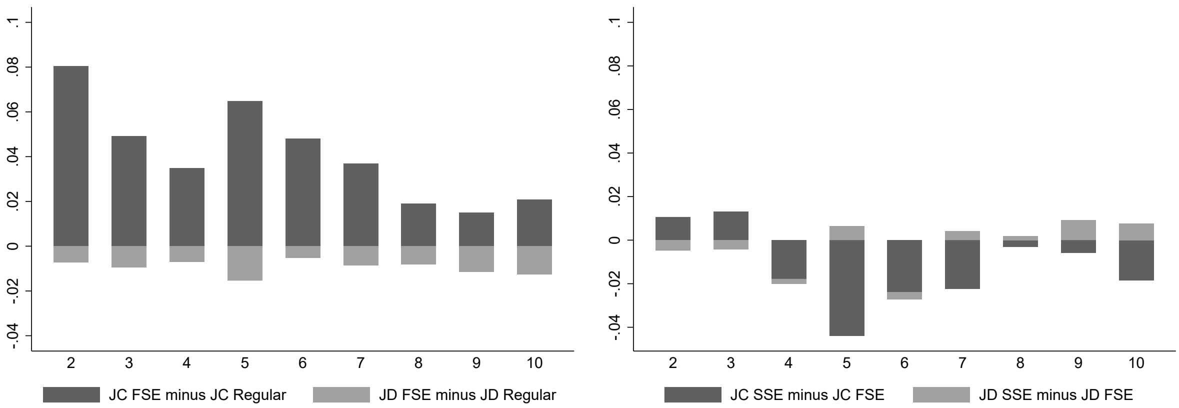


Notes: The left panel shows average firm size by firm age, while the right panel shows average exit rates by firm age. Both subpanels depict regular and serial entrepreneur businesses, where the latter are split into first and subsequent businesses of serial entrepreneurs.

Figure 8: Job creation of continuing firms and job destruction from exit: Regular, FSE and SSE

(a) FSE minus Regular

(b) SSE minus FSE



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.

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 for the

Table 8: FSE and SSE premia

	Regular	FSE	SSE	Premia FSE-R	Premia SSE-R	Premia SSE-FSE
Size (workers)	4.7	16.4	13.7	0.54***	0.59***	0.06***
Exit (in %)	8.8	5.7	5.8	-1.99***	-2.34***	-0.23***
Growth (in %)	8.9	10.5	10.2	3.75***	2.66***	-1.16**
Productivity (agg.=1)	0.83	1.19	1.23	0.34***	0.33***	-0.03

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 (7): "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.

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

$$y_{i,s,t} = \alpha + \beta \mathbb{1}_{\mathrm{s,s\_comp}} + \delta F_{i,s,t} + \epsilon_{i,s,t}, \tag{7}$$

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 $s \in \{\mathrm{R}, \mathrm{FSE}, \mathrm{SSE}\}$. 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 $\mathbb{1}_{\mathrm{s,s\_comp}}$ 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) $\mathbb{1}_{\mathrm{R,FSE}}$ 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) $\mathbb{1}_{\mathrm{R,SSE}}$ 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) $\mathbb{1}_{\mathrm{FSE,SSE}}$ 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 (7) we again control for age, industry and year fixed effects ($F_{i,s,t}$).

Table 8 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 (7). The results document that both FSE and SSE firms are larger, exit less frequently, grow faster and are more productive relative to regular businesses (columns 4 and 5). However, the premia are comparably negligible or even overturn in sign when comparing subsequent and first serial entrepreneur firms (column 6).[19] There-

[19] In a recent paper, Shaw and Sørensen (2021) document that the second business of young serial

fore, these findings lead to our final fact:

Fact 4: Better from the Beginning
Already the very first businesses of serial entrepreneurs are larger, grow faster, exit less often and are more productive than regular firms.

These findings are informative about the underlying sources of firm heterogeneity. In particular, the superior performance of FSE firms points towards strong ex-ante forces, for instance because of innate ability of serial entrepreneurs or persistent effects of favorable initial conditions (see e.g. Sterk ⓡ al., 2021).[20] We discuss these and other implications in the next subsection.

4.5 Implications for Theoretical Macroeconomic Models

The previous four subsections described our novel facts about the firms of serial entrepreneurs. Our results, however, do not "only" provide new facts about a particular group of firms, they also have important implications for *theoretical and quantitative* macroeconomic models which we discuss in this subsection. In addition, the Appendix sketches how accounting for serial entrepreneurship can change our understanding and modeling of other key economic questions such as (top) income inequality.

Disciplining Macroeconomic Models with Heterogeneous Firms. Modern macroeconomic models with firm heterogeneity embrace the constant business churn observed in the data. Firm-level heterogeneity in these models ultimately shapes the model's *aggregate* dynamics. However, heterogeneity across firms generated by these models is determined by *unobserved* firm-specific driving forces, such as productivity or demand shocks. In order to discipline these firm-level drivers, researchers typically require the model to match salient features of the data related to firm dynamics, such as observed up-or-out patterns, the firm size (growth) distribution or job creation and destruction shares for different groups of firms. In this context, our results constitute a new set of moments to which macroeconomic models with firm heterogeneity can be parameterized and evaluated against in a more nuanced way.

Economic Mechanisms and Effects of Policy Changes. Heterogeneous-firm models of the macroeconomy have been successfully employed in analyzing a range of topics

entrepreneurs substantially outperforms their first. In contrast to them, we do not condition on entrepreneur age and do not distinguish between the second and other subsequent businesses when estimating premia of SSE firms compared to FSE businesses.

[20]The Appendix shows that entrepreneurial characteristics can partly account for the estimated serial entrepreneur premia. However, a large fraction remains unexplained, inviting further research into the determinants of the superior performance of serial entrepreneurs.

– including the identification of novel economic mechanisms and the quantification of effects of policy interventions. Examples in which the firm size (growth) distribution or firms' up-or-out dynamics play a central role in identifying and quantifying the strength of particular mechanisms include the study of financial frictions (see e.g. Midrigan and Xu, 2014; Cole et al., 2016), misallocation (see e.g. Hsieh and Klenow, 2014; Eslava and Haltiwanger, 2199), size-dependent policies (see e.g. Gourio and Roys, 2014), pro-growth interventions (see e.g. Acemoglu et al., 2018), market power (see e.g. Peters, 2020), selection and managerial delegation (see e.g. Akcigit et al., 2021), informality (see e.g. Ulyssea, 2021) or demographic change (see e.g. Hopenhayn et al., forthcoming).

Given that – as explained above – the aggregate behavior of such models is shaped by the extent and form of (unobserved) firm-level driving forces, the model's empirical targets are crucial in identifying and quantifying economic mechanisms. Accounting for serial entrepreneurship can, therefore, quantitatively alter the conclusions in the above studies or, indeed, lead to the identification of novel mechanisms or policy implications.

Sources of Firm Heterogeneity. While differences across firms have often been largely attributed to transitory post-entry shocks (see e.g. Hopenhayn, 1992, for a seminal contribution), there is growing empirical evidence that, so called "ex-ante", differences in growth potential are needed to match salient features of the (now available) micro-data (see e.g. Decker et al., 2014; Schoar, 2010; Sterk r al., 2021). In addition, there are theoretical contributions arguing that models lacking such ex-ante heterogeneity cannot explain certain empirical features related to firm growth (see e.g. Luttmer, 2011; Gabaix et al., 2016a; Akcigit et al., 2021; Sterk r al., 2021). The results presented in this paper, therefore, offer serial entrepreneurship as a new – up until now ignored – form of such ex-ante differences in firms' growth profiles.

Development of New Models. While serial entrepreneurship has enjoyed some empirical attention, the shortage of *economy-wide* high-quality data – which would allow the systematic study of the macroeconomic impact of serial entrepreneurship – has led to an effective absence of serial entrepreneurs from theoretical and quantitative macroeconomic models. Therefore, our headline result that serial entrepreneurs are important determinants of macroeconomic outcomes points to an important gap in the literature. We believe that our results may inspire future research into this largely ignored but quantitatively important phenomenon, but also offer guidance in terms of the necessary economic mechanisms which would allow such new frameworks to successfully match the empirical patterns. For instance, our last fact points towards mechanisms favoring (selection on) ex-ante characteristics or persistent effects of initial conditions as key driving forces of firm growth (see e.g. Sedláček and Sterk, 2017; Sterk r al., 2021). In contrast, they provide relatively less quantitative support to other mechanisms such as entrepreneurial learning or transitory ex-post shocks (see e.g. Lazaer, 2005; Lafontaine and Shaw, 2016).

5 Concluding Remarks

In this paper we use a unique administrative dataset from Portugal, which enables us to link firms to their owners and track both over time. Our primary focus is on serial entrepreneurs – business owners who simultaneously own multiple firms. Using this data, we document four novel facts about serial entrepreneur firms: (i) they contribute disproportionately to aggregate job creation and productivity growth, (ii) their firm size distribution is wider and fans out faster compared to that of regular businesses, (iii) they are key drivers of aggregate up-or-out dynamics and (iv) already the very first firms of serial entrepreneurs display superior performance.

Our results make a strong case for the analysis of serial entrepreneurs – a topic that has been largely understudied. This is true not only for empirical work, which has been held back by a lack of reliable data sources, but especially for theoretical and quantitative research from which serial entrepreneurs are effectively completely missing. Therefore, our results not only provide new empirical facts, but can also be applied as a means to discipline existing models or inform the development of novel frameworks.

Our results also open the door to further empirical questions which are, however, beyond the scope of this paper. For instance, what are the sources of the superior performance of serial entrepreneur firms. In the Appendix we provide a first step in this direction by showing that up to 20 percent of the estimated serial entrepreneur premia is explained by entrepreneurial characteristics (education playing a key role). Other open questions include the way how serial entrepreneurs respond to policy changes or what is the impact of existing institutional arrangements on the incentives to pursue serial entrepreneurship. Answering these and other questions will further our understanding of not only entrepreneurship and firm growth, but also of how the macroeconomy operates. Therefore, while Elon Musk enjoys the attention of more than 72 million followers on Twitter, we believe that he and other serial entrepreneurs deserve more attention still.

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Appendix

A Additional Empirical Results

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

A.1 Alternative measurement of serial entrepreneurs

The results in Section 4, use the "fixed effect" definition of serial entrepreneurship where we treat any business owner who simultaneously owns multiple businesses as a serial entrepreneur *throughout the entire sample*. In this Appendix, we document that very similar results are obtained using the alternative, "year-by-year" definition, where we count as serial entrepreneurs only those business owners who own multiple businesses in a given year. This is intuitive, since in Section 4.4 we show that first and subsequent firms of serial entrepreneurs have very similar characteristics.

Specifically, Table A1 and A2 document that even under the year-by-year definition serial entrepreneur firms still enjoy a significant premium over regular businesses and that they disproportionately contribute to aggregate job creation and productivity growth (Fact 1). In addition, the following Figures show that under the alternative definition serial entrepreneur firms still have a wider size distribution which fans out faster with firm age (Fact 2 and Figure A1), they shape average up-or-out dynamics (Fact 3 and Figure A2) and that even the very first businesses of serial entrepreneurs outperform regular businesses (Fact 4 and Figure A3).

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

	Regular	Serial	SE Premium
Size (workers)	5.9	12.8	0.53^{***}
Exit (in %)	8.4	7.1	-0.70^{***}
Growth (in %)	10.3	11.4	1.99^{***}
Productivity (agg. = 1)	0.87	1.24	0.31^{***}

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 size (employment), exit rates, (employment-weighted) net employment growth and average labor productivity scaled by labor productivity of all firms. Ordinary Least Squares estimates with robust standard errors clustered at the firm level in parentheses. *** stands for statistical significance at the 1% level. Serial entrepreneur businesses are defined using the year-by-year definition.

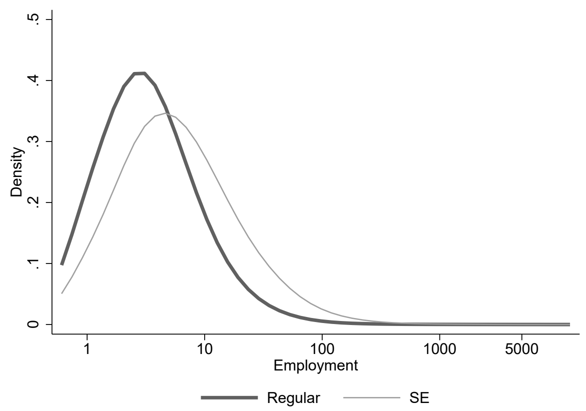
Table A2: Contributions to aggregates (in %): year-by-year definition

	Firms	Employment	Job creation	Job destruction	Productivity growth
Regular	82.4	61.5	65.7	71.3	86.3
Serial	17.6	38.5	34.3	28.7	13.7

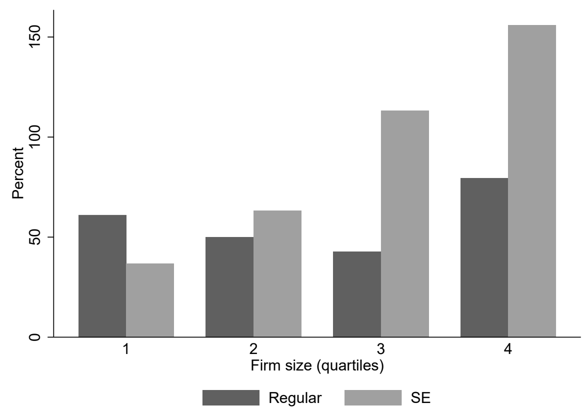
Notes: The table shows, respectively, the contributions (in %) of "regular" and "serial entrepreneur" businesses to the aggregate number of firms, employment, job creation, job destruction and productivity growth. Serial entrepreneur businesses are defined using the year-by-year definition.

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

(a) Overall firm size distribution



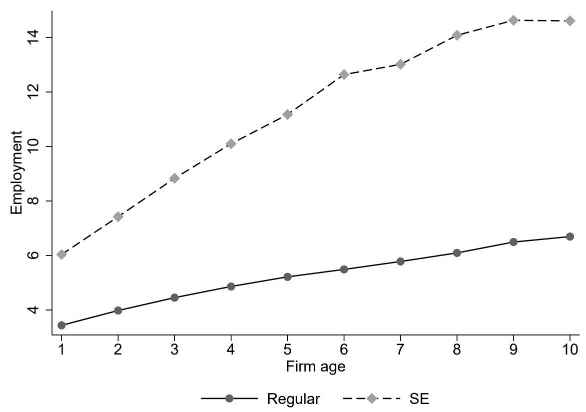
(b) Evolution of firm size distribution



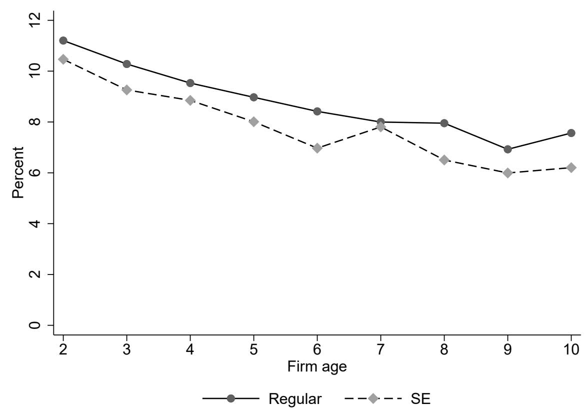
Notes: Panel (a) of the figure shows the firm size distribution of regular and serial entrepreneur firms and Panel (b) visualizes the respective evolution by plotting the size growth (between startups and 10 year old firms) in the quartiles of the respective distributions. Serial entrepreneur businesses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

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

(a) Firm size



(b) Exit rates

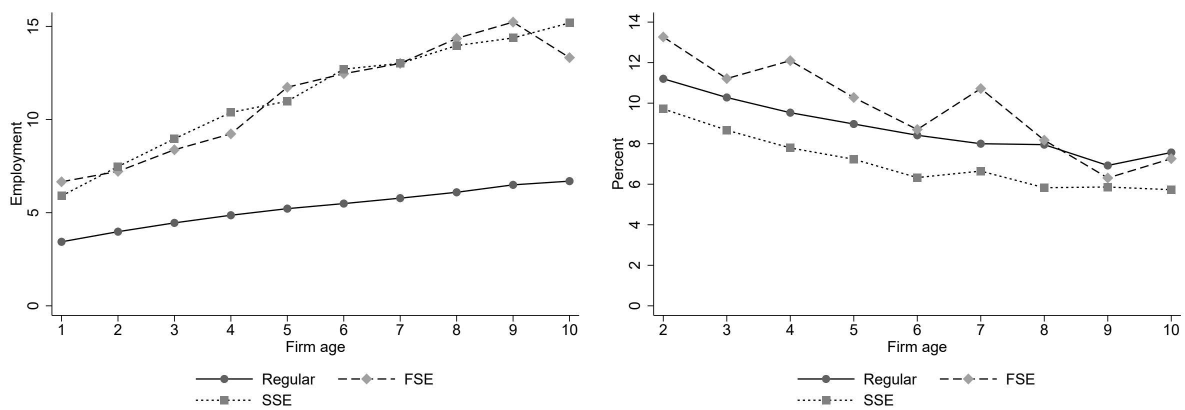


Notes: The left panel shows average firm size by age, while the right panel shows average exit rates by age. Both subpanels depict regular and serial entrepreneur businesses. Serial entrepreneur businesses are defined using the year-by-year definition.

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

(a) Firm size

(b) Firm exit



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

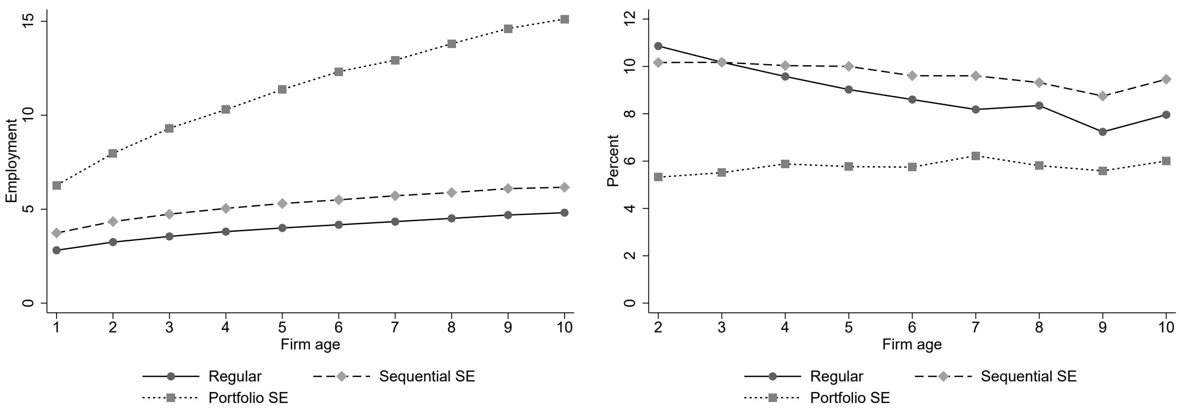
A.2 Sequential vs Portfolio Entrepreneurs

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

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

(a) Firm size

(b) Exit rates



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

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

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

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

	Regular	Seq. SE	Portf. SE	Premia	
				Seq.-R	Portf.-Seq.
Size (workers)	4.3	5.6	14.7	0.20***	0.64***
Exit (in %)	8.6	9.3	5.8	0.98***	-1.86***
Growth (in %)	8.8	8.9	10.3	0.15	3.25***
Productivity (agg.=1)	0.79	0.89	1.22	0.07***	0.37***

Notes: The first three columns show, respectively, the averages of regular, portfolio and sequential serial entrepreneur firms. Columns 4 and 5 show, respectively, premia estimated from (7): "Seq.-R" is the premium of sequential entrepreneur businesses over regular firms and "Portf.-Seq." is the premium of portfolio over sequential serial entrepreneur firms. The rows depict, respectively, average size (employment), exit rates, (employment-weighted) size growth and firm-level labor productivity scaled by labor productivity of all businesses. Ordinary Least Squares estimates with robust standard errors clustered at the firm level in parentheses. *** and ** stand for, respectively, statistical significance at the 1% and 5% levels.

A.3 Analysis on a truncated sample period

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

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

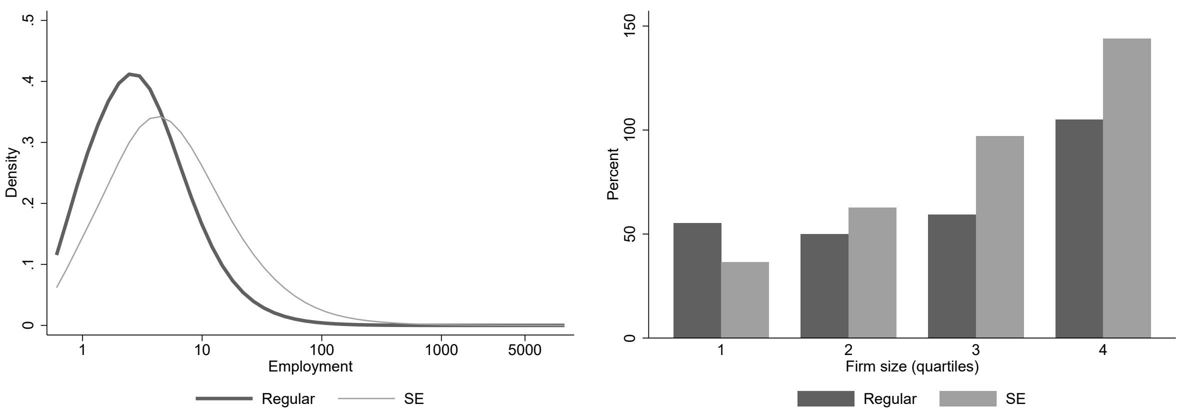
	Firms	Employment	Job creation	Job destruction	Productivity growth
Regular	83.6	65.8	69.4	74.5	29.7
Serial	16.4	34.2	30.6	25.5	70.3

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

Figure A5: Firm size distribution and evolution: truncated sample

(a) Overall firm size distribution

(b) Evolution of firm size distribution

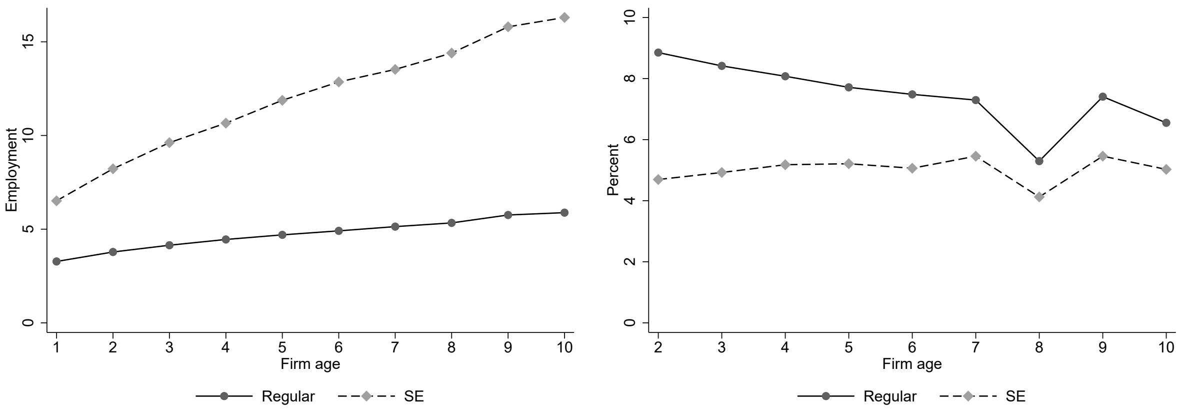


Notes: Panel (a) of the figure shows the firm size distribution of regular and serial entrepreneur firms and Panel (b) visualizes the respective evolution by plotting the size growth (between startups and 10 year old firms) in the quartiles of the respective distributions. Estimates are based on a truncated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

Towards this end, we redo our analysis on a truncated sample. Specifically, we truncate the end of our sample in 2009 instead of letting it end in 2017. This truncation closely mimics the average number of years it takes a serial entrepreneur to start their second business. The truncation results in "reclassifying" 12.6 percent of serial entrepreneurs in our baseline specification as regular entrepreneurs because they start their subsequent

Figure A6: Size and exit profiles by age: truncated sample

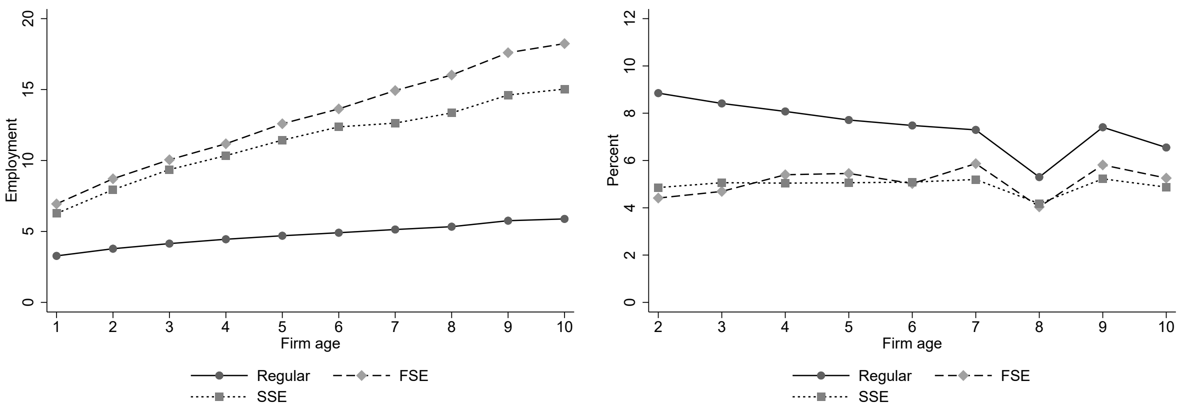
(a) Firm size (b) Exit rates



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

Figure A7: Size and exit profiles by age: Regular, First SE and Subsequent SE firms: truncated sample

(a) Firm size (b) Firm exit



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

businesses after 2009. Nevertheless, Table A4 and Figures A5 to A7 show that are key results remain to hold even for this truncated sample.

A.4 Sole ownership only

In the main text, we classify serial entrepreneur firms as any business for which at least one owner is a serial entrepreneur. In this Appendix, we refine this definition to focus only on those businesses which have only a *single* owner. Those with a single serial entrepreneur owner are classified as SE firms, while all other businesses (i.e. including firms with multiple owners – serial entrepreneurs or not) are classified as regular. Table A5 and Figures A8 to A10 show that our key results remain to hold. This is not surprising as 2/3 of all businesses in Portugal are single-owned.

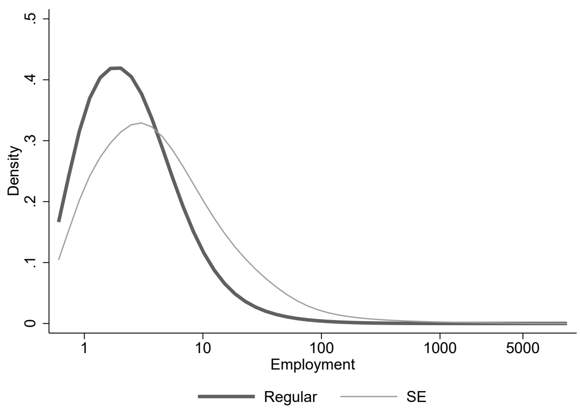
Table A5: Contributions to aggregates (in %): sole serial entrepreneurship

	Firms	Employment	Job creation	Job destruction	Productivity growth
Regular	94.4	81.8	85.1	88.7	82.0
Serial	5.6	18.2	14.9	11.3	18.0

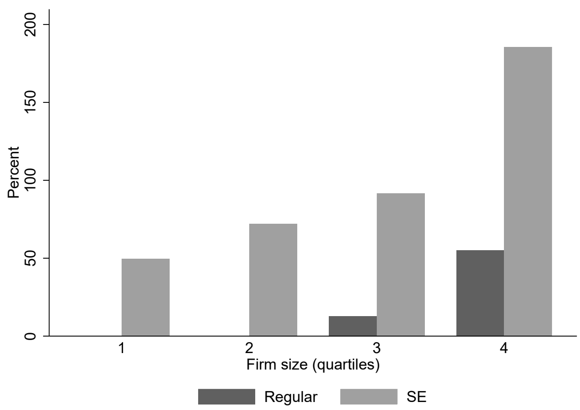
Notes: The table shows, respectively, the contributions (in %) of "regular" and "serial entrepreneur" businesses to the aggregate number of firms, employment, job creation, job destruction and productivity growth. In contrast to the main text, SE firms are restricted to have only a single owner.

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

(a) Overall firm size distribution



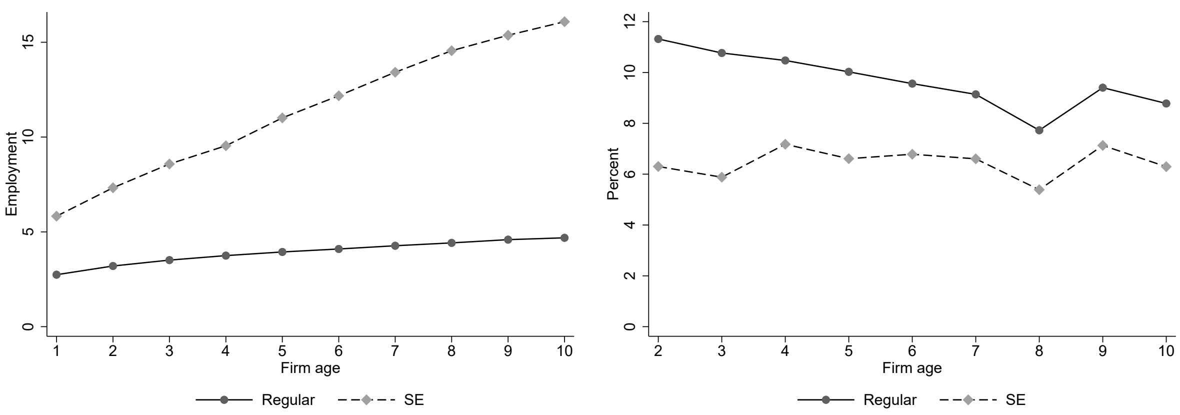
(b) Evolution of firm size distribution



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

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

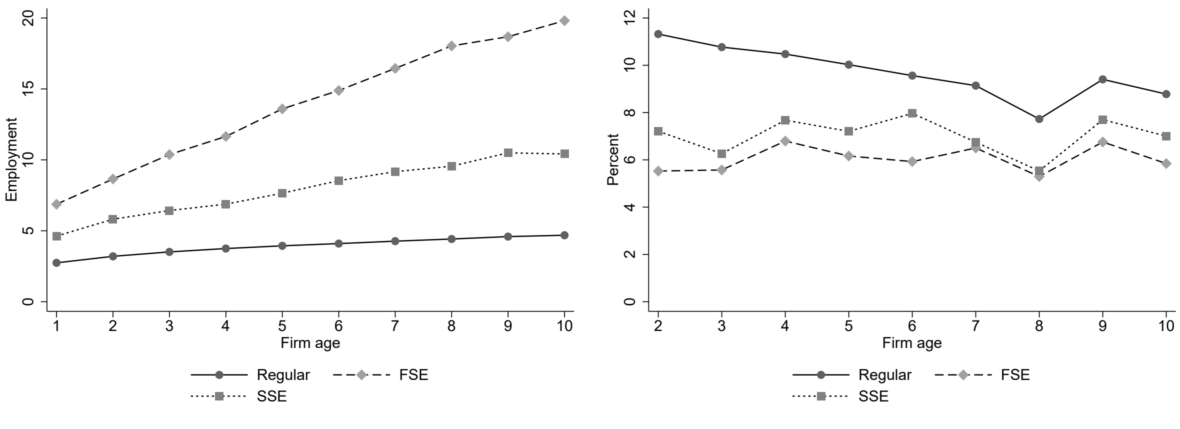
(a) Firm size (b) Exit rates



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

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

(a) Firm size (b) Firm exit



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

A.5 Alternative definition of high-growth firms

The main text defined gazelles following the Eurostate-OECD definition (see European Commission, 2007). In this Appendix, we consider an alternative definition of gazelles. In particular, we follow Haltiwanger et al. (2017) and define gazelles as firms with annual growth rates higher than 25 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.

Tables A6 and A7 replicate Table 6 and 7 in the main text. The results in this Appendix, therefore, suggest that even under an alternative definition of gazelles, high-growth firms still remain to be disproportionately important for aggregate employment and job creation and gazelles owned by serial entrepreneurs outperform regular high-growth firms.

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

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

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

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

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

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 size (employment), job creation rates. Ordinary Least Squares estimates with robust standard errors clustered at the firm level in parentheses. *** stands for statistical significance at 1%.

A.6 Entrepreneurs and serial entrepreneur premia

Fact 4 in the main text shows that already the very first businesses of serial entrepreneurs outperform those of regular business owners. These results point to either (selection on) ex-ante characteristics or to the persistent effects of initial conditions. In this Appendix, we make use of the (still rather limited) information on individual characteristics of entrepreneurs to gauge to what extent serial entrepreneurs are inherently different from regular business owners and whether such differences can significantly explain the estimated serial entrepreneur premia.

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

$$y_{i,t} = \alpha + \beta \mathbb{1}_{i \in SE} + \gamma F_{i,t} + \delta G_{i,t} + \epsilon_{i,t}. \tag{A1}$$

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.[1]

Table A8 shows the results. The first row estimates (A1) 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.

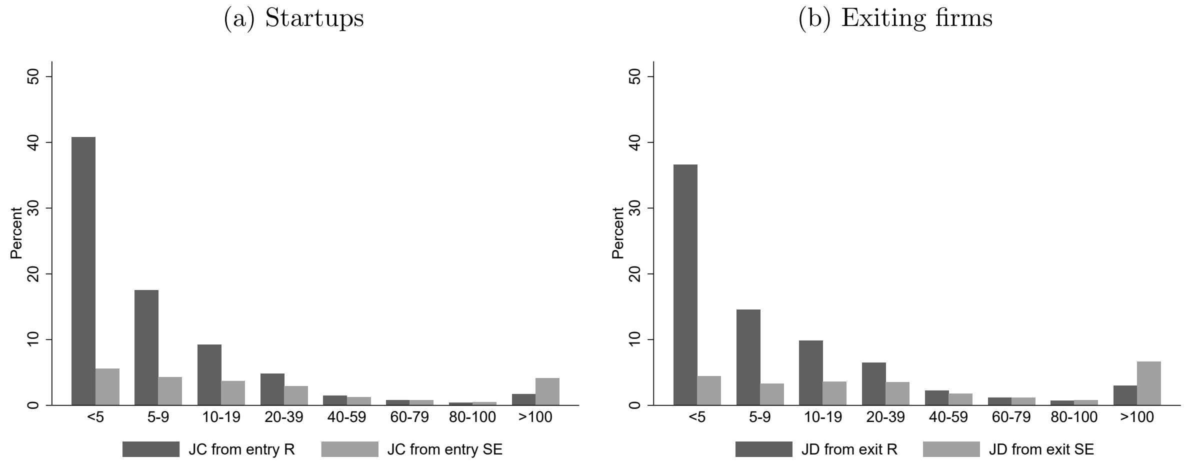
[1] The Appendix shows that similar results are obtained when considering a "year-by-year" measurement of entrepreneurial characteristics.

Table A8: Serial entrepreneur premia and owner characteristics

	Size	Exit	Growth	Productivity
Unconditional	0.572	−2.245	3.143	0.315
Conditional on $G_{i,t}$	0.527	−2.046	2.716	0.245
Contributions of individual entrepreneurial characteristics				
Total contribution	0.045	−0.199	0.427	0.070
- age	0.018	−0.068	0.417	−0.005
- gender	−0.001	−0.030	−0.019	0.009
- education	0.028	−0.101	0.029	0.066

Notes: The table reports results from estimating equation (A1). The first row reports "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 growth regression which is statistically insignificant.

Figure A11: 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.

A.7 Entering and Exiting Serial Entrepreneur Firms

The main text documents that serial entrepreneur firms disproportionately contribute to aggregate job creation and destruction. In this section we show that this holds also when we condition on startups and exiting firms only. In particular, Figure A11 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 A11) 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.

B Serial Entrepreneurship and Income Inequality

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

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

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

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

Simple model of entrepreneurs and top income inequality. Jones and Kim (2018) provide a simple model linking entrepreneurship, business dynamism and top income inequality.[2] In particular, they assume that when an individual becomes an entrepreneur (a "top earner"), he or she earns y_0. As long as the entrepreneur remains in business, their income grows over time at a rate μ. Therefore, income per person after a years of operation is given by $y(a) = y_0 e^{\mu a}$.

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

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

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

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

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

B.1 Allowing for serial entrepreneurship

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

For tractability, let us assume that serial entrepreneurship is only a means of diversifying business risk. Specifically, we assume that every period – at a constant rate σ – each firm encounters a new "opportunity" enabling it to start an additional (spin-off) business. However, we assume that total per-period entrepreneurial income remains unchanged with the expansion of business operations. Instead, total income is diluted into the multiple businesses of serial entrepreneurs and continues to grow exponentially at a rate μ.[3] 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.

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

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

[3]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.

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

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

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

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

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

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

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

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

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

Combining the above two equations shows that

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

Serial entrepreneurship and top income inequality. Therefore, even if serial entrepreneurship is only a means of risk diversification, it affects top income inequality. Intuitively, the possibility of serial entrepreneurship increases expected business longevity as it takes longer for *all* firms of serial entrepreneurs to shut down. Formally, the Appendix shows that the expected amount of years for which entrepreneurs remain in business,

$\mathbb{E}[A_e]$, is higher than the expected lifetime of individual firms, $\mathbb{E}[A_b]$:

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

where s_{SE} is the share of serial entrepreneurs.[4] Finally, since longer expected business longevity allows entrepreneurs to accumulate more income, serial entrepreneurship raises top income inequality. Formally, using (A2), we can write the income share of the top p percent of earners as

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

The following paragraphs quantify the impact of serial entrepreneurs on top income inequality in Portugal. Towards this end, we proceed in two distinct ways. First, we use the above theoretical result and moments from our dataset to quantify the share of top income inequality driven by the presence of serial entrepreneurs. Recall, however, that this value is based on assuming that serial entrepreneurship is only a means of risk diversification. We know from Section 4 that, in fact, serial entrepreneurship comes with a premium. Therefore, as a second quantitative exercise, we generalize the simple model in order to account more appropriately for the presence of serial entrepreneur premia.

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

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

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

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

Having obtained values for ζ_b, we then use (A4) to compute the implied top income shares in the absence of serial entrepreneurship. The results are shown in Table A9. 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

[4] 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).

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.[5] Therefore, even when serial entrepreneurship is viewed as only a means of risk diversification, it has quantitatively important implications for top income inequality.

B.2 Generalized model: SE firms with estimated premia

In order to account for the empirical serial entrepreneur premia, we generalize our simple model along several dimensions. In particular, we assume that the economy is populated by two types of entrepreneurs indexed by $i = \{H, L\}$. Each type of entrepreneurs faces a different income process $(\mu_i,\ y_{0,i})$, 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 businesses of the same type as their existing firms. Compared to our model thus far, however, we assume that each additional business starts at a level of income (size) $y_{0,i}$ (and leaves the income (size) of all the other incumbent businesses of the serial entrepreneur unchanged). In other words, serial entrepreneurship is no longer only a means of business risk diversification, but it also raises entrepreneurial income.

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

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

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

Table A9: Top income inequality (in %): data and model

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

Notes: The table shows top income inequality in the "data" and "model". The former is taken from the World Inequality Databse. The latter is based on assuming SE firms are only a means of risk diversification, second row, or assuming that SE firms are characterized by the premia estimated in Section 4, third row. In both cases, we use the formula (A4) to compute the implied top income shares.

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 A10 shows the results of our estimation. The first two columns report the moments in the data and those implied by our estimation, showing that the model fit is very good. The third and fourth columns then show the parameter estimates. High-type firms are estimated to grow more than twice as fast and exit by about 10 percent less frequently than low-type firms. At the same time, high-type entrepreneurs are estimated to encounter additional business opportunities four times as frequently. However, the absolute level of these encounters is relatively low (2 percent per year). Finally, the unconditional share of high-type firms among startups is about 15 percent.

Generalized model: Results. The last row of Table A9 shows the impact of serial entrepreneurship on top income inequality. These values are based on a counterfactual exercise in which we "switch off" serial entrepreneurship in our generalized model by assuming that $\sigma_H = \sigma_L = 0$. Leaving all other parameters at their estimated values, we then simulate the model to obtain new values for average firm growth and exit rates, and therefore also of the Pareto tail coefficient $\zeta_{\text{no SE}} = \mu_{\text{no SE}}/\delta_{\text{no SE}}$. Finally, using the latter in (A4), we compute the implied top income inequality which would prevail in the absence of serial entrepreneurship.

Table A10: Model estimation: moments and parameters

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

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

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.