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The entrepreneurial ecosystem clock keeps on ticking – Regional persistence of high-growth firms

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Abstract

The entrepreneurial ecosystem framework rests on the assumption that regional conditions enable productive entrepreneurship. However, existing studies lack longitudinal designs, and thereby provide limited evidence for causal mechanisms. In a first longitudinal step Coad and Srhoj (2023) argue that the relationship between entrepreneurial ecosystems and productive entrepreneurship only holds if the prevalence of high-growth firms, a proxy for productive entrepreneurship, in a region is persistent. They do not find consistent evidence of regional persistence of high-growth firms in Croatia and Slovenia. This leads them to conclude that the entrepreneurial ecosystem framework is not valuable for policymakers. We argue that their interpretation and generalization are incorrect. In fact, we argue that their findings are consistent with a further articulated entrepreneurial ecosystem theory. We provide a more articulated entrepreneurial ecosystem theory by formulating three hypotheses on causal mechanisms between entrepreneurial ecosystems and productive entrepreneurship. To test these hypotheses, we first replicate the study by Coad and Srhoj (2023) at two regional levels in the Netherlands with three measures of high-growth firms and in European regions with a measure of potential high-growth firms. We then extend the study by Coad and Srhoj (2023) and show that there is a positive relation between entrepreneurial ecosystem quality as well as entrepreneurial ecosystem size and regional persistence of high-growth firms. Our results challenge the dismissal of the entrepreneurial ecosystem theory. We propose a more nuanced understanding that considers regional differences in the effects of entrepreneurial ecosystem quality and size on the persistence of high-growth firms.

Keywords: entrepreneurship, economic change, economic development, entrepreneurial ecosystem, regional persistence, high-growth firms.

JEL: L25, L26, M13, O18, R11, R58

Comments welcomed to: Erik Stam, e.stam@uu.nl.

1. Introduction

High-growth firms (HGFs) and the conditions enabling them, captured in the so-called entrepreneurial ecosystem (EE) framework, have become a prominent topic in both academic and policy debates (Leendertse et al., 2022; Spigel, 2017; Stam, 2015; Stam and Van de Ven, 2021; Wurth et al., 2022). An EE is defined as a set of interdependent actors and factors, that are governed in such a way that they enable productive entrepreneurship within a particular territory (Stam, 2015; Stam and Spigel, 2018). In the EE literature productive entrepreneurship is considered as the output of EEs and it is often proxied using HGFs (Fotopoulos, 2023; Henrekson and Johansson, 2010; Stam and Van de Ven, 2021). Even though substantial scientific progress has been made since Stam's (2015) sympathetic critique of the EE framework (see Wurth et al., 2023), there is still much to be done to improve our understanding of EEs and to increase the policy relevance of the framework.

The EE framework posits that productive entrepreneurship is consistently enabled by regional EE conditions (Leendertse et al., 2022; Spigel, 2017; Stam, 2015). This upward causation between the EE elements and its outputs is one of the key mechanisms argued for in the EE literature (Wurth et al., 2022). Several qualitative (Mack and Mayer, 2016; Spigel, 2017) and quantitative studies (Leendertse et al., 2022; Schrijvers et al., 2023; Stam and Van de Ven, 2021) have provided empirical validation for this hypothesis. However, Coad and Srhoj (2023) criticize the validity of this mechanism. They rightfully point out that these studies are not longitudinal in design and as a result these studies provide evidence for correlation and not yet for causation.

Longitudinal studies on entrepreneurship are not uncommon. There has been a multitude of studies showing the long-term regional persistence of self-employment and new firm formation in for example the UK (Fotopoulos, 2014; Fotopoulos and Storey, 2017), Germany (Fritsch and Wyrwich, 2014), and Sweden (Andersson and Koster, 2011). However, the regional persistence of HGFs has hardly been studied. An exception is a study by Friesenbichler and Hölzl (2020) who found moderate regional persistence of HGFs in Austria.

The study by Coad and Srhoj (2023) further investigates the persistence of HGFs. They argue that the elements of EEs are partly persistent and, based on a simulation model, show that this entails that the prevalence of HGFs should also be persistent over time. This means that the quality of EEs should not just affect the prevalence of HGFs, it should also affect *persistence* in the prevalence of HGFs. In their empirical analyses they do not find regional persistence of HGFs in Croatia (2004-2019) and Slovenia (2007-2019). Therefore, they state that the hypothesis 'High-quality EEs have a higher prevalence of HGFs than low-quality EEs' has to be rejected. They then formulate a novel 'broken clock' critique on EEs: "the relationship between inputs and outputs is so noisy that we conclude that the EE approach, according to its most recent formulations (Leendertse et al., 2022) is not a useful approach for policymakers with regards to generating the main outputs of ecosystems, i.e. HGFs." (Coad and Srhoj, 2023: p. 17). Coad and Srhoj (2023) highlight and address an important gap, but, we do not share their interpretation of their findings, for several reasons. First, the EE quality of the regions they analyze to test their hypotheses are below the European average (Leendertse et al., 2022), which provides a too limited context for rejecting entrepreneurial ecosystem theory. Second, the regions they study are very small in population size, which makes it less likely that HGFs emerge from the available human capital. In fact, we argue that their findings are consistent with a *further articulated* EE theory, for which the foundations were laid in Stam and Van de Ven (2021) and Leendertse et al. (2022). The mechanism between EE elements and outputs has so far been specified as consisting of a positive relation between the quality of EEs and the prevalence of HGFs (Audretsch and Belitski, 2017; Leendertse et al., 2022; Stam and Van de Ven, 2021; Vedula and Kim, 2019). Our further articulated theory adds the persistence in HGFs to the EE theory. We therefore aim to answer the following research question in this paper:

What is the influence of the quality and size of entrepreneurial ecosystems on the persistence of high-growth firms?

To answer our research question, we formulate a series of hypotheses in which we argue that after reaching a critical mass in terms of quality or size of the EE, there is a positive relationship between EE quality or EE size and the persistence of HGFs. Empirically, we first replicate and extend the analyses of Coad and Srhoj (2023) in a larger country: The Netherlands, which has respectively 4 and 8 times the population size of Croatia and Slovenia) and has relatively high-quality regional EEs, at the NUTS-2 and NUTS-3 regional level (respectively 12 and 40 regions). Our results show persistence in HGFs. To explain these differences, we formally test our hypotheses on European NUTS-2 regions using data from Crunchbase (see Leendertse et al., 2022), which confirm our findings. We then discuss how different empirical studies on the persistence of HGFs are consistent with our further articulated EE theory. We conclude with a discussion of our findings, and suggestions for research and policy.

2. Theoretical background

The entrepreneurial ecosystem literature studies how the elements of entrepreneurial ecosystems, defined as the combination of interdependent actors and factors, influence the presence and performance of productive entrepreneurship in a region, which in turn influence economic growth (Stam, 2015; Stam and Spigel, 2018). Productive entrepreneurship is defined as any entrepreneurial activity "that contributes directly or indirectly to the net output of the economy or to the capacity to produce additional output" (Baumol, 1993, p.30). In the EE literature HGFs are considered a key proxy for productive entrepreneurship due to their contributions to economic development and growth (Fotopoulos, 2023; Henrekson and Johansson, 2010; Stam and Van de Ven, 2021). The relation between HGFs and economic growth has been extensively studied (and mostly confirmed) in many other papers (e.g. Bisztray et al., 2023; Bos and Stam, 2014; Henrekson and Johansson, 2010).

Wurth et al. (2022) identify five mechanisms that play a role in the entrepreneurial ecosystem framework: (1) the interdependencies between the entrepreneurial ecosystem elements, (2) an upwards causation where the entrepreneurial ecosystem influences the output, the presence of productive entrepreneurship, and (3) a mechanism where productive entrepreneurship consequently affects the outcome, economic growth (4) downward causation, and where it (5) interacts across the boundaries of entrepreneurial ecosystems. Coad and Srhoj (2023) focus on the second mechanism (which is visualised in Fig. 1.), and so do we in this paper.

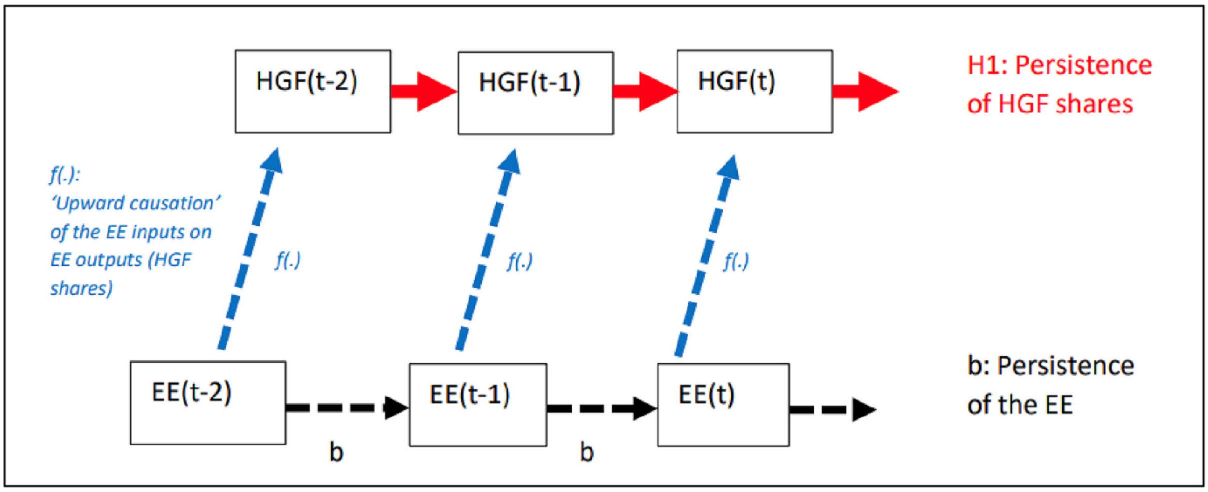


Fig.1. Conceptual diagram of the relation between EE inputs and outputs, adapted from Coad and Srhoj (2023).

2.1. Prevalence and persistence of high-growth firms

The occurrence of HGFs in a region can be measured as either the presence or the prevalence of HGFs. We define the presence of HGFs as the absolute number of HGFs in a region. The prevalence is the number of HGFs in a region relative to the population of firms (e.g. Coad and Srhoj, 2023) or the human population (e.g. Leendertse et al., 2022). In line with these previous studies, we focus on the prevalence of HGFs as this measures how well an EE enables the emergence of HGFs accounting for the size of regions.

We define the persistence of HGFs as the consistent occurrence of HGFs in a region over time. Persistence was always implied in EE research (Leendertse et al., 2022; Spigel, 2017; Stam, 2015), in the sense that it assumed that well-developed EEs have a persistent high output of HGFs. However, no empirical attention was paid to the persistence of HGFs in relation to the quality of EEs. Coad and Srhoj (2023) empirically study persistence but did not relate this to EE quality. This paper follows-up on that agenda, by making that connection. In line with Coad and Srhoj (2023) we study persistence in the prevalence of HGFs.

2.2. The influence of entrepreneurial ecosystem quality on the prevalence of HGFs

The elements of EEs can be categorized in two layers (Leendertse et al., 2022; Stam and Van de Ven, 2021). First, the fundamental institutional arrangements including formal and informal institutions that subsequently influence the governance and allocation of resources in the second layer. This second layer includes actors and resources (such as talent, knowledge, and finance) that enable entrepreneurs to develop HGFs. The combination of these layers determines the quality of the EE. We define EE quality, along the lines of Leendertse et al. (2022), as the combined strength of its elements.

The mechanism between EE elements and outputs has been identified in previous research as consisting of a positive effect of EE quality on the probability that HGFs occur in a region and thus on the prevalence of HGFs within a region (Audretsch and Belitski, 2017; Leendertse et al., 2022; Stam and Van de Ven, 2021; Vedula and Kim, 2019). This relationship is non-linear: the effect increases when EE quality increases (Leendertse et al. ,2022).This finding can be explained by regional agglomeration effects: the more firms collocate together, the more efficiently they can organize the provision of critical resources, which makes it in turn more attractive to found new businesses (Delgado et al., 2010; Van Oort and Bosma, 2013). In addition to resources, Tiba et al. (2020) argue that the successful entrepreneurs can serve as lighthouse or beacons for new talent to found similar firms in an EE, which makes high quality EEs even more successful. We formulate hypothesis 1 to test this non-linear relationship between EE-quality and the prevalence of HGFs:

Hypothesis 1: There is an increasing positive relationship between EE quality and the prevalence of HGFs.

2.3. The influence of entrepreneurial ecosystem quality on persistence of HGFs

As innovative and high growth entrepreneurship is surrounded by uncertainty (McMullen and Shepherd, 2006), one can view the founding and growth of HGFs as a probabilistic event. HGFs are a rare occurrence and individual HGFs are unlikely to consistently repeat high-growth over time (Coad et al., 2013; Mason et al., 2015; Raby et al., 2022). However, on a regional level the quality of an EE has a consistent positive effect on the probability that HGFs occur in a region (Leendertse et al., 2022; Stam and Van de Ven, 2021), which means that it becomes less of a rare event. As such, one can expect that the quality of an EE is related to regional persistence in HGFs over time (Spigel, 2017). In lower quality EEs HGFs will emerge, but less often and less persistent as in higher quality EEs. We expect that the relationship between EE quality and persistence is positive, but that the positive effect decreases as the quality of the EE increases. For this we first have a theoretical reason: HGFs rely strongly on a network of peers and benefactors for exchange of knowledge and resources that are critical for survival (Neck et al., 2004; Van Weele et al., 2018). Hence, a network is a critical aspect of an EE, and a critical asset to its quality (Wurth et al., 2022). In line with critical mass theory (Marwell et al., 1988), simulations showed that EEs need a critical mass of networked HGFs to become stable over time (Van Rijnsoever, 2020). This is because firms go bankrupt (Hyytinen et al., 2015), or that ties decay over time (Burt, 2002). This critical network mass is dependent on the level of development of the EE (Van Rijnsoever, 2020; 2022). After stabilizing, the effect of the network on the EE remains positive with a decreasing trend (Van Rijnsoever, 2020). This is because each additional tie in the network has associated diminishing returns (Uzzi and Spiro, 2005). A second reason for the relationship is methodological. Persistence is a measure that is theoretically bound by a maximum, one cannot be more persistent than 100%. This means that the positive relationship will also decrease as the value of HGF persistence approaches its maximum.

Hypothesis 2: There is a decreasing positive relationship between EE quality and HGF persistence.

2.4. The influence of entrepreneurial ecosystem size on persistence

An ecosystem, be it biologic (Fahrig, 2001), or economic (Baldwin et al., 2024) should be large enough to sustain a species over time. Hence, we argue that persistence is also influenced by ecosystem size, which we define as the extent to which a region is able to facilitate the creation HGFs. In this case, ecosystem size is largely a function of the size of the population, since entrepreneurs and the employees from firms largely come from the same region (Dahl and Sorenson, 2012; Stam, 2007). We expect a decreasing positive relationship between EE size and HGF persistence. Ecological research suggests an extinction threshold, a minimum size of the ecosystem for species to show persistence (Fahrig, 2001, p.1998). In a similar vein, for HGFs to occur consistently over time, there needs to be a sufficient number of prospective entrepreneurs and employees in a region. This is again because of the critical mass that an ecosystem needs to maintain a network, for exchanging knowledge and resources (Van Rijnsoever, 2020). Beyond the critical mass, the network becomes stable enough to grow over time, but the marginal returns of each additional ties are diminishing (Uzzi and Spiro, 2005).

For the influence of ecosystem size we thus argue for a positive effect on persistence, but that positive effect decreases with the size of the population. This is because of the diminishing returns of a growing network, and because of the maximum value that persistency can take.

Hypothesis 3: There is a decreasing positive relationship between EE size and HGF persistence.

3. Methodology

To replicate the Coad & Srhoj (2023) study we use three databases, two with Dutch firms and one with European firms. Subsequently, we discuss our extension where we test our three hypotheses using the database with European firms.

3.1. Research design and data collection

To replicate the analyses by Coad and Srhoj (2023) we use three different datasets to collect data on three indicators of HGFs. The first dataset is from Statistics Netherlands (the Dutch Census Bureau), which allows us to study HGFs in 12 NUTS-2 regions in the Netherlands, the second dataset comes from a collaboration between the Dutch newspaper 'Het Financieele Dagblad' and the Dutch Chambers of Commerce (Het Financieele Dagblad, 2020), which has data for 40 NUTS-3 regions in the Netherlands.[1] For the third dataset we follow Leendertse et al. (2022) who use firms registered in Crunchbase (Crunchbase, 2019; Dalle et al., 2017). We downloaded the Crunchbase data on July 6th 2022 using academic access. We also use the Crunchbase dataset to replicate the analyses of Coad and Srhoj (2023) at the European level by analyzing 273 NUTS-2 regions from 28 countries.

To test our three hypotheses, the second part of our study, we use the Crunchbase dataset as it encompasses the most regions (273 NUTS-2 regions from 28 European countries). In addition, we use data on the quality of these EEs from Leendertse et al. (2022) and regional population data from Eurostat (2023).

3.2. Operationalization

Replication study

For the replication study we operationalize three different proxies of productive entrepreneurship, which are employment HGFs, sales HGFs, and innovative start-ups (potential HGFs).

We operationalize the employment HGF variable using data from Statistics Netherlands (the Dutch Census Bureau). This dataset includes firms that employed at least 10 Full Time Equivalents (FTEs) at the start of the three-year period and that have at least an average employment growth of 20 percent per year in the following three years. This definition is the same as the HGF definition of the OECD used by Coad and Srhoj (2023) and Friesenbichler and Hölzl (2020) and matches the HGF employment variable of Coad and Srhoj (2023). This measure is available at the NUTS-2 level for the Netherlands and the dataset covers the 2013-2020 period.[2]

We operationalize the sales HGF variable using the dataset from the Dutch newspaper Het Financieele Dagblad, constructed in collaboration with the Dutch Chambers of Commerce (Het Financieele Dagblad, 2020). This dataset includes firms with a minimum revenue of 250,000 EUR at the start of a three-year period, which have a turnover growth of at least 20 percent per year

[1] In line with existing studies (e.g. Leendertse et al., 2022; Stam & van de Ven, 2021; Coad and Srhoj (2023) we use the administrative boundaries as the borders of EEs. However, there is an ongoing debate on the potential limitations of this approach (e.g. Schäfer, 2021; Fischer et al., 2022). This is a potential limitation of our study.

[2] The absolute number of employment HGFs is rounded to the nearest 5. This would disproportionately influence the data when considering a smaller regional level than NUTS-2.

over three years. In addition, the firms had to be profitable for at least two of the last three years, and the dataset exclude branches that are part of a larger corporation such as franchises. This sales HGFs definition is very similar to the sales based HGF definition of Coad and Srhoj (2023). The main differences are that our definition includes profitability criteria and that the initial size is based on revenue not employment size. This measure is available at both the NUTS-2 and NUTS-3 level for the Netherlands and the dataset covers the period 2013–2020. A full overview of the average number of HGFs in each NUTS-2 region is provided in Table A1 in the Appendix.

For the third dataset we follow Leendertse et al. (2022) who use firms registered in Crunchbase (Crunchbase, 2019; Dalle et al., 2017) that are founded in the past five years, and regionalize the data to the NUTS-2 level. Crunchbase predominantly captures venture capital oriented innovative start-ups and largely ignores companies without a growth ambition and is thus a good source for data on potential HGFs (Dalle et al., 2017; El-Dardiry and Vogt, 2023; Leendertse et al., 2022). Crunchbase is increasingly used for academic research (Dalle et al., 2017; Nylund and Cohen, 2017). El-Dardiry and Vogt (2023) show that there is substantial overlap between the data from a commercial start-up registry (such as Crunchbase) and HGFs based on the business register, but that there are also distinct differences. The Crunchbase data largely comes from two sources, a community of contributors and an extensive investor network. These data are then validated with other data sources using AI and machine-learning algorithms (Leendertse et al., 2022). We find that 26% of the innovative start-ups in our Crunchbase data have attracted venture capital. To only include startups (and not long established firms) we selected firms founded between 2015-2020.[3] In our Netherlands replication study, we follow Coad and Srhoj (2023) by studying the HGFs shares in a region, the prevalence, by looking at the number of HGFs per 10,000 firms. In our replication at the European level, we operationalize the prevalence of HGFs through the number of firms per 10,000 inhabitants rather than per 10,000 firms due to uneven availability of the latter data across Europe (see Leendertse et al. 2022). For the Netherlands these two measures are very strongly correlations, with correlations between 0.929-0.997 for the different years.

Testing hypotheses

To test our hypotheses, we use the same Crunchbase data to operationalize the innovative start-ups (potential HGFs) variable.

We operationalize the persistence of HGFs by constructing a measure for persistence at the regional level. For this we use the prevalence of HGFs for each of the years between 2015-2020. We calculate persistence as the inverse of the Coefficient of Variation. The Coefficient of Variation is calculated as the standard deviation divided by the mean of a series of variables. The standard deviation measures the variation in a variable over time. However, with standard deviation a higher value also leads to a higher standard deviation. we correct for this by dividing the standard deviation by the mean. A higher standard deviation indicates more variation and thus less persistence. Hence, we multiply the Coefficient of Variation with -1, so that a higher value means more persistence. The measure for persistence is thus calculated through the following formula.

[3] We also have data for 2021, however given the lag between firm founding and inclusion that is inherent in how Crunchbase collects data this data is not yet complete. Our findings remain robust when also including data from 2021.

$$Persistence_i = -\frac{\sigma_i}{\mu_i}$$

Where:
σ_i is the standard deviation of the values in row i
μ_i is the mean of the values in row i

We operationalize EE quality using the EE index from Leendertse et al. (2022). Leendertse et al. (2022) developed a set of metrics to measure the ten elements of EEs, as defined by Stam (2015), for European NUTS-2 regions. They combined these metrics to develop an EE index which measures the quality of EEs. To construct this index, they first standardized and normalized the quality of each element. They then set the maximum score for any single element to five, to prevent a disproportionate influence of strong performing ecosystem elements on the overall index. They then calculated the index in an additive way (E1 + E2 +...+E10). For the full operationalization of the EE index see Leendertse et al. (2022). Finally, to measure the size of an EE, we use the number of inhabitants (population) for each region (Eurostat 2023). We use the average population between 2010-2014 to ensure a time lag between our independent and dependent variable.

Table 1 presents the descriptives of the data at the European level. The 273 NUTS-2 regions have an average of 1,865,398 inhabitants and on average 47.1 innovative start-ups are founded per year per region. At the NUTS-3 level this translates to 10.0 innovative start-ups per region per year. The NUTS-2 level therefore seems to be the more appropriate level to test persistence. Furthermore, it is notable that the correlation between the two persistence measures (based on prevalence and based on presence) is 1.000. There is thus no added value in using both measures and we only use the prevalence-based measure for persistence. In doing so we follow Coad & Srhoj (2023) who also look at prevalence-based persistence.

Table 1

Descriptives and Pearson correlations (based on 2015-2020 averages)

#		*n*	*Mean*	*S.D.*	*1*	*2*	*3*	*4*	*5*
1	Innovative start-ups (presence (absolute)	273	47.095	144.443					
2	Innovative start-ups prevalence (relative)	273	0.220	0.443	0.892				
3	Persistence of Innovative start-ups (absolute)	272	-0.592	0.361	0.189	0.223			
4	Persistence of Innovative start-ups (relative)	272	-0.595	0.360	0.185	0.218	1.000		
5	EE index	272	8.935	6.462	0.469	0.565	0.339	0.329	
6	Population (per 10,000 inhabitants)	273	186.540	152.552	0.357	0.094	0.313	0.314	0.101

3.3. Analyses

We replicate the analyses of Coad and Shroj (2023) with our datasets. This means we calculate the persistence for three different measures of HGFs in the Netherlands (at the NUTS-2 and NUTS-3 levels) and for one HGF measure in Europe (NUTS-2 level). Following Coad and Shroj (2023) we first visualize the correlations between two time periods by normalizing the data per year, such that each year has a mean of zero. We then pool the data. Then, similar to Coad and Shroj (2023), we compare the prevalences of HGFs in regions between different time periods through single variable regression analyses by taking the three-year averages of the share of HGFs as the independent and dependent variable. [4]

Next, we test our three hypotheses. For hypothesis 1 we perform regression analyses using the prevalence of innovative start-ups (potential HGFs) as the dependent variable and the EE index as the independent variable. To model the increasing positive effect, we added a quadratic term to the model. If the data fits the right side of the quadratic curve, and it has a positive slope, then this supports hypothesis 1. For hypothesis 2, we first illustrate the relation between EE quality and regional persistence of HGFs by combining our replication results with earlier results found in the literature. Second, we use regression analyses to test the relation between EE quality and regional persistence of HGFs. To account for a non-linear effect, we take the logarithm of the independent

[4] Coad and Srhoj (2023) also report the correlations between the time periods in their paper. However, because correlations and single variable regressions are the same type of analyses and thus provide nearly identical results, we only report the correlations in the Appendix.

variable. To test hypothesis 3, we use the natural logarithm of population size as the independent variable.

4. Results

In section 4.1 we replicate the analyses of Coad and Srhoj (2023) for the Netherlands using three HGF measures. In section 4.2 we test our three hypotheses.

4.1.1. Replication of Coad and Srhoj (2023) for the Netherlands

The regions of our Netherlands replication study differ substantially in population size from the regions in Croatia and Slovenia included in the Coad and Srhoj (2023) study. The Netherlands replication study consists of 40 NUTS-3 regions with an average of 435,190 inhabitants, these NUTS-3 regions are embedded in 12 NUTS-2 regions with an average of 1,450,633 inhabitants. Croatia consists of 21 NUTS-3 regions with an average of 193,246 inhabitants, that are embedded in 2 NUTS-2 regions with an average of 2,029,082 inhabitants. Slovenia consists of 12 NUTS-3 regions with an average of 175,748 inhabitants, these regions are embedded in 2 NUTS-2 regions with 1,047,931 inhabitants (all in 2020). The NUTS-3 regions in Croatia and Slovenia are thus much smaller than the NUTS-3 regions in the Netherlands.

Based on the EE index as calculated by Leendertse et al. (2022) the EE quality of the NUTS-2 regions in the Netherlands ranges between 10.9 and 25.2. The EE index for the regions in Slovenia ranges between 3.5 and 7.3 and for Croatia between 1.8 and 2.1. These EEs thus all score below the European average on the EE index. The Croatian regions even score in the bottom 10% of all European regions.

In the first step of our replication study, we visualize the correlations between time periods for the three prevalence of the HGF measures (Fig. 2a-c). For all three HGF variables regions with a high (or low) share of HGFs consistently also show a high (low) share in later years. In our replication of the single variable regressions by Coad and Srhoj (2023) we consistently find persistence (Table 2). We find a consistent highly significant positive relation between consecutive time periods for all three types of HGFs. For the employment HGFs variable we can correlate multiple time periods. The results show that persistence becomes weaker when the time period between the two variables increases. For the sales HGFs variable and the innovative start-ups variable our data covers a shorter time period (2013-2020); hence we could only compare two time periods.

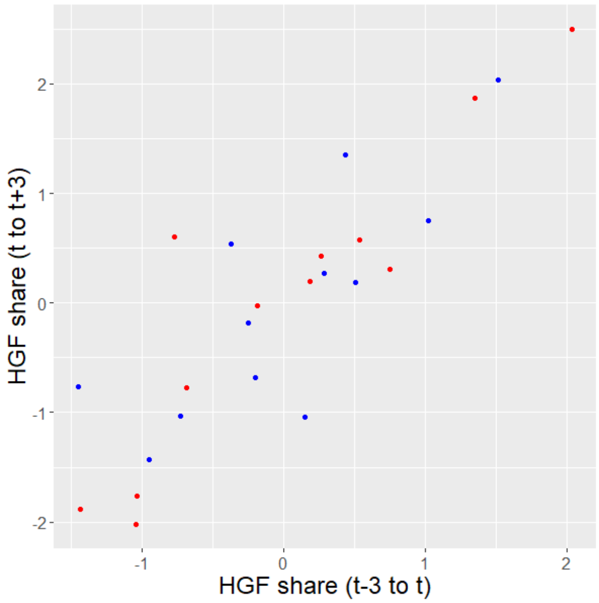


Fig. 2a. Standardized regional persistence of employment HGFs (NUTS-2 level, 12 regions). *Note: Blue dots represent the correlation between 2010 - 2012 and 2013 - 2015; Red dots represent the correlation between 2013 - 2015 and 2016 - 2018.*

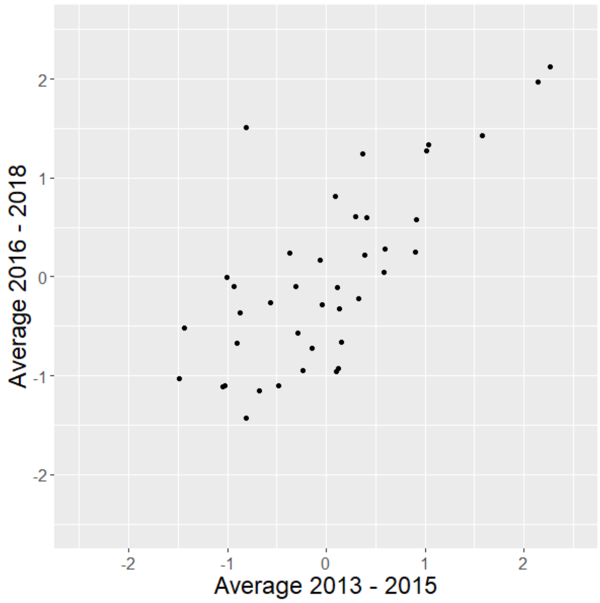


Fig. 2b. Standardized regional persistence of sales HGFs (NUTS-3 level, 40 regions)

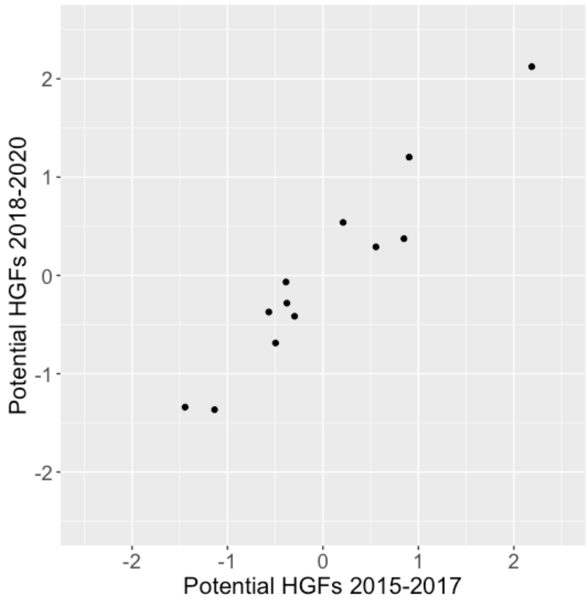


Fig. 2c. Standardized regional persistence of innovative start-ups (potential HGFs) (NUTS-2 level, 12 regions)

The correlation tables (see Appendix A2-A4) confirm our findings and show that there is a lower persistence between time periods if the time between them is longer. This suggests that the regional share of HGFs, the prevalence, slowly changes over time. We perform a robustness test using presence (absolute numbers) instead of prevalence. We consistently find persistence for all time periods and all HGF measures (see Table A5 in the Appendix). Finally, we perform a further robustness test using the average of two instead of three years, this yields similar results (Appendix A6-A7). Our Netherlands replication study thus shows strong persistence in the regional prevalence and presence of HGFs over time. This finding contrasts the results by Coad and Srhoj (2023), but can be explained by our hypotheses that high quality EEs and larger EEs deliver more persistent HGFs than lower quality and smaller EEs. We provide further proof for these hypotheses in our extension.

Table 2

Regression results for the regional persistence of three measures of HGFs in the Netherlands at NUTS-2 and NUTS-3 levels

	Dependent variable				
	Employment HGF (NUTS-2)			Sales HGF (NUTS-3)	Innovative start-ups (NUTS-2)
	2016 – 2018		2013 – 2015	2016 – 2018	2018 – 2020
	1	2	3	4	5
Employment HGF 2013 – 2015	1.234*** (0.175)				
Employment HGF 2010 – 2012		0.898 (0.457)	0.989* (0.246)		
Sales HGF 2013 – 2015				1.298*** (0.192)	
Innovative start-ups 2015 – 2017					0.686*** (0.059)
Constant	50.201 (40.931)	108.186 (115.870)	- 18.716 (62.311)	18.223 (9.163)	-0.001 (0.002)
Observations	12	12	12	40	12
Adjusted R^2	0.815	0.207	0.580	0.534	0.925

. $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; standard errors reported in brackets

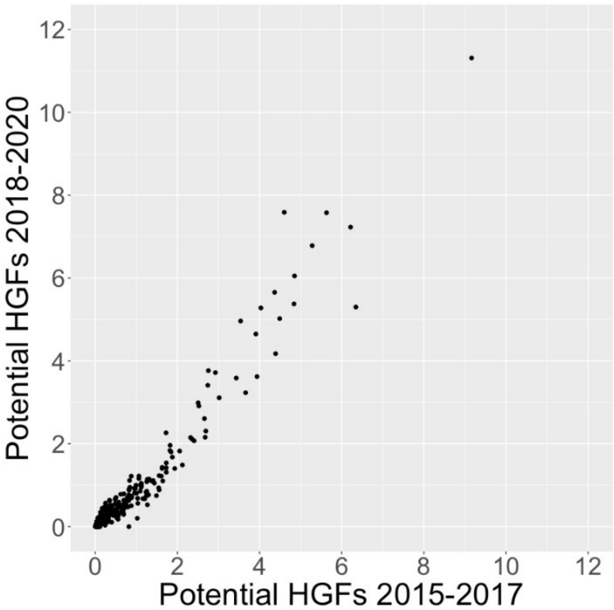
4.1.2. *Replication for Europe*

We also replicate the analyses of Coad and Srhoj (2023) using the persistence of innovative start-ups (potential HGFs) in 273 European NUTS-2 regions. As a first step we visualize the correlations[5] between time periods for the three prevalence of HGF measures (Fig. 3). We see a clear pattern of persistence.

[5] The correlation table (as provided in Coad and Srhoj (2023)) can be found in the Appendix as Table A8.

In our replication of the single variable regressions by Coad and Srhoj (2023) for Europe we also find clear and highly significant persistence (Table 3). Our findings thus show that, in contrast to the findings of Coad and Srhoj (2023) for regions in two small European countries, a large-scale European replication reveals high persistence in the regional shares of innovative start-ups.

Fig. 3. Regional persistence of innovative start-ups (potential HGFs) in Europe (NUTS-2 level)[6]



[6] The region UKI3&4 (Inner London) is not included in this scatterplot. The extreme values (25+ after normalization) reduced the readability of the scatterplot

Table 3
Regional persistence of innovative start-ups in Europe (NUTS-2 level, 273 regions)

	Dependent variable
	HGF 2018 – 2020
HGF 2015 – 2017	1.161***
	(0.011)
Constant	-0.161***
	(0.025)
Observations	273
Adjusted R^2	0.974

. $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; standard errors reported in brackets

4.2. Extension
To better understand the relationship between HGF prevalence and persistency and entrepreneurial ecosystems we extend our analysis. We test our three hypotheses .

4.2.1. Prevalence
With hypothesis 1 we expect an increasing positive relationship between EE quality and the prevalence of HGFs. Our tests show a consistent and positive relation between EE quality and subsequent prevalence of (potential) HGFs (Table 4).[7] These regressions are similar to those in Leendertse et al. (2022), yet with more recent data of the dependent variable. As such we increased the time-lag between the dependent and independent variable and reduce the risk of reverse causality. Our findings are also consistent with those of Leendertse et al. (2022). We fitted both models with a linear term and with an added quadratic term. Both yield significant effects. Moreover, the quadratic term is positive, and gives a substantial increase in explained variance compared to the models with only a linear term. The turning point of the curve can be found at EE index values of 3.88 for the 2015-2017 time period and 4.42 for the 2018-2020 time period, which are at the very left hand side of the distribution, after which the curve increases quadratically. This supports hypothesis 1.

[7] We also run this analysis for the presence of firms. Our results do not change (Appendix Table A9)

Table 4

The relation between EE quality and prevalence of innovative start-ups in Europe (NUTS-2 level, 273 regions)

	Dependent variable: Innovative start-ups prevalence			
	HGF 2015 – 2017	HGF 2018 – 2020	HGF 2015 – 2017	HGF 2018 – 2020
	1	2	3	4
EE index	0.048***	0.029***	-0.021.	-0.015.
	(0.004)	(0.003)	(0.011)	(0.008)
EE index squared			0.003***	0.002***
			(0.000)	(0.000)
Constant	-0.151***	-0.102***	0.140*	0.085*
	(0.045)	(0.031)	(0.061)	(0.043)
Observations	272	272	272	272
Adjusted R^2	0.338	0.280	0.428	0.363

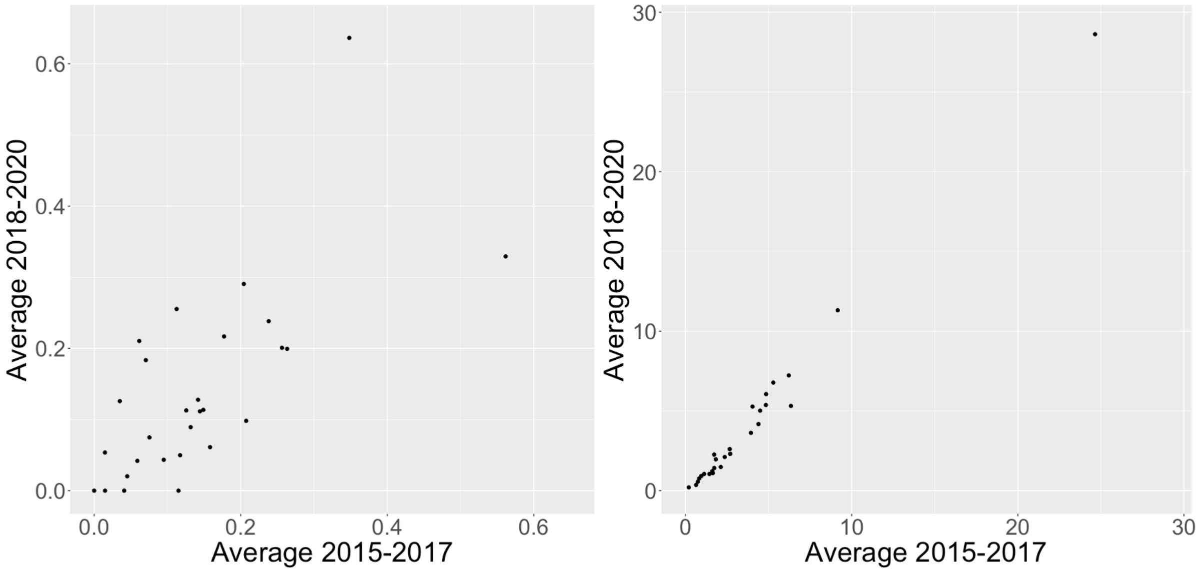
. $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; standard errors reported in brackets

4.2.2. Persistence

As a first step in addressing hypothesis 2, which posits a decreasing positive relation between EE quality and HGF persistence, we visualize the correlation between the prevalence of innovative start-ups separately for the bottom 10 % of EEs in terms of EE quality (on the left) and the top 10% of EEs in terms of EE quality (on the right) between the 2015-2017 and 2018-2020 time periods (Fig. 4). We find some persistence[8] for the bottom 10 % with a Pearson correlation of 0.684 and clear persistence for the top 10%, with a Pearson correlation of 0.994 (on the right).

[8] We also see this in a correlation table for the bottom 10% of regions (see Appendix, Table A8). We find much lower persistency levels for this group than for the full sample and when considering the individual years furthest apart (2015 and 2020) the persistency is not significant.

Fig. 4. Regional persistence of innovative start-ups for the bottom 10% (left) and top 10% (right) in EE quality across 273 European regions.



Next, we formally test the relation between EE quality and persistence (Table 5, column 1.)[9] We find a significant positive relation. When we model the natural logarithm of the EE index (Table 5, column 2), we observe that the model fit dramatically improves, which supports hypothesis 2.

In a similar vein, we test hypothesis 3 on the influence of ecosystem size on the persistence of HGFs (Table 5, columns 3 and 4). The results also show that the natural log of the population fits the data much better than a linear relationship, providing support to hypothesis 3, that there is a decreasing positive relation between EE size and HGF persistence.

As robustness test, we construct two sets of dummies variables, where each variable either represents a 10% increment in the EE index, or a 10% increment in size. We run dummy regressions with the bottom 10% as the reference category (Appendix table A11). The results show that in both models all other groups have significantly more persistence than the bottom 10% in EE quality (hypothesis 2) and EE size (hypothesis 3), after which there is an overall gradually increasing trend. This is in line with the critical mass argument that lies at the basis of hypotheses 2 and 3. Some estimators are lower than the previous increment, but these differences are not significant. As a further robustness test we run a model with random effects for the countries. The results remain the same (Appendix Table A13).

[9] We also run this analysis for presence based persistence. Our results do not change (Appendix, Table A10).

Table 5

The influence of EE quality and population size on the prevalence of innovative start-ups in European NUTS-2 regions [10]

Dependent variable: Persistence of innovative start-up prevalence				
	1	2	3	4
EE index	0.017***			
	(0.003)			
Log (EE index)		0.178***		
		(0.025)		
Population (per 10,000 inhabitants)			0.001***	
			(0.000)	
Log (Population (per 10,000 inhabitants))				0.227***
				(0.025)
Constant	-0.744***	-0.929***	-0.732***	-1.719***
	(0.034)	(0.051)	(0.033)	(0.124)
Observations	271	271	272	272
Adjusted R^2	0.104	0.158	0.091	0.236

. p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001; standard errors reported in brackets

4. Discussion

We can further illustrate the relation between EE quality and persistency by combining the operationalization of EE quality employed by Leendertse et al. (2022), our replication for the Netherlands (section 4.1), the results of Coad and Srhoj (2023) and those of Friesenbichler and Hölzl (2020). This dataset, which encompasses EE data for 273 European NUTS-2 regions, allows us to construct regional EEs, albeit at the NUTS-2 level, in Slovenia and Croatia (cf. Coad and Srhoj, 2023), Austria (cf. Friesenbichler and Hölzl, 2020), and the Netherlands (this paper). We provide an overview in Table 6, where we show that there is low persistency in low-quality EEs and high persistency in high-quality EEs. Hence, the findings of all three national studies, and our European study are fully in line with the argument that low-quality EEs show lower persistency.

[10] One region is removed from the analyses as this region did not record any innovative start-ups in any year. Hence, the mean was 0 and it was impossible to calculate our measure for this region.

Table 6

Persistence of HGFs in countries with different EE development levels

	Number of NUTS-2 regions	Number of NUTS-3 regions	Startups per NUTS-2 region per year	Startups per NUTS-3 region per year	Range of EE-index	HGF persistency	Source
Croatia	2	21	17.25	1.64	1.82-2.08	Low	Coad and Srhoj (2023)
Slovenia	2	12	15.92	2.65	3.47-7.34	Some	Coad and Srhoj (2023)
Austria	9	35	14.67	3.77	7.85-22.26	Moderate	Friesenbichler and Hölzl (2020)
Netherlands	12	40	181.04	54.31	10.86-25.18	High	Our study

Combining the data sources also gives a coherent story for EE size and persistence. When we return to the regions studied by Coad and Srhoj (2023) using the Crunchbase data. We find that on average respectively 34.50 and 31.83 innovative start-ups (potential HGFs) are founded per year in Croatia and Slovenia. Given these numbers, the 21 NUTS-3 regions for Croatia, and to a lesser extent the 12 NUTS-3 regions for Slovenia, are too small to expect persistence in the prevalence of HGFs. The regions have an average of respectively 1.64 and 2.65 innovative start-ups per region per year for Croatia and Slovenia.[11]

In our analyses of European NUTS-2 regions there is still some persistence, even in the bottom 10% of regions. This could serve as an argument for the use of NUTS-2 regions rather than NUTS-3 regions if the latter have relatively low numbers of inhabitants (and a low prevalence of high-growth firms or innovative start-ups).

5. Conclusion and implications

In this paper we further articulated the EE-framework, by showing that the quality of an EE is positively related to the persistence of the emergence HGFs in a region, in addition to the prevalence of HGFs. However, whereas the slope of relationship between EE quality and prevalence is increasingly positive, the positive relationship between EE quality and persistence is decreasing. Moreover, the size of EEs is also decreasingly positive related to the persistence of HGFs.

Thus, this study addressed the valid criticism of Coad and Srhoj (2023), who found that EEs do not lead to persistent emergence of HGFs. We showed that this indeed is true for EEs of a lower quality or of a smaller size. However, our Netherlands and European replication studies add nuance to their findings, by placing their results in a broader picture. Based on our hypotheses, we would indeed expect that regions in Croatia and Slovenia have a lower regional persistence of HGFs, as they score relatively low on the EE index. In contrast, regions with better developed EEs, like the regions in the Netherlands in our analyses and the Austrian regions studied by Friesenbichler and Hölzl (2020) indeed show higher regional persistence of HGFs. Moreover, the regions in Croatia and Slovenia have a low number inhabitants. Hypothesis 3 shows the importance of EE size for persistency, which indicates that the NUTS-3 level can be a too fine-grained spatial scale to identify persistence of HGFs, especially in the case of sparsely populated regions. Overall, we conclude that our findings, combined with those by Coad and Srhoj (2023), and Friesenbichler and Hölzl (2020) all fit with our further articulation of the EE framework. Our articulation is theoretically grounded in ideas about critical mass in social networks (Marwell et al., 1988), and decreasing marginal returns in social networks (Uzzi and Spiro, 2005), as well as on empirically grounded simulations on EEs (Van Rijnsoever, 2020). Thereby, it has a solid theoretical base.

Our work combined with Coad and Srhoj (2023), and Friesenbichler and Hölzl (2020) contributes to the EE framework (Wurth et al., 2022), by pointing scholarly attention to the matter of the persistence of EE outputs over time. This is a research direction that received little quantitative

[11] Coad and Srhoj (2023) do not communicate any descriptives about the number of HGFs in their data and we can thus not confirm this for their HGF variables. However, for the Netherlands we find that the three HGF measures are similar in magnitude regarding their occurrence (see Table A1).

empirical attention, but that is key for the argumentation behind the EE framework. We encourage future researchers to keep taking a longitudinal approach, and to account for EE quality and scale, to better understand entrepreneurial ecosystems, their effects and evolution. More research also is needed in additional mechanisms that can influence regional persistence of HGF. Possible candidates are the density of the population, or sectoral diversity. Further, until now, studies used the NUTS-2 or NUTS-3 level as unit of analysis of EEs. However, it is well possible that EEs do not adhere to these administrative boundaries (Fischer et al., 2022; Schäfer, 2021). More research is needed on the boundaries of EEs, and inter-ecosystem connections to see how regions can strengthen each other, or possibly compete.

Our paper also answers calls for more replication studies in economics (Hamermesh, 2007), management (Bettis et al., 2016), and entrepreneurship (Davidsson, 2016). Much more data-driven, and more longitudinal studies, taking into account longer time periods are needed to fully understand persistence, randomness, the appropriate territorial boundary of an EE, and the role of critical mass and cumulative causation in the evolution of EEs and their outputs (cf. Wurth et al., 2022). Until now studies considered persistence at the EE output level. This is the case because the required longitudinal data on the inputs of EEs is not yet systematically available (Leendertse et al., 2022), however the increased availability of data in this area makes such an approach increasingly viable.

Finally, Coad and Srhoj (2023) conclude their paper with a “broken clock” critique of the EE approach. A broken clock tells the correct time twice a day, but still is not useful to tell the time. The clock metaphor applies according to the authors to the EE approach: sometimes right but not useful for policy. Based on our results we conclude that the clock keeps on ticking, but perhaps less accurate in lower quality or smaller EEs. Ultimately the clock metaphor may be misleading in the context of EEs and especially EE policy, in two ways. First, improving the quality of EEs is a no-regret policy for EEs of sufficient critical mass. improving the quality of EEs is a viable policy approach for EEs of sufficient critical mass. In doing so, policymakers can capitalize on the increasingly positive relationship between EE quality and the regional persistence of high-growth firms (HGFs). However, we also caution that policymakers should carefully examine which elements require strengthening. For EEs of insufficient quality or size, it is important to assess whether achieving critical mass is feasible. Scaling the administrative size might contribute to building a more coherent EE across regions, but this approach may pose challenges in sparsely populated areas where establishing interactions between EE elements is difficult. This bring us to the to the harder (and perhaps more interesting) question, which is how to improve each EE in a meaningful, effective and efficient way. Second, in a conceptual sense, entrepreneurial ecosystems are enabling the emergence of novelty and structural change, not the continuation of a ticking clock. To paraphrase Mark Twain, in well-developed entrepreneurial ecosystems history doesn’t repeat itself, but it often rhymes, in unexpected ways.

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Appendix

Table A1

Average absolute number of HGFs per NUTS region over available time period

NUTS CODE	Name region	Employment HGFs (2010-2019)	Sales HGFs (2013 - 2020)	Innovative startups (2015-2021)
NL11	Groningen	58.5	21.0	55.6
NL12	Friesland (NL)	55.5	13.9	50.9
NL13	Drenthe	47.5	4.1	37.9
NL21	Overijssel	133.0	42.6	104.7
NL22	Gelderland	245.0	49.0	174.1
NL23	Flevoland	46.5	8.8	49.1
NL31	Utrecht	197.5	86.4	161.6
NL32	Noord-Holland	469.0	138.8	538.6
NL33	Zuid-Holland	466.0	106.9	404.3
NL34	Zeeland	39.5	8.3	21.4
NL41	Noord-Brabant	343.0	95.5	223.9

Table A2

Regional persistence of employment HGFs in the Netherlands (NUTS-2 level, 12 regions).

Employment HGFs per 10,000 firms		
	(1)	(2)
	Pearson correlation [p-value]	Spearman's rank correlation [p-value]
Pooled (2010-2020)	0.854 [0.000]	0.823 [0.000]
Period: 2010-2012 and 2013 – 2015	0.786 [0.002]	0.762 [0.006]
Period: 2010 – 2012 and 2016 - 2018	0.528 [0.078]	0.364 [0.246]
Period: 2013 – 2015 and 2016 - 2018	0.912 [0.000]	0.811 [0.002]

Table A3

Regional persistence of sales HGFs in the Netherlands (NUTS-3 level, 40 regions).

Sales HGFs per 10,000 firms		
	(1)	(2)
	Pearson correlation [p-value]	Spearman's rank correlation [p-value]
Pooled (2013-2020)	0.799 [0.000]	0.771 [0.000]
Period: 2013 - 2015 and 2016 – 2018	0.739 [0.000]	0.691 [0.000]

Table A4

Regional persistence of innovative start-ups (potential HGFs) in the Netherlands (NUTS-2 level, 12 regions).

Innovative start-ups (potential HGFs) per 10,000 firms		
	(1)	(2)
	Pearson correlation [p-value]	Spearman's rank correlation [p-value]
Pooled (2015-2020)	0.869 [0.000]	0.848 [0.000]
Period: 2015-2017 and 2018 – 2020	0.965 [0.000]	0.909 [0.000]
Period: 2015 and 2020	0.835 [0.000]	0.853 [0.000]

Table A5

Regression results for three measures of HGFs in the Netherlands at NUTS-2 and NUTS-3 level using presence of regional HGFs

	Dependent variable				
	Employment HGF			Sales HGF	Innovative start-ups
	2016 – 2018		2013 – 2015	2016 – 2018	2018 – 2020
	1	2	3		
Employment HGF 2013 – 2015	1.465*** (0.028)				
Employment HGF 2010 – 2012		1.404*** (0.072)	0.963*** (0.035)		
Sales HGF 2013 – 2015				1.797*** (0.045)	
Innovative start-ups 2015 – 2017					0.718*** (0.015)
Constant	4.673 (5.559)	-2.354 (14.841)	-5.499 (7.158)	-0.245 (0.747)	-3.099 (4.302)
Observations	12	12	12	40	12
Adjusted R^2	0.996	0.972	0.986	0.976	0.996

. $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; standard errors reported in brackets

Table A6

Regression results for sales HGFs at the NUTS-3 level in the Netherlands using prevalence of regional HGFs, two year averages

	Dependent variable					
	HGF 2019 - 2020			HGF 2017 - 2018		HGF 2015 - 2016
	1	2	3	4	5	6
HGF 2017 – 2018	0.868***					
HGF 2015 – 2016		0.952***		0.949***		
HGF 2013 – 2014			1.236***		1.271***	0.834***
Constant	15.871	25.181	32.183	19.482	24.840	25.760
	(8.009)	(11.108)	(11.991)	(10.347)	(11.051)	(8.86)
Observations	40	40	40	40	40	40
Adjusted R^2	0.690	0.449	0.346	0.483	0.399	0.307

. p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001; standard errors reported in brackets

Table A7

Regression results for innovative start-ups (potential HGFs) at the NUTS-2 level in the Netherlands, two year averages

	Dependent variable		
	HGF 2019 – 2020		HGF 2017 – 2018
	1	2	3
HGF 2017 – 2018	0.554***		
	(0.091)		
HGF 2015 – 2016		0.596***	0.980***
		(0.071)	(0.088)
Constant	-0.003	-0.003	0.002
	(0.003)	(0.002)	(0.002)
Observations	12	12	12
Adjusted R^2	0.766	0.864	0.917

. p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001; standard errors reported in brackets

Table A8

Regional persistence of innovative start-ups in Europe (NUTS-2 level, 273 regions)

Innovative start-ups per 10,000 inhabitants		
	(1)	(2)
	Pearson correlation [p-value]	Spearman's rank correlation [p-value]
Pooled (2015-2020)	0.962 [0.00]	0.884 [0.00]
Period: 2015-2017 and 2018 – 2020	0.987 [0.00]	0.921 [0.00]
Period: 2015 and 2020	0.909 [0.00]	0.789 [0.00]

Table A9

The relation between EE quality and presence of innovative start-ups in Europe (NUTS-2 level, 273 regions)

	Dependent variable	
	Innovative start-ups presence (negative binomial)[12]	
	HGF 2015 – 2017	HGF 2018 – 2020
	1	2
EE index	0.135***	0.148***
	(0.010)	(0.011)
Constant	2.359***	1.605***
	(0.112)	(0.119)
Observations	272	272
Adjusted R^2	0.440	0.460

. $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; standard errors reported in brackets

[12] The reported R^2 values for the negative binomial models are the McFadden R^2 (McFadden, 1974).

Table A10

The influence of EE quality on the persistence of presence innovative start-ups in European NUTS-2 regions [13]

	Dependent variable	
	Persistence of innovative start-up presence	Persistence of innovative start-up presence
	2	2
EE index	0.018***	
	(0.003)	
Log(EE index)		0.183***
		(-0.025)
Constant	0.747***	-0.937***
	(0.034)	(0.051)
Observations	271	271
Adjusted R^2	0.112	0.167

. $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; standard errors reported in brackets

[13] One region is removed from the analyses as this region did not record any innovative start-ups in any year. Hence, the mean was 0 and it was impossible to calculate our measure for this region.

Table A11

The influence of EE quality and region size (population) on the persistence of innovative start-ups in European NUTS-2 regions using quantile dummies. Dummies use bottom 10% as reference category

Dependent variable: Innovative start-ups persistence		
Independent variable	EE quality dummies	Population size dummies
	1	2
Bottom 10%		
10-20%	0.301*** (0.085)	0.271** (0.088)
20-30%	0.337*** (0.086)	0.369*** (0.088)
30-40%	0.389*** (0.086)	0.415*** (0.088)
40-50%	0.360*** (0.086)	0.439*** (0.088)
50-60%	0.397*** (0.086)	0.527*** (0.088)
60-70%	0.476*** (0.086)	0.480*** (0.088)
70-80%	0.484*** (0.086)	0.500*** (0.088)
80-90%	0.513*** (0.086)	0.510*** (0.088)
Top 10 %	0.544*** (0.086)	0.606*** (0.088)
Constant	-0.968*** (0.061)	-1.006*** (0.063)
Observations	271	272
Adjusted R^2	0.158	0.177

. $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; standard errors reported in brackets

Table A12

Regional persistence of innovative start-ups for the bottom 10% of European regional EEs (NUTS-2 level, 27 regions)

Innovative start-ups (Crunchbase start-ups per 10.000 inhabitants)		
	(1)	(2)
	Pearson correlation [p-value]	Spearman's rank correlation [p-value]
Pooled (2015-2020)	0.625 [0.000]	0.540 [0.000]
Period: 2015-2017 and 2018 – 2020	0.684 [0.000]	0.646 [0.000]
Period: 2015 and 2020	0.224 [0.261]	0.128 [0.525]

Table A13

The influence of EE quality and population size on the prevalence of innovative start-ups in European NUTS-2 regions including random intercepts

Dependent variable: Persistence of innovative start-up prevalence		
	1	2
Random effects (variance)	0.030	0.034
Country (Intercept)	(0.172)	(0.185)
Fixed effects		
Log (EE index)	0.198***	
	(0.037)	
Log (Population (per 10,000 inhabitants))		0.219***
		(0.024)
Constant	-0.960***	-1.67***
	(0.078)	(0.121)
Observations	271	272
Conditional R^2	0.407	0.466