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Firm Survival as a Function of Individual and Local Uncertainties: An Application of Shackle's Potential Surprise Function

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Abstract: The link between the management of uncertainty and knowledge creation is the core element behind firm survival, as these two factors are critical for true innovation. This article links the survival of highly innovative firms to their knowledge creation and application in the context of two types of uncertainty management: (i) the individual firm's ability to handle uncertainty; (ii) the aggregate local "neuroticism" in facing uncertainty that characterizes the geographic location where the firm operates. The study is inspired by Audretsch and Dohse's (2007) model of firm growth and geographic location. We augment this model with George Shackle's (1949a) *potential surprise function* for handling individual uncertainty. Additionally, we extend the model by also considering the psychological profile of localities, in particular their level of *neuroticism* according to the so-called *Big Five* taxonomy. Using data for the highly innovative Cambridge Region (UK) for the period 2010–2014, we find that, on individual level, the daring companies survive less frequently, but appear to live longer if they manage to survive. Survival also appears to be influenced by locational characteristics related to the local level of *neuroticism*. In particular, being located in a place with higher "neuroticism" is associated with lower survival rates.
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Firm survival has for a long time been perceived and analyzed in evolutionary economics as a function of the local (geographic) context. More recent literature has further clarified and expanded this understanding in various directions, in particular in relation to the significance of human capital and knowledge creation (see, for example, Ganotakis 2012; Rauch and Rijsdijk 2013; Hyytinen, Pajarinen, and Rouvinen 2015; Huggins, Prokop and Thompson 2017). The modern concept of Culture Based Development (CBD) is based on a more filigree consideration of the simultaneous significance of the attitudinal cultural biases on both individual and local levels, which in interaction may interfere in virtually any economic choice process, and turn the survival of the company into a stochastic process determined by the knowledge function of the individual decision maker and her/his environment (see Tubadji 2012, 2013; Tubadji and Nijkamp 2015). G. L. S. Shackle was one of the most original contributors in economic thought on the link between uncertainty, knowledge/ignorance, and investment decisions, a view that he labeled as the *potential surprise function*. We adopt, in our study, this potential surprise function, and we apply the CBD perspective of the mixed effect from context and individuals in the decision making process. We offer this CBD-extended Shacklean potential surprise function to explain the stochastic variation of knowledge creation in the economic growth and location model of firms proposed by David Audretsch and Dirk Dohse (2007). Thus, we aim to test whether the Shacklean uncertainty stochastic component can be successfully incorporated in the existing firm survival models in order to improve their precision and accuracy in capturing the biases stemming from both the individual and local characteristics of firms with regard to the capability to handle uncertainty.

Most recent empirical work has identified the controversy between innovation and firm survival, which seems to be related to, among other factors, the firm's high absorptive capacity, with some work actually suggesting that more absorptive capacity might even turn out producing a negative impact on survival (see Hyytinen, Pajarinen, and Rouvinen 2015). A mechanism potentially explaining this paradoxical empirical dependence between innovation and firm survival is suggested by the work of George Shackle in the 1940s but which remained largely neglected in economic research. We will focus here on his consideration of the crucial role of the capability to handle uncertainty in the process of knowledge creation. This idea was articulated by Shackle (1949a) in his conceptualization of the potential surprise function, a function that automatically ignores innovative ideas that are associated with unacceptable levels of uncertainty, because their implementation is ambiguous and unpredictable, and hence implies surprising results. As we know from the Schumpeterian literature, and as confirmed by recent contributions, innovation is a main factor for firm survival (see, for example, Christian Helmers and Mark Rogers [2010] on the case of the UK and the effect of intellectual property rights on firm survival, and similar results by Elena Cefis and Orietta Marsili [2005] for the Netherlands). Yet even a uniform risk-loving propensity motivating the intention to focus on an innovative topic might still be associated with a different degree of ability to handle the sphere of unknowns where risk cannot be estimated and thus another basic driver for decision making—this is what we call here the "fear of uncertainty"[1]—dominates the decision process. Therefore, the main hypothesis of our article, inspired by Shackle's potential surprise function, is that entrepreneurial capability to handle uncertainty (as a driver of innovation) co-determines a firm's survival.

To operationalize our hypothesis, we adopt and extend the Audretsch and Dohse (2007) model of a firm's economic growth as a function of knowledge creation and location. Moreover, following the CBD rationale that both individual and local levels determine economic outcomes of actors, we augment and adapt the Audretsch and Dohse (2007) model to include both the individual firm uncertainty (as is originally the case with Shackle's concept) and the local firm's context uncertainty (which is our CBD extension of Shackle's ideas).

[1] Our reasoning is based on a parallel made between Shackle's concept of potential surprise function based on a management of uncertainty and some anthropological and sociological research (see Hall 1966; Jackson 2011) which explains animal herd behavior as an attempt to cure one's fear and anxiety from uncertainty. Thus, our analogy here is that sticking to one's pack is equivalent to sticking to one's culture and to what we already know, and the truncation driven by ignorance and driven by the uncertainty and anxiety generated from the ignorance we liken to the fear behind sticking to one's pack in animal behavior. Therefore, we label the Shacklean uncertainty on individual level as a "fear of uncertainty."

To empirically test our CBD-augmented model, we use—for the first time in economics research—the unique Cambridge Ahead dataset collected independently by the Cambridge University Centre for Business Research (CBR), exclusively provided to us for the purposes of this study. This dataset contains all functioning companies that were established in the Cambridge Ahead region since 1919, the observations in the dataset accounting for over 20,000 companies, all tracked regarding their performance during the period 2010–2014. Cambridge belongs to one of the most innovative and entrepreneurial regions in the UK and is therefore a very suitable case study with regard to studying firm survival in the context of innovation and knowledge creation. Our main factor of interest—the stochastic disturbance generated by handling of uncertainty during the knowledge creation process—is operationalized on an individual level by firm ownership type (where completely independent ownership is identified with the propensity and ability to handle the highest levels of uncertainty on individual level [see de Jong and Marsili 2015]). Local uncertainty (i.e., the locality specific ability to handle uncertainty) is next approximated with the level of *neuroticism* of a place, quantified through the levels of neuroticism in the *Big Five* psychological types dataset (see Ciavarella et al. 2004).

Our findings on individual uncertainty, based on the use of parametric and non-parametric techniques (Kaplan-Meier for two distinct groups, daring and non-daring type of firms) suggest that while innovative specialism does not explain survival, firm survival is significantly less frequent for daring companies. However, a Cox proportional hazard model finds that the companies that survive longer are again the daring type companies. This paradoxical finding is both in line with existing recent research results (see Wennberg, Delmar and McKelvie 2016) and is fully consistent with Shackle's potential surprise function expectations. Namely, if a firm is a daring type, it survives with more difficulty, but if it survives, then it lives longer than the rest of the firms. To trace the local-level impact, we use a multi-level modeling approach; and find that the handling of uncertainty, approximated by the local level of neuroticism, is clearly associated with a West-East locational divide of the Cambridge Ahead area, where the daring companies cluster to the West of the center place of firm survival, while the companies to the East of the center place of Cambridge Region are predominantly of a non-daring type.

The structure of the present article is as follows. (i) an introduction to the literature on which our model for firm survival and uncertainty management is based. Distinguishing between Shackle's potential surprise function on an individual level, and our CBD conceptual and operational extension of Shackle's function on the context/local level, the suggested model—based on adapting Shackle's function as a source of stochastic component of the traditional model—accounts for the stochasticity created by individual and local management of uncertainty in decision making; (ii) a statement of our operational model; (iii) a description of our unique Cambridge Ahead dataset and our estimation strategy; (iv) the empirical results and interpretations; and (v) some concluding remarks.

General Economic Fundamentals on Firm Survival

Sol Lucet Omnibus

Textbook economics suggests that individual firm behavior is related to profit and price maximization goals under imperfect competition, with deadweight loss and market structure being the main determinants of firm performance and, ultimately, survival. The new institutional economics broadens this perspective by arguing that firm performance (survival) is a function of its context, in other words, a result of the "exposure to the sun to which the more exposed plants survive better" (Alchian 1950). After Armen Alchian's (1950) contribution, it was soon realized that the sun that shines for all firms is "the sun of knowledge" and that, consistent with Joseph Schumpeter (1942, 84), innovation "strikes not at the margins of the profits and the outputs of the existing firms but at their foundations and their very lives." The joint focus on knowledge and information represents the starting point of modern endogenous growth theory, but the consideration of the characteristics of the context in this model is still not an established practice, while evidence exists that it should be a matter of precise modeling since it potentially might exert considerable effects on firm performance (see Pe'er and Keil 2013; de Jong and Marsili 2015).

Firm Survival and Location

The recent literature on firm survival has started reconciling evolutionary theory (and its accent on the context) with standard endogenous growth models. The survival is modeled and tested as a function of financial and human capital inputs, intertwined with knowledge creation and learning from context (see Unger et al. 2011; Rapse and van Oort 2011; Huggins, Prokop, and Thompson 2017). But the evidence is controversial, since there are also important contributions reporting evidence of a negative impact from the openness to the context (see Ciavarella et al. 2004, de Jong and Marsili 2015). This gives rise to an awareness of the need to properly address the source of these empirical inconsistencies.

Naturally, delving into the effect of the context in this direction involves examining the effects from industry, region, and time. Michael Fritsch, Udo Brixy, and Oliver Falck (2006) study the effect of these factors on new business survival rates for firms in West-German districts in the period 1983–2000. Their findings suggest that firm survival is relatively low in industries characterized by a high minimum efficient size and high numbers of entries. This means that regional characteristics are a significant factor in explaining the survival of a company.

More recent contributions offer further insights into the direction of endogenous growth and the interplay between individual and local level characteristics. For example, in a recent contribution in this stream of research, Huggins, Prokop, and Thompson (2017) analyze the case of Wales in the UK. The authors examine how the factors of human capital, growth motivation, and locational conditions relate to each other in explaining firm survival within a region. Using a cohort of firms, the article studies survival rates and finds that human capital related to the experience of the entrepreneurs, as well as the firm strategy (i.e., its growth motivation), are the two crucial factors determining the rates of survival. Thus, the findings of this study confirm the role of both human capital and the local environment for the likelihood of survival. Moreover, the firm's involvement with these two factors is confirmed to be a function of its environment. This suggests that the locational factors affect the overall firm durability through interaction with the individual characteristics of the firm over time.

Other recent contributions delve deeper into the entrepreneurial cultural profile of the locality and its impact on firm agglomeration and innovation. For instance, Michael Fritsch and Javier Changoluisa (2017) study survival of German companies and find a pronounced positive effect of high levels of historical self-employment on entrepreneurship and innovation activities nowadays. These results support the interpretation that the persistence of regional entrepreneurship is a function of the cultural milieu and local attitudinal context. Moreover, their results suggest that regions with a pronounced regional culture of entrepreneurship appear to have both higher levels of new business formation today and higher levels of innovation activity in terms of shares of research and development (R&D) employment and patents per employee.

Yet, in the above studies, as well as in the bulk of classical and most recent literature on this topic, the question remains as to why exactly the location and its milieu matter for innovation and firm survival. Endogenous growth theories indeed suggest a human-capital related mechanism behind the individual dimension of firm survival (Romer 1994). The local effect on firm survival, however, remains mostly empirically detected and reported as a fact of life interfering and moderating human capital utilization in the firm, without it being modeled as a particular mechanism. Moreover, more filigree research has demonstrated that the firm characteristics (such as age, type of ownership, size) also determine the firm capacity to benefit from the context in terms of learning and other positive agglomeration spillovers (see Pe'er and Keil 2013; Hyytinen, Pajarinen, and Rouvinen 2015; de Jong and Marsili 2015; Wennberg, Delmar, and McKelvie 2016). Therefore, uncertainty at the individual and local level is relevant for firm survival, and an adequate model of firm survival should account for that. Our analysis addresses this niche of research. We start with uncertainty on the individual level, integrating it in the endogenous human-capital based mechanism, and augment it, so that it also captures the impact from the uncertainty generated by the psychological type of the locality on the individual in the process of decision making that is conducive to innovation and firm survival.

The Individual Human-Capital-Based Mechanism

A typical study in the direction of individual human capital effect modeling is Andreas Rauch and Serge Rijsdijk (2013) who analyze newly founded business ventures and their long-term growth and survival. Using a sample of 201 business start-ups, the authors study firm growth and failure over a period of twelve years. Their findings suggest that general and specific human capital are both important factors for survival. In particular, they find that the effect of general human capital on failure is mediated by growth, while overspecialization of human capital was found to exert negative effects on firm survival.

Following this line of thought, another study for the UK was offered by Panagiotis Ganotakis (2012), who explores the impact of entrepreneurs' general and specific human capital on the performance of new technology-based firms. Using a resource-based approach to entrepreneurship theory, the authors analyze the survival of 412 surveyed firms operating in both high-tech manufacturing and in the services sectors. Their findings suggest that specific managerial human capital is more important for the performance of the firm than general human capital.

Not strictly in the vein of human capital theory, but very closely relevant to it is the work by Aviad Pe'er and Thomas Keil (2013) and Aviad Pe'er, Ilan Vertinsky and Thomas

Keil (2016), who explore the relationship between firm's characteristics among Canadian manufacturing firms in the period 1984–1998 (in terms of resources and capabilities) and agglomeration effects on firm survival. Their findings directly show a dependence between firm characteristics and firm ability to benefit from opportunities in their cluster in order to survive, even if the effect from the cluster is moderated by the size of the local competition.

Similarly, Jeroen de Jong and Orietta Marsili (2015) study the relationship between firm characteristics and the availability of entrepreneurial role models among family and friends. They find a positive relationship only in the case of a specific type of firm ownership, namely, in cases where the business has been taken over from a family member or friend, with this relationship found to be even a negative factor for survival in the case of owners with previous entrepreneurial experience.

Finally, individual firm characteristics are also addressed from the point of view of psychological type of owners. An interesting and relevant contribution in this framework is Ciavarella et al. (2004) who study firm survival as a function of the entrepreneurs' personality type classified according to the Big Five personality attributes: extraversion, emotional stability (i.e., the opposite to vulnerability to uncertainty), agreeableness, conscientiousness, and openness to experience. Interestingly, their results suggest a negative effect from openness characteristics. This triggers two questions. First, what is the role of the characteristics of the context towards which a firm is open? We expect here that across different local contexts different personality types may prevail as determinants of entrepreneurial success. Second, why do only some of the individual psychological characteristics play a role in the particular context examined?

The findings of the above studies underline the importance of considering the micro contribution and local context as equally relevant and carefully operationalized, simultaneously considered factors; and they call for a filigree understanding of the nature of the contribution of these two factors as an input for firm growth and survival, even in the presence of a standard endogenous growth modeling approach.

The Audretsch-Dohse Model of Knowledge Access on Individual and Local Levels

A seminal contribution that unites the endogenous growth approach with locational contributions was offered by Audretsch and Dohse (2007). In their study, Audretsch and Dohse (2007) model firm growth as a function of firm characteristics, knowledge creation, and location. The authors focus on the performance of new technology firms, and explain it by means of firm age, industry characteristics, and characteristics of the geographic location. The Audretsch and Dohse (2007) main operational model can be expressed as follows:

$$\text{FIRM GROWTH} = \beta_0 + \beta_1\,\text{SIZE} + \beta_2\,\text{AGE} + \beta_3\,\text{INDUST} + \beta_4\,\text{KNOWLEDGE} + e \qquad (1)$$

where FIRM GROWTH is measured as employment growth, SIZE stands for capital size and is a vector of firm-size related measures, AGE is company age, INDUST is a vector of industry dummies and other region-specific variables, and KNOWLEDGE is a region-specific knowledge or agglomeration variable.

Growth and knowledge-based innovation are dimensions of firm life which naturally link to firm survival and this reasoning is widely accepted in the literature. However, the elaboration of this line of research has been mostly on the side of innovation and types of innovation, without delving into the relationship between context and individual innovation (see, for example, Cefis and Marsili [2005] who focus on procedural innovation).

We consider the Audretsch and Dohse (2007) model as a useful starting point for the analysis in our article, but we aim to delve a bit further into how individual and local characteristics engage in the process of knowledge access. We will base our understanding of context and individual knowledge access on the interplay between individual and local handling of uncertainty.

Shacklean Uncertainty of Individual and Local Levels

Our focus on integrating uncertainty in a firm survival model is motivated by the appearance of several empirical investigations on firm survival and business dynamics which have shown that entry and exit rates are significantly correlated, and do not exhibit a clear pro- or counter-cyclical pattern (Audretsch and Mahmood 1995; Geroski 1995; Storey and Wynarczyk 1996; Santarelli and Vivarelli 2007; Pe'er and Vertinsky 2008; Carree, Verheul and Santarelli 2011). In fact, firm exit is a normal feature of industrial dynamics and, from a Schumpeterian "creative destruction" perspective, may be seen as part of the mechanism that favors the exploitation and exploration of new technological and entrepreneurial opportunities (Coad et al. 2013, 2016). This view has prompted new departures in economic research and related fields, often associated with the notion of uncertainty (von Gelderen, Frese, and Thurik 2000; Alvarez and Barney 2005; McMullen and Shepherd 2006; Saffo 2007; York and Venkataraman 2010).

Undoubtedly, the Austrian economic school has strongly accentuated the very role of attitudes to risk and uncertainty in the economic life of a firm (see, e.g., Menger 1950), while neo-Keynesian economics has generated prolific insights into the relationship of these factors with economic choices and firm survival (see, e.g., Keynes 1936, Knight 1921 Soros 2014; Feduzi, Runde, and Zappia 2014). Yet, most of this research has not benefitted from the use of big individual datasets and advanced econometric techniques.

There is some interesting empirical work concerning the debate of context uncertainty and strategic "entrepreneurial orientation" of the firm. For example, Thomas Lumpkin and Gregory Dess (2001) link two dimensions of entrepreneurial orientation to firm performance: the moderating role of the environment and the industry life cycle. The "entrepreneurial orientation" is generally defined by the authors as strategy-making processes and styles of firms that engage in entrepreneurial activities, expressed by levels of autonomy, innovativeness, risk taking, proactiveness, and competitive aggressiveness. Using a study of 124 executives from ninety-four firms, the decision maker's proactiveness and competitive aggressiveness were analyzed in various contexts. The effect from these two factors was found to be subject to the life cycle of the firm. Moreover, the authors found that in dynamic environments characterized by rapid change and uncertainty, proactive firms had a higher performance relative to competitively aggressive firms.

None of this existing empirical research, however, has been backed with conceptual or theoretical explanation. We suggest as a potential explanation the concept of Shackle (1949a) which he calls the potential surprise function. Shackle's original concept is on individual levels. We propose our CBD extension of the potential surprise function, where the uncertainty on local levels is also taken into consideration within the potential surprise function.

Shackle's Original Propositions on the Potential Surprise Function

It is noteworthy that an especially filigree functional understanding of the involvement of uncertainty in the process of knowledge creation was suggested by Shackle (1949a). In his highly original contribution, Shackle defines individual decision maker's uncertainty as a driver of the so-called potential surprise function in the process of knowledge creation and investment in research and development activities.

Shackle defines uncertainty as another name for ignorance (see Shackle 1949a, 115–116). Thus, he is interested in the: "form of wishful thinking that is by no means stupid or even illogical; but is, indeed, the natural and reasonable response of human nature to intractable uncertainty; the main attractiveness of a given course may spring paradoxically from a hypothetical outcome which is regarded by the individual himself as less likely than some others" (Shackle 1949a, 2).

Shackle distinguishes clearly between two types of events:

> (i) Counter-expected event: an hypothesis which has been considered and to which as a consequence of this examination a high degree of potential surprise has been assigned; (ii) Unexpected event: a contingency which has entirely escaped attention, which has formed no part of any hypothesis. A person's structure of expectations may be more completely demolished by an unexpected event than by a counter-expected event. The former reveals not merely a misjudgement [sic], but the fact that the individual is not only unable to know some essential features of the situation but has been ignorant of the existence and extent of his ignorance. (see Shackle 1949a, 73, in footnote)

The second type of event is of particular interest to Shackle, as it is a source of overconfidence in the probabilities of the outcomes (from our choice) of what we know about and our ignorance about outcomes for which we do not know anything and therefore cannot even imagine them or assign them any probabilities as there is absence of frequency of observed similar outcomes in the past (see Shackle 1949b).

Shackle (1949a, 7) defines potential surprise on as "degree of belief" in one's certainty of the outcomes. Or as he puts it elsewhere:

> Thus we shall say that a person can compare his own respective degrees of belief in two different outcomes of some course of action or two different answers to a question by taking each of these outcomes or answers in turn and asking himself what intensity of shock or surprise he would feel if, without there having been meantime any change in the knowledge available to him on which he based his belief in it, he were to learn that this belief is mistaken. The measure so obtained is what we may call the potential surprise associated, by a particular person at a particular date, with the falsity of the answer or the non-occurrence of the outcome. (Shackle 1949a, 10)

Next, he summarizes an understanding of a single function potential surprise function. Namely: "It is likely that the degree y of potential surprise associated with a continuous variable x will itself be a continuous function of the variable, and we shall call the function $y = y(x)$ the potential surprise function" (Shackle 1949a, 11).

The role of this function is: "to permit or deny to the imagination effective access to some particular idea. A man's judgement compels him to attach certain degree of potential surprise to given hypotheses of gain" (Shackle 1949a, 40).

> This potential surprise function naturally feeds into the formation of the decision maker's expectations, which Shackle defines as: "imagination constrained into congruity or consonance with the individuals conception of the orderliness of the universe, his beliefs about the way things happen and his notion of what could happen within given time when the starting point is the existing situation. Expectation is thus the act of imagining things which are looked on as possible, it is the act of anticipating experience." (Shackle 1958, 106)[2]

In this context, Shackle underlines that it is knowledge that is the input at stake in this function and is driven by the fact of life that: "the individual excludes that his relevant knowledge might change at some date other than m" (Shackle 1949a, 49) (i.e., the actual moment).

Most importantly, Shackle's insight suggests that: "By the mental process we have described, the individual reduces any uncertain-situation to the simplicity of an ordinary bet, in which only two possible outcomes are considered, one of which is a definite amount of gain and the other definite amount of loss" (Shackle 1949a, 18). We will turn in the next subsection to why this insight of Shackle's is crucial and empirically particularly alluring and suitable for testing.

Shackle (1949a, 61) clearly refers to the potential surprise function as the element of choice of a blueprint in an investor's decision making. Relevance for firms and the business cycle is hinted with Shackle's contribution on the potential surprise function (1949a, 58). The relevance of the context where the firm is situated is also touched upon but only the most basic aspect concerning taxation rather than other more culturally specific characteristics of the milieu are discussed. Thus, the primary focus of Shackle's work remains on the individual decision and the role of the potential surprise function in it.

CBD Interpretation of Shackle's Potential Surprise Function

There is one main aspect of Shackle's potential surprise function that we highlighted above as most important from the CBD perspective. Namely, this is its relationship to anthropological and sociological research on fear and the reason why animals stick to their pack in order to reduce their own anxiety from uncertainty (see Hall 1966; Jackson 2011; Kets and Sandroni 2016). Thus, we suggest that it seems likely that the reason why the potential surprise function operates in the first place is the human fear of uncertainty, due

[2] There are other interesting details about the conceptualization of potential surprise but the extent of this detail is not relevant for the analysis we would like to focus on here. Yet, it might be worth paying attention to the plot of the potential surprise function available in Shackle (1949a, 12), in other words, his "bell-shaped curve" which resembles a tube diagram; as well as his explanation of the gambler preferences (33) and focus gain and loss (again there) which describe the indifference curves and indifference maps of people making decisions under the potential surprise function. Dynamics of the process over time are also discussed.

to which the unthinkable outcomes are considered as not existent in order to avoid anxiety from the unknown. Put differently, we suggest that people stick to what is known and accepted by the culture of their context as the "pack" and seek feelings of certainty and security (as opposed to feelings of uncertainty, anxiety, and fear). Second, as we noted, the most interesting part of Shackle's detailed description of the potential surprise function seems to be his description of this function as essentially a process of truncation (cutting away) a certain set of outcomes. Thus, CBD proposes to interpret Shackle's truncating process as a fear-based knowledge creation function that truncates (ignores) investment opportunities for research and development if they are such that so little knowledge on their successful implementation exists in the local context that they might lead to unpredictable results,[3] with the individual being moved by the desire to avoid the anxiety of fear from the unpredictable loss which these uncertain outcomes inspire.

We wish to point out here that our above interpretation of Shackle's explanation of uncertainty as a driver of success or failure can be used to reconcile the standard perspective on individual profit maximization, with the neo-Keynesian demand-side consideration of the role played by the "context" in shaping economic activity (see also Stephan 2011). We suggest that the context is the "recipient" of individual firm level innovation (i.e., the aggregate face of the client/consumer). Therefore, the context's psychological receptiveness to innovation will determine whether the innovative product suggested by the company will be successful on the market, given one and the same success in generating true innovation on the side of the company. If the local context is closed to uncertain and hitherto untried solutions, a true innovation might not succeed or might encounter more difficulties to percolate in spite of its objective innovative qualities. The role of the context as an openness-varying network through which innovative ideas strive to percolate has been modeled according to the six-degrees of connectedness suggested in sociological literature (Milgram 1967). It has been found that it requires at least six people randomly selected in a row from a locality to be open to innovation in order for an innovative idea to percolate within it (see Tubadji and Nijkamp 2016). Put differently, it takes not only firm innovativeness, but also an innovation-receptive demand, and a local network that is uncertainty-friendly for cooperation to absorb and generate agglomeration spillovers that help innovative companies to survive and thrive in a place.[4] Moreover, in line with Pe'er and Keil (2013), a combination of an uncertainty-loving attitude by both firm and place is required to positively influence the likelihood of firms established in such a place to emerge, succeed, and survive. The individual and local openness to uncertainty can be expected to accelerate across firms and thus create a multiplier effect on firm performance.

There are some contemporary conceptual contributions relying on Shackle's work, such as the work by Stephen Batstone and John Pheby (1996); and Marcello Basili and Carlo Zappia (2010). However, none of these studies have an empirical-analytical nature. Our study serves to contribute to: (1) the entrepreneurial literature on location and firm survival, by incorporating Shackle's potential surprise function to explain the creation of a stochastic

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[3] See Tubadji and Nijkamp (2021) for an operationalization of such an empirical analysis of a truncated modeling on individual decision making.

[4] This reasoning is, in principle, in line with the evolutionary perspective on diffusion of technology in manufacturing suggested by Richard Nelson (1968).

effect from the local level on knowledge creation and innovation; and (2) the Shackle-specific literature by testing empirically Shackle's original claim on the role of individual decision-maker's uncertainty in knowledge creation approximated in our study (through a Schumpeterian interpretation) with firm survival.

Meanwhile, there are solid empirical contributions such as Hyytinen, Pajarinen, and Rouvinen (2015) who find that when one consults an ex-ante measure of the firm innovativeness (as opposed to capturing only the ex-post established successful innovators) this casts very different light on the relationship between innovation and firm survival. Put differently, the standard approach to innovation is to look at only those firms that have survived, which naturally represents a selection bias case, omitting to consider all those firms who did not survive. Hyytinen, Pajarinen, and Rouvinen (2015) demonstrate that when this bias is corrected for through the use of ex-ante approaches, innovativeness is actually negatively associated with firm survival. These findings are consistent with the expectations of Shackle's potential surprise function. Therefore, this function is likely to be the mechanism that provides an economically relevant explanation behind the accumulated findings in the literature.

The next section presents the particular methodological synthesis in which we integrate the Shacklean uncertainty on individual and local level in an augmented and modified version of the Audretsch and Dohse (2007) model for firm performance. We pursue this augmentation by adopting the above-mentioned Culture-Based Development (CBD) approach.

A Culture-Based Development Model of Firm Survival: Knowledge, Culture, and Uncertainty

We present here a Culture Based Development (CBD) model for firm survival, which provides an integrative view based on Shackle's uncertainty concept. The CBD model builds on the fundamentals of the Audretsch and Dohse (2007) model for firm growth, knowledge creation and location in the sense that we keep these three components as main elements of the CBD model as well. These components are given, however, a slightly different operationalization in the CBD model, which is augmented by the component related to knowledge creation both in the direction of the firm and the locality. This augmentation is related to knowledge creation on individual level as a function of individual firm uncertainty—a rationale that is borrowed from Shackle (1949a) and his potential surprise function. We also lift Shackle's (1949a) conceptualization to an aggregate level, by recognizing that according to the Audretsch and Dohse (2007) model, local context (and specifically its tolerance to uncertainty and daring behavior) acts as a limit for the behavior of the company. This is the mechanism through which context affects the firm's innovation, productivity, and, ultimately, its survival.

In a general sense, this CBD model can be understood as explaining firm survival from the viewpoint of total factor productivity and investment from an R&D perspective (in a Romer-type of endogenous growth model). Next, we include explanatory factors for demand represented by the size of the internal (within Cambridge) and external (country-wide and internationally-wide) product-specific market, the context (in terms of size and sector-diversity of the geographic cluster of firms around the firm of interest), and the firm strategy (approximated with the level of innovation the company is likely to address throughout its life-span). This model can be formulated as follows:

$$FS_i = f(SIZE_i, AGE_i, INDUSTRY_{ij}, KNOWLEDGE_i, KNOWLEDGE_j) \quad (2)$$

where *i* indicates the firm and *j* indicates the region in comparison to the country, and where:

FS–firm survival, equal to 1 when the firm survives, and 0 otherwise;[5]

SIZE–a vector of inputs, firm financial and human capitals (approximated by firm assets in the last observed year of operation);

AGE–a vector of different relevant aspects of firm age;

INDUSTRY–a vector of context-related factors, approximated by the spatial concentration of firms in the district and the industry specialization of the company (which is the INDUST component of the Audretsch-Dohse model); this vector includes also some demand-related factors, e.g. approximated by the size of the competition in this sector in terms of peer group firms (which can be perceived as relevant regional characteristics from the Audretsch-Dohse model);

KNOWLEDGE–a composite vector of firm strategy in terms of Shackle's factor of knowledge creation as a function of facing uncertainty; this vector has two dimensions—individual and local—namely: (1) $KNOWLEDGE_i$—individual factors, in other words, the daring attitudes of the firm that can be approximated by the firm's choice over ownership-type[6] (independent ownership being understood as the highest form of openness to uncertainty) or alternatively the knowledge intensity level of the firm according to Audretsch and Dohse (2007); and (2) $KNOWLEDGE_j$—the local level of uncertainty that the local milieu where the company operates may moderate the daring behavior of the firm by imposing cultural limits to what level of daring is socially acceptable.[7] Clearly, we are using here two proxy variables for the way knowledge is affected by the daring behavior on individual and local levels. If these proxy variables are found to be statistically significant it will be very interesting to delve further into the mechanism behind generating these two types of daring behaviors on individual and local levels. For the present study, the main research question of interest is whether these two proxy variables are indeed playing a role in firm survival as Shackle's potential surprise function would suggest. If this essential element is found to be statistically significant, all further details proposed by Shackle will be worthwhile of exploration in order to understand whether the potential surprise function itself operates in the way that Shackle suggests or in a different manner. Here we want to understand only whether the main component of the potential surprise function—the

[5] We use two alternative measures fit for the two different empirical methods at stake. The two measures and their complete consistency with regard to the economic interpretation are explained where relevant in the text in the following data and estimation strategy regarding sections.

[6] Indifferent of the factors which may have led to the single ownership type, the understanding here is that once being characterized as a certain type of owner, this will be predictable for a certain type/level of daring behavior that will be likely to be observed by you as a decision maker because of the legal obligations you have to consider other decision makers in your processes from now on.

[7] The local level of uncertainty is captured by a measure which has nothing to do with the company ownership itself and it is irrelevant whether the owner might have happened to be interviewed in the neurotic characteristics of the place or not. The context is not a simple sum of its parts but a result of the distribution of its parts and the threshold that these distributions set within the system for certain complex processes at stake and power dynamics between groups.

management of uncertainty—is significant for firm survival. Also, we infer here the observed type of ownership, distinguishing between shared type of ownership as opposed to an independent decision maker associated with single ownership. We do not question whether the utility of the owner to choose or end up being framed as such type of a decision maker is comparable across individuals. What matters for our analysis is that after they have become this type of owner, they are clearly distinguished as decision makers under two different types of daring conditions due to the social and institutional barriers to dare that firm ownership sets for the owners.[8]

As openness to uncertainty has a crucial role in our model, we provide here a detailed reasoning on the mechanisms behind and approximation of: (1) a firm daring type as a solo firm ownership and (2) local psychological openness to uncertainty as context uncertainty.[9] On an individual level, a firm's daring type is associated with the level of ownership due to the cumulative effect of three mechanisms: (1) single ownership assumes that the owner and single decision maker has made the important decision to enter into business without seeking to hedge this major risk taking initiative through sharing the responsibility and investment with any partner, and is prepared to face the eventual losses alone as well, which is considered common knowledge in the standard financial literature (see for instance Acharya and Bisin 2009; Chew 2012); (2) firm ownership is known in the literature to drive firm location (see for instance Keeble et al. 1999); thus, single-owned companies will have higher tendencies to firm location choice, while shared ownership firms will have more fuzzy preferences divided between the preferences for location harbored by the different owners; therefore, the single ownership results into a more resolute (i.e., more daring) type of choice over firm location; (3) a single-owned firm is more daring in terms of being more determined with regard to specialization, as often the expertise of the single owner defines the expertise of the firm; this type of daring choice over specialization is supported by the literature on ownership and the unity of ownership and direction literature (see Gomez and Korine 2008).

Indifferent of the reasons behind it, however, firm ownership is a readily observed fact (we treat this fact as an ownership choice, it can be a random result of other factors). Becoming a certain type of owner describes you as an owner that has accepted a certain type of setting for risk taking and decision making. If you are a single owner you will be daring on your own, if you are not a single owner you may be curbed in your daring behavior by

[8] This reasoning is also in line with Shackles remark that: "Hopes which are mutually exclusive are not additive; fears which are mutually exclusive are not additive" (Shackle 1949a, 38). In the sense that once having chosen to be a less independent decision maker you exclude being a daring decision maker by legal status, even if by nature and character you would derive high utility from daring. As long as you have decided to act as a non-daring owner, you are now on objectively constrained to act as such.

[9] Our conceptual reasoning is further backed by the rationality that sole ownership is equivalent to a choice for a "unity of ownership and direction," in the spirit of Polanyi (1944). It stands for being more certain of one's direction rather than experiencing a psychological need for sharing the responsibility and spreading one's freedom for choice with others in finding the right direction (see also Gomez and Korine 2008, 108). Meanwhile, we do know that entrepreneurs still have different sensitivities to risk (see for instance Wennberg, Delmar, and McKelvie 2016); therefore, capturing their sensitivity to uncertainty should facilitate addressing empirically the heterogeneity that exists in the risk and uncertainty related differences among the entrepreneurs analyzed in our study. Moreover, Philippe Aghion, John Van Reenen, and Luigi Zingales (2013) offer a clear theoretically reasoned and empirically supported relationship traced between type of ownership and level of innovativeness and daring behavior in terms of the type of product produced (venturing into substitutes versus true product market competition). The paper offers also a theoretical reasoning on the interplay between ownership and the role of the context which are consistent with our further empirical expectations about the interaction between the individual and context levels.

other owners and this state is what we want to capture here, without exploring whether this state is a natural or conditioned state of the individual decision maker. At an aggregate level, we consider the general psychological type of the context. It took a long evolution of economic science until economics recognized adequately the role of the psychological side of human choice on a micro level (see Tibor Scitovsky 1941, 1976; Daniel Kahneman 2011). The advantage of considering the psychological type of the context is that a representative measure of the average psychological characteristic can be reliably obtained from established psychological datasets with the local psychological being a good expression to the aggregate average utility of the market (Huggins, Thompson, and Obschonka 2018).

Our working hypotheses based on model (2) above—and inspired by Shackle's (1949a) proposition that daring to accept uncertainty is related to the level of innovation attainable by a firm—are now as follows:

H01: *Firm survival is directly affected by the firm's individual attitude to dare to accept uncertainty.*

H02: *Firm survival is directly affected by the firm's surrounding context through its attitude to dare to accept uncertainty.*

The remainder of this article describes the empirical testing of these two hypotheses using the full population of Cambridge Ahead companies. Our analysis provides new insights and lessons, in terms of policy implications, derived from this dataset regarding firm survival and attitudes to uncertainty on individual and local levels.

Testing a Firm Survival Model with Integrated Shackle's Uncertainty Concept on Individual and Local Levels

In this section, we describe the unique database that was provided to us by the Cambridge Centre for Business Research for the purpose of this study on Shacklean uncertainty. We also lay out here the estimation strategy for using this data in order to operationalize our model.

Database

We use the unique Cambridge Ahead dataset collected by the Cambridge Centre for Business Research that contains the full population of over 20,000 companies based within a twenty-mile radius from the center of Cambridge, UK. These firms are private companies and limited partnerships (LLPs), excluding sole proprietorships and other forms of un-incorporated businesses; the data is corrected for mergers and acquisitions (see Appendix 2 for more details).

Using the information from this dataset, we obtain for the purpose of our study: the total assets availability in the last year of operation, the peer group size (transformed into a Herfindahl index for competition with assumed equal market shares among peers), and an eyeball indicator (a dummy variable equal to one if the company endured a switch of industry specialization). We have also available control variables for: size (following the Financial Analysis Made Easy (FAME) classification, transformed to a scale of 1 to 5 from small to big companies, which we use as dummy variables, omitting the fifth category), location (dummy variables for twelve of the thirteen Cambridge districts[10]) and industry (dummy variables for twelve of the thirteen districts). We use these variables to stochastically explain the survival of the company.

Additionally, the dataset contains useful information about the company knowledge-intensity classification based on the so-called London Analysis, Identifying Science and Technology Businesses in Official Statistics. Thus, the Cambridge Ahead definition for a knowledge-intensive company broadly includes high technology and medium-high technology manufacturing and Organization for Economic Co-operation and Development (OECD) knowledge intensive services (KIS)[11] high-tech service sectors (a detailed definition by standard industrial classification (SIC) sector-code can be found in Appendix 2). Low and medium-low technology manufacturing, KIS market services, KIS financial services and other KIS branches are also generally classified as knowledge-intensive. We use this classification to compare the survival between knowledge-intensive and non-knowledge intensive companies.

Our main dependent variable of interest is the survival of the company. The available variables in our dataset can be used in two alternative ways, with consistent economic interpretation. The one measure focuses on the surviving companies, the other measure focuses on the death of companies. These two sets are mutually exclusive, thus if we find an effect on the survival of a company this is likely to have the same effect with opposite sign for the dying group of companies. The use of the surviving or dying part of the observations is linked to the particular estimation method used and is therefore presented in further detail in the sections below, which delve into the particular estimation methods that will be used. Put in a nutshell, while the measures and methods employed might look different, the economic interpretation of the two alternative indicators and the statistical results obtained are fully consistent and require only a change of the sign depending which side of the dying/surviving will be considered for the technical reasons of the analysis.

In our attempt to operationalize our main explanatory factor of interest—Shackle's (1949a) definition of daring to accept uncertainty, we approximate daring with type of ownership on an individual level. The Cambridge-based companies with no parent are defined as a daring type (because they are independently managed and independently facing risk and economic-shock situations owners), as opposed to any other form of ownership: no domestic owner, but foreign-owned; being owned by a domestic company, but with an ultimate foreign owner or owned by a UK non-corporate organization.[12]

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[10] The thirteen districts we have in our dataset are: Bedford, Braintree, Cambridge, Central Bedfordshire, East Cambridgeshire, East Hertfordshire, Fenland, Forest Heath, Huntingdonshire, North Hertfordshire, South Cambridgeshire, St. Edmundsbury, Uttlesford. These districts correspond to the LAU2, which is the lowest level in the EUROSTAT NUTS classification division in the Eurostat nomenclature.

[11] The OECD definition classifies the knowledge intensive services (KIS) into four groups: financial services; market services; high-tech services and other services. The Cambridge Ahead definition of knowledge intensive company covers, in general, only the high-tech dimension of the latter OECD KIS definition.

[12] Type of ownership is widely recognized as an important factor in the entrepreneurial literature. The identification of the daring type of firm with the single ownership is first logically motivated by the above discussed mechanisms behind the economic choices of single owners. Second, especially in the banking and finance literature, empirical research has found that entities that are owned by a single private owner are much more risk taking in their investment behavior than banks with shared types of ownership (such as a private and public one, for example) (see Garcıa-Marco and Robles-Fernandez 2008; Barry, Lepetit, and Tarazi 2011; Barinov 2017).

Our expectation is that the daring companies are more successful in terms of survival, since according to Shackle, daring to accept uncertainty allows more innovative ideas to be addressed, while according to Schumpeter (1942) this should allow us to identify the winners among the entrepreneurs on the market. Yet as we see in our descriptive statistics, a large number of Cambridge companies throughout the whole area ascribe to the daring characteristics, so statistically it is also likely that this is so widespread a characteristic that it does not necessarily explain differences in survival. If we still find the daring characteristic playing an important role, especially with the presence of other controls, this will be a powerful support for the conceptual rigor of Shackle's potential surprise function (see Table 1 for more details). In addition, by using the unique Cambridge Ahead dataset and thus focusing on only one region, our analysis is not affected by potential institutional differences and delves into the differences in daring attitude towards the rest of the world, as demonstrated by the firm itself and its context.

Finally, we create a special augmentation of the Cambridge Ahead dataset with data concerning the five psychological traits known as the Big Five (see Peter Rentfrow, Markus Jokela and Michael Lamb (2015)), aggregated at a district level. Data were collected via a noncommercial internet website within the ongoing, global Gosling-Potter Internet project (Gosling et al. 2004). People can voluntarily participate in this study by completing a questionnaire. Among other questions, they are asked to assess (based on a 5-point Likert scale) the following personality traits: extraversion, conscientiousness, openness, agreeableness, and "neuroticism." Neuroticism, specifically, is defined as the opposite of emotional stability. This means that neuroticism is associated with low levels of psychological resilience, low motivation, depression,[13] and fearfulness (see Goldberg 1990; Robinson, Larson and Shawn (2014). Therefore, we select as a second most important proxy of interest the mean values of neuroticism per district in the Cambridge area. We will use this measure to further explain the agglomeration effects on firm survival with the cultural factor that causes these agglomeration effects. This framework describes our CBD interpretation of the original Shackle hypothesis of the uncertainty-based potential surprise function, lifted here from individual to aggregate regional level (see also Tubadji and Nijkamp (2021) for a similar regional implementation).

Estimation Strategy

The main purpose of our empirical strategy is to demonstrate that even when all relevant and well-known factors for firm survival are taken into account, the Shacklean potential surprise function still brings in significant statistical and economic meaning to the firm survival model. Moreover, if the potential surprise function shows statistical significance even in the presence of all relevant controls, this will mean that Shacklean uncertainty basically explains the stochasticity of the knowledge component in a unique manner and which the standard model would otherwise be unable to capture.

[13] Sonia Roccas et al. (2002) describe the essence of neuroticism as a Big Five characteristic as follows: "Individuals high on Neuroticism tend to be anxious, depressed, angry, and insecure. Those low on Neuroticism tend to be calm, poised, and emotionally stable. We anticipate no positive associations between value priorities and Neuroticism. Neuroticism is not likely to facilitate the attainment of the motivational goal of any type of value. Moreover, as Bilsky and Schwartz (1994) reasoned, "The depression characteristic of people high on neuroticism might result from failure to attain the desired level of any one of the ten values" (171).

Using the Cambridge Ahead data described in the previous section, we initially had 26,267 companies, with different starting times (different years of establishment), all tracked for four periods from 2010 until 2014). As clearly not all of them survived after 2014, the data that we employ represents a case of right censoring. Our main outcome of interest is the duration of company life from start-up until the last year of measurement available in our dataset (2014).[14] This means that companies entering earlier survived longer than those that entered at the end of the period of measurement. Given this fact, and the clearly nonlinear empirical hazard rate function presented in Figure 1, an OLS estimation would produce biased estimates (see Cox and Oakes 1984). Therefore, we use a series of non-parametric, parametric, and semi-parametric tests in order to capture a realistic picture of the determinants of firm survival in the Cambridge district.

Analyzing the Effects from Individual Uncertainty

Operationalizing the Effects from Firm's Individual Uncertainty

As a first step, we analyze the Cambridge Ahead companies by identifying the shape of their survival, hazard, and cumulative hazard functions. Put differently, we obtain their survival time (actual duration during the observed five year period) and their risk of failure (hazard rate). We estimate the hazard rate as the number of events proportional to the number of observations at risk: The Nelson-Aalen estimator serves to obtain the cumulative hazard function by summing up the values of the hazard functions over time. The Kaplan-Meier estimator is used to obtain the survival function by taking the ratios of the companies that did not survive over those at risk, the product multiplied with time. Next, given that it is generally expected that innovative and knowledge-intensive companies are the best performers per se, we divide the sample into two groups—knowledge-intensive and non-knowledge-intensive companies—and compare the Kaplan-Meier function across the two groups. The same comparison is carried out between daring and non-daring companies (i.e., independent ownership versus any form of dependent company survival). The expectations for the latter from an evolutionary tacit knowledge perspective could be that more complex ownership serves as a source of tacit knowledge or social capital that hedges the company and facilitates survival (see Nelson and Winter 1982). On the other hand, according to Shackle (1949a), daring (i.e., being more open to facing independently the unknown) should be associated with less truncation of potentially highly profitable and innovative new ideas. Thus, daring companies may be expected to show higher rates of survival (which is also to be expected if single ownership is interpreted from the point of view of unity, and t-consistency of strategy for the single-owned firm; see, for example, Nelson 2003). The sign of the difference between the survival of daring and non-daring companies remains an empirical question.

Secondly, we estimate four parametric models for the hazard function for all companies and per group of companies. Parametric models allow for a stochastic analysis that can empirically address the determinants of the survival of companies in the Cambridge region. They can also assume different parametric forms for the hazard function. Here we try,

[14] In the sensitivity analysis, due to the specificity of the zero-inflated model where the inflation should be coded as zeroes, we use as a dependent variable a transformation of the main dependent variable described here. The exact transformation is described later in the estimation strategy for the survival analysis.

respectively, an exponential hazard function (with constant hazard rate over time) and functional forms with varying hazard rates over time (captured differently by a Weibull, Gompertz, and log-logistic function).

Finally, as a third step, we contrast the results from the parametric tests against a semi-parametric model (a Cox [1972] Proportional Hazard Model). The advantage of this model is that it estimates stochastically the parameters of the independent variables without requiring an estimation of the baseline hazard function, which is allowed to be equal to the base level of the hazard rate, without consideration of the existence of any exogenous factors, while it is proportionally changing over time. This setting corrects for biased estimations under the conditions of censored observations, as is the case in our data (Cox and Oakes 1984, 93). The Cox model estimates the hazard function as:

$$\lambda(t \mid \boldsymbol{x},\boldsymbol{\beta}) = \lambda_0(t)\ exp(\boldsymbol{x}'\boldsymbol{\beta}), \tag{3}$$

where λ is the hazard rate at time t, λ_0 is the baseline hazard rate without stochastically considered independent variables, x is a vector of independent variables, in other words, factors for company survival (which include in our case: total assets in GBP at the last year of existence, a Herfindahl index of competition between peers, eyeball change of industry of the company, company age over twenty-five years, and daring type (independent ownership), as well as size, industry, and location dummies, with one dummy omitted per each category, as we do not suppress the constant). We estimate the proportional hazard rate according to model (3), first for all companies and then separately for each group of companies (i.e., daring vs. non-daring firms). In this way, we obtain an understanding of the factors that determine the longevity of a company in the Cambridge area, in total and per type defined through their level of daring to accept uncertainty.

Correcting for Zero-Inflation in Terms of No Observed Firm Deaths During 1919–2010

As suggested by, among others, Wennberg, Delmar, and McKelvie (2016), the age of the company is highly important together with the experience accumulated over time. Therefore, robustness checks with higher sensitivity to firm age are conducted in the form of two sensitivity analyses. Namely, we conduct: (i) a zero-inflated model, where the zeros represent the survivors and firm death is the event analyzed, and (ii) a re-estimation of the results with the set including only the young companies (over twenty-five years of age). We will first use a model for the zero-inflation in the data. In our dataset, for the companies created during the period 1900–2010, we observe only survivors, while for the companies created within the period 2010–2015, we observe both those surviving and those exiting (i.e., becoming closed down or dormant). Furthermore, a closer look at the data shows that for the period under tracking only six companies of those over twenty-five years old actually died or became dormant. Secondly, we address the same problem by only examining the survival of those companies younger than twenty-five years of age, in other words, within the same managerial and ownership generation—a so-called succession study (see Diwisch, Voithofer, and Weiss 2009). The dependent variable for our sensitivity analysis is reversed in comparison to the Cox proportional hazard estimations. Namely, while up to here the spells survived were used to define our output variable, our sensitivity analysis focuses on explaining the speed of death within the time of observation, in other words, the number of spells not survived in comparison to a zero value assigned to survival during the whole period of observation or longer. Thus, if a company survived during the whole period or more, it is assigned a zero value, and if it survived three spells it is assigned a speed of death equal to 1, surviving two spells is assigned a value of 2, and if it survived only one spell, it is assigned a speed of death 3.

Analyzing the Effects from Local Uncertainty

Once our results on the individual level are also validated with robustness checks, we delve one level deeper, in particular into the agglomeration effects from local uncertainty. If there are clear differences in regional firm survival rates, even within small local divisions such as districts of the same Cambridge area, then we would not only have to detect these, but also to explain them. To do so, we adopt a hierarchical (multilevel) type of model, which approaches the data nested into districts by accounting separately for the existence of regional means and the deviation from them, and which corrects the linear model estimation for this violation of the assumption of randomness and homogeneity. Specifically, we explain the companies' speed of survival, by accounting for the local levels of psychological uncertainty across the thirteen different districts of the Cambridge area. This estimation allows us to question empirically whether the Shacklean uncertainty potential surprise function is only caused by a characteristic of the company that counts for its survival, or whether it is also an ecological factor from the firm's environment that determines the degree of evolution and development of all firms in a locality. Ultimately, this allows us not only to provide empirical evidence on the role of agglomeration, but also to explain stochastically what its cultural roots are.[15]

Results and Analysis

Background and Descriptive Statistics

Background of Cambridge Region

The Cambridge Region (UK) is often regarded as a highly successful science and technology pole, characterized by an entrepreneurial boom known as the "Cambridge Phenomenon." Wicksteed Segal Quince (1985) used the term Cambridge Phenomenon for the first time to describe the rapid emergence of over 300 high technology firms in the Cambridge area, after the opening of the Cambridge Science Park in 1980s. The number of hi-tech establishments and employment in the innovative and especially high-tech industry in the Cambridge area has been on the rise ever since.

[15] We have available only thirteen districts to include in our multilevel model, and this is the lowest spatial division we can address and the only one for which we have the data of interest. This is not a division we have chosen or imposed artificially—there are these thirteen areas covered in our Cambridge Ahead dataset. Also, the number of observations within a cluster is always more than sufficient. Thus, the estimations with regard to the main effects on the individual level should not be affected by the thirteen areas. As far as the estimations for the thirteen areas themselves are concerned, what is known is that the coefficients are not biased either. The standard errors might be affected. Therefore, in order to cross-check for the adequacy of the analysis on the cluster level we conducted additional tests for clustering effects, akin to Halbert White's heteroskedasticity test following Nichols and Schaffer (2007). The results are supportive to our findings.

Cluster development in Cambridge has progressed farther than its Oxford counterpart, with a higher density of cluster actors and networks in Cambridge (Huggins 2008). During the period following the economic crisis it was one of the UK's most resilient economies and remains one of the nation's strongest regional economic development drivers. It is largely informal channels and personal relationships that have shaped the formation of the Cambridge cluster, such as the links between Cambridge University and its spin-off companies. These businesses have emerged from the science base of the university, especially its core strength in the field of early diffusing technologies (Garnsey and Longhi 2004; Huber 2012a, 2012b; Huggins and Prokop 2017).

The region of Cambridge is a center of both computer hardware and software, which is continuing to create the localized multiplier effects associated with clusterization. In particular, the university provides important socio-cultural preconditions not only for learning but also for the creation of new spin-off firms, interfirm networks, and local scientific and managerial recruitment practices (Garnsey and Heffernan 2005; Huber 2012a, 2012b).

It has been found that more than three quarters of firms in the Cambridge cluster possess close links and networks with other local firms (Huggins 2008). Cambridge is best known for possessing significant clusterization around university sites such as the Cambridge Science Park and the St. John's Innovation Centre as well as a significant number of international R&D establishments. These consist of both publicly and privately funded facilities such as the laboratories of the UK Medical Research Council, Hitachi, Microsoft, AT&T, Schlumberger, and Toshiba.

During the past fifty years, this cluster of creative firms has outperformed the rest of the UK in terms of profitability and innovativeness, thanks to a package of breakthrough inventions including heart transplants, liver transplants, pacemakers, Clearblue pregnancy tests, arm chips, electronic delay storage automatic computers (EDSAC), inhalers, virtual network computing software for remote access to computers, extended operating frequency radios (T6 radio), smart meters, runnerscapes, gene sequencers, the pioneering internet service provider UNIPALM IPs, the micro-computers Sinclair Spectrum, and so forth (see Kate Kirk and Charles Cotton 2016).

The background of the emergence of the Cambridge Phenomenon has been addressed extensively in the extant literature, but the underlying explanations remain relatively unclear and ambiguous. Several hypotheses on the impact of universities on regional growth in the Cambridge area have been formulated, even though other high-tech localities in the country in close proximity to a university, comparable to the case of Cambridge, appear not to show a significant statistical impact of the university on firm performance. One of the reasons for these firms to locate in Cambridge city and its vicinities, emerging in the literature since the beginning of the analysis of the phenomenon (such as Segal 1985), is the fact that a very high percentage (around 70%–80% according to different studies) chose to locate or even relocate to Cambridge because the owner of the establishment lived there. Later findings of Keeble et al. (1999) support the importance of the attractiveness for a locality as a living place in terms of the firm's location choice.

The geographic notion of Cambridge Region employed in our study includes Cambridge city and an area falling within a twenty-miles radius from the center of Cambridge city. This includes Cambridge city and the election areas (called wards): Bedford (to the west of Cambridge), Huntingdonshire (northwest), Fenland, East Cambridgeshire, and Forest Heath (northeast), St. Edmundsbury (east), Braintree (southeast), South Cambridgeshire, Uttlesford (south) and Central Bedfordshire, East Hertfordshire, and North Hertfordshire (southwest). This is the definition of the area coming from our dataset. It should be noted that there are significant socio-economic disparities across the wider region. Recent data indicates that the central Cambridge district has a GVA per capita of £38,675, which is far higher than second placed St. Edmundsbury (£24,657) and third placed Stevenage (£24,635). The district of East Cambridgeshire has the second lowest GVA per capita (£16,594), with only Braintree ranked lower (£15,004) (Huggins and Thompson 2016). In terms of entrepreneurship, there is also some considerable variation in business registration rates: East Hertfordshire, Uttlesford, and North Hertfordshire having the highest number of business starts per capita, with almost double the start-up rate in Fenland and St. Edmundsbury (Huggins and Thompson 2016).

As cross-regional comparisons are likely to provide relatively little insight, one alternative attempt to address this issue would be to zoom in only on the Cambridge region itself and to identify the determinants of the firms' survival and success in relation to their innovation potential and other moderating factors (Cefis and Marsili 2005).

Knowing the success drivers of this innovative entrepreneurial cluster is essential to determine: (i) whether the Cambridge Phenomenon is a long-lasting sustainable process, and not just the outcome of a fashion-driven "bubble-effect," where phenomenal economic growth will be likely to be followed by (relatively) fast decline in the form of a regular business cycle (see Garber 1989, 2000; Cochrane 2001; Dufwenberg, Lindqvist and Moore 2005); (ii) whether this innovative cluster needs to be supported by specific policy actions aimed at avoiding the negative effects of possible market failures; (iii) whether innovation policy can create the conditions for replicating similar experiences elsewhere.

It is noteworthy that there has also been a clear and persistent trend for Cambridge City and South Cambridgeshire to have the most significant share of the total growth of establishments (Athreye 2000). However, comparably little has been reported in the literature about the exact geography of innovation within the Cambridge area.

Descriptive Statistics

This section provides the various empirical findings from our modeling experiment. Although the Cambridge Ahead dataset contains an original full population of 26,265 companies, we focus here only on 21,610 companies established after the beginning of the nineteenth century for which the peer group size is known. The sample further narrows to 21,404 companies, if we want to use the total assets in the last year of life of the company. Still, the total database remains representative, while the spatial distribution of the companies remains intact. We refer to Figure 1 below for a confirmation.

Figure 1: Compositional Differences Between the Original (Full 26000-Plus Companies) Dataset and the Final (Reduced to 20000-Plus Companies) Dataset

The descriptive statistics are presented in Table 1 below.

Table 1: Descriptive Statistics of Main Variables

Note: The table presents the data, used for the estimations, by variables used, their coding, description and main descriptive statistics.

As we can see for five survival-spells, most firms in the Cambridge Ahead dataset survive—indeed during an average of 4.09 spells—though the standard deviation is also relatively large, which means that there is enough heterogeneity to expect significant results, with about 26% of the firms experiencing an exit. The total assets at the year of closure vary greatly as does the peer group size (i.e., the competition met by a company in the Cambridge area). Yet, when a more precise measure of competition is calculated through the Herfindahl Index (HI), this heterogeneity seems to fall significantly, while the age of the company also varies greatly in our dataset, including newly established companies of age 0 and companies with over 150 years of tradition. The average age of a company is approximately ten years, while companies over twenty-five years (and facing generational ownership change; see Morris et al. 1997; Santarelli and Lotti 2007 Chrisman, Chua and Steier 2011) amount to about 1% of all companies. A very small number of companies appear to attempt a change of sector (0.02%).

The ownership of the Cambridge Ahead companies is primarily the independent daring type, with only 4% of the companies being in a more complex hierarchical ownership type. However, this amount of non-daring companies is sufficient to allow the capture of statistical significance, if this exists. The size of the Cambridge Ahead companies seems to be predominantly small, with a FAME size 1 covering 78% of the companies, 10% being of second larger size and the largest size of companies covering only 2%. The spatial distribution by district (the European Union Nomenclature of Territorial Units for Statistics (NUTS3) level) shows the highest clustering of companies in South Cambridge (24%), followed by Huntingdonshire (19%), then Cambridge (16%), then East Cambridgeshire (10%). Most of the other NUTS3 areas contain about 1% of companies each, which is an indication of a strong agglomeration effect in three to four NUTS3 regions.

Finally, industry-wise, a predominant number of companies are found in business services (21%), other services (11%), or property and finance (10%). Next, information technology and telecoms cover 13% of the companies, and if the Cambridge Ahead definition of a knowledge-intensive company is used, this would include 20% of the companies. The traditionally strong sector of construction and utilities covers 12% of the sample. All other industries take less than 10% of the companies each, the smallest share (2%) belonging to life sciences and healthcare, as well as the knowledge-intensive services and primary sectors—each covering 3% of the companies.

Individual Uncertainty and Firm Survival

Non-Parametric Exploration—Comparing Knowledge Intensity and Uncertainty as Factors for Firm Survival

Our first approach to this database is a non-parametric technique. Non-parametric tests help us describe better the duration of survival, the risk of failure, and the shape of the survival function itself. As we see from Figure 2 below, by the end of the period more than 20% of the companies did not survive.

Figure 2: Non-Parametric Survival Analysis—ALL Companies

We also see that the smoothed hazard ratio function shows a nonlinear decrease in the number of companies over time. The cumulative hazard ratio, in other words, the percentage of companies from the whole sample that did not survive over time (captured by a Nelson-Aalen estimator [see Nelson 1969; Aalen 1976]), is an increasing step function depicting what seems to be a proportional jump in every discrete period. Also, the Kaplan-Meier (1958) survival function, showing the percentage of surviving companies over time, is a decreasing step function with a jump at each discrete event time. This means that our data can be expected to behave normally when our planned parametric and semi-parametric methods are applied to it. Before doing so however, we have to specifically check the behavior of certain types of companies.

On the one hand, the Cambridge Ahead initiative is focused on knowledge-intensive companies, seeking to generate their success in knowledge-and-technology types of innovation. So, we would like to see whether the survival rate of these companies is significantly different from that of the remaining ones. On the other hand, we are interested in the differences in the survival functions when distinguishing companies in groups according to the daring/non-daring typology, and for this purpose we compare the Kaplan-Meier survival functions for these groups and apply a t-test to estimate the statistical significance of the difference in survival between the groups. Figure 3 presents these results.

Figure 3: Non-Parametric Survival Analysis, Knowledge-Intensive vs. Non-Knowledge-Intensive and DARING vs. NON-DARING Companies' Survival

As we see from Figure 3, both the visual examination of the Kaplan-Meier function and the long-rank test show that being a knowledge-intensive company is not associated with a significantly higher or lower likelihood of survival. However, as the Shackle (1949a) hypothesis expects, the daring type of companies matters for survival. Our finding is that the daring type companies die faster and their survival is statistically significantly different from the non-daring companies (according to the log-rank test). This finding is in line with some previous findings in the literature (see Van Praag 2003). It means that companies, which face the world without the tacit knowledge and the social capital of a group (and which we therefore associate with a higher propensity to accept uncertain choices), survive in lower numbers than the ones less open to uncertain choices.

Parametric and Semi-Parametric Tests—Differences in Survival of Daring and Non-Daring Companies

As a next step, we now delve into the stochastic effects from the factors that explain the successful survivor of companies. Figures 4a and 4b below present the spatial distribution of daring and non-daring companies across the thirteen districts in the Cambridge Region. As we can see, these types of companies exhibit a different spatial concentration.

Figure 4a: Map—Daring Companies Distribution across Cambridge Districts, 2010–2015

Figure 4b: Map—Non-Daring Companies Distribution across Cambridge Districts, 2010–2015

While the daring companies are spread equally densely across four different districts, the concentration of the non-daring companies is twice as likely to be located within only two districts. Also, the districts with most daring (Figure 4a) and most non-daring companies (Figure 4b) are not adjacent, indicating that the spatial distribution of these two types of companies is not a mere reflection of the overall distribution of companies in the districts of the Cambridge Region. A center place of intense firm activity is easily identified on the maps as well as the presence of an east and west divide, where the daring companies (Figure 4a) are concentrated to the west of the center place, while the non-daring are predominantly to the east of the center place (Figure 4b). This east-west divide is also in line with the endowments of the areas to the east and west of the Cambridge Region in terms of quality of schools and overall well-being and welfare. These results are also consistent with the findings of Pe'er and Keil (2013) which suggest that location in a cluster does not produce equal positive effects across all agglomerated firms. We add to this the insight that a spatial divide may emerge within the cluster itself where good performing and poorly performing companies sort spatially and segregate into strong and weak zones based on ownership type, which approximates the firm's daring behavior.

In Appendix 3, we show the results from three different parametric tests and one semi-parametric test. These tests assume different functional forms of the hazard function in relation to time. The semi-parametric Cox proportional hazard function is our main reference point, as it clearly separates the hazard ratio and has a non-parametrically estimated time-invariant variable that explains the rest of the variation of the survival stochastically over time.

Appendix 3 shows that, irrespective of the specific estimation method, our statistical results concerning the survival of all companies in the Cambridge area offer a very stable pattern. From the company characteristics inferred, the total assets at the time of closure, the competitiveness measured with a Herfindahl index, and the age dummy (for companies over twenty-five years of age), do not seem to play a significant role in the survival of the company. Rather, company survival is driven by company size, with the smallest companies surviving the best, and the bigger ones surviving the worst. The attempt to change to another industry appears to be a significantly negative factor for survival, which can be explained through the marketing and branding costs involved (i.e., market positioning losses of such an attempt). Size and specialization are logically very related to ownership type for two reasons: (i) if there is only one owner, this might be indicative that the size of the firm can be expected to be smaller (as management can be undertaken by a single person); (ii) the specialization of the owner, if a single one, is less flexible to change compared to a portfolio of skills created by the expertise of several owners.

Thus, in light of the above results, it is natural that finally, our main explanatory variable of interest, the daring type of company, is associated with a better survival (i.e., longer survival over time). Shackle's (1949a) explanation for this finding would be that companies that dare to accept more uncertain choices are actually open to the most innovative ideas. Compared to our non-parametric tests, which show that daring companies on average die in higher numbers, we may be able to identify a paradox for firm survival in the Cambridge area. The daring companies survive less often, but if they survive, then they appear to survive longer than the non-daring type of companies. This seems to be an overlooked fact of the life of successful companies that is highly positively associated with the duration of their survival.

The context-related explanatory variables in our estimated models cover spatial and industry (structural) aspects. As we can see, three localities in the Cambridge area are associated with significantly faster death: Bedford, East Hertfordshire, and Fenland. This fact can be interpreted as a clear agglomeration effect, as these three districts are the ones that also hold the smallest number of companies (each having about 1% of the companies' overall populations). Finally, regarding industrial specialization, it turns out that specializing in any industry is clearly associated with a significant risk for survival, while specialization in basic or public goods (such as education, life sciences and healthcare, or primary sector) is associated with no significant hazard for survival. This means that it is likely that the life-sciences' sectoral specialization—and not their knowledge intensity—contributes to their successfulness in the Cambridge area.

Next, we sub-divide our dataset into daring and non-daring types of companies. Table 2 below shows the results for daring and non-daring companies, respectively.

Table 2: Parametric and Semi-Parametric Tests for Firms' Survival – Hazard Ratios

Note: Authors' calculations.

We find a striking difference between the estimation results: while the survival of daring companies is explained by company and context characteristics, the survival of non-daring companies seems to be rather random, and only weakly associated with their financial size. While spatial effects in the Cambridge area do exist, for daring companies the localities of Braintree and East Hertfordshire are the ones associated with more frequent deaths. The effects from the basic needs and public-goods related industries are preserved.

Two Robustness Checks—a Zero-Inflated Model (with all Observations) vs. A Test with Only Firms Within Twenty-Five Years of Age

To cross-check the robustness of our findings, we perform two sensitivity analyses. The results are presented in Appendix 4 The results from the zero-inflated model confirm the significance of the same internal firm characteristics (firm size, change of industry, and daring type of ownership) and the spatial and structural (industry specialization related) effects from the local context. Additionally, we find a clear confirmation that the daring type is what preselects the survivors in our dataset. Moreover, the daring type of ownership seems strongly related to the age of the company. Finally, when we concentrate only on companies below twenty-five years of age, our results from the same parametric and semi-parametric tests are preserved. There is only a difference in the spatial effect, where the only statistically significant negative location for survival is identified to be East Hertfordshire. This means that especially for young companies, it is harder to survive in this locality. Besides the agglomeration effect previously found in the data, this finding may also be interpreted as an indication of a possible monopolistic competition effect. East Hertfordshire is not only among the best places for living, but it is also the location where one of the most successful companies in the Cambridge area, GlaxoSmithKline (GSK), has its research and manufacturing center located and acts as the main employer in the locality.

An alternative explanation for this spatial negative survival effect of East Hertfordshire could be sought in the fact that this area has, in fact, only one single motorway, and—as we know from the literature (see, for example, Melo, Graham and Noland 2010)—transport infrastructure has a significant effect on economic success. More extensive data and research are necessary to highlight the mechanism for this strong spatial effect that is predominantly present throughout the different specifications and robustness checks undertaken. A perhaps minor, but nevertheless interesting, sensitivity issue to be noted is that including the age of a company according to its true level leads to age taking over all other effects, especially among the young companies (under twenty-five years). Instead, if one controls for age over twenty-five and age lower than one year, the results appear to remain stable and lead essentially to an economic interpretation that is the same as the ones presented above. The main finding is that the individual daring type (i.e., private ownership of the firm) has a significant role for the better survival of the firms and this effect holds for the two robustness checks.

Local Uncertainty and Firm Survival

Now that we have confirmed that there are agglomeration effects, size effects, industry specialization effects, and individual daring type effects that determine the survival of companies (i.e., an individual Shacklean uncertainty effect), we will pay more attention to the geographic context. Actually, the speed of death of companies varies significantly across districts, as shown in Table 3 below.

Table 3. Descriptive Statistics—Speed of Death per District and Local Uncertainty (Neuroticism) Levels

Note: The table shows frequency of firms per respective level of speed of death from 0 to 3, total number of firms and per region, and mean level of neuroticism in a district at the Cambridge area.

The group of survivors appears to vary between 64% and approximately 80% across different districts, with the slow dying companies (speed of death 1) varying between 4% and 16%. We see that uncertainty levels are oscillating around 3% across these same districts. However, a better understanding of the highly heterogeneous nature of cross-district data with a linear model requires more attention to the random effects in the error term (i.e., we have to correct for the clustering per district). The multilevel (hierarchical) model (HLM) (see Raudenbush and Bryk 2002; Heck and Thomas 2008) introduces this necessary correction and allows us to explain it stochastically. Table 4below presents our results.

Table 4: Hierarchical (Multilevel) Model - Random Effect: Location District Means

Note: The table presents hierarchical linear model (HLM) estimations, accounting for the agglomeration effect per regionally clustered group f companies (on district level). Specification 2 and 3 stochastically explains the agglomeration effect on company death with psychological type - respectively mean level of uncertainty and mean level of conscientiousness All Big Five psychological types (see Rentfrow et al. 2015) were tried and all but uncertainty had the same performance as conscientiousness.

Table 4 shows a company death regression, where all established factors from our previous regressions are used and the same effects are confirmed by the HLM estimation. In specification 1, we account for the clustering effect per district and we find that it is statistically significant and accounts for about 3%, which is a crucial percentage for economic growth processes (see Barro and Sala-i-Martin 2004). In specification 2, we stochastically explain this regional effect with the mean level of uncertainty-psychological type from the Big Five dataset. We find that deviations in psychological milieu characterized by uncertainty account for about one third of the regional clustering effect. Alternatively, we also use all other psychological types, but while significant, the magnitude of their effect in terms of the size of their coefficients is much smaller.[16] Therefore, we interpret these results in favor of previous findings from other research (see Tubadji and Nijkamp 2021)—namely, the validity of the impact from the aggregate contextual uncertainty on Shackle's individual uncertainty-based potential surprise function. Put differently, very small deviations in the tolerance to uncertain decisions in the local cultural milieu can, in general, explain one-third of the significant agglomeration effects across districts and the differences in survival of companies across districts in the Cambridge Ahead area.

Since our dataset is representative, we consider these results generalizable and fit for suggesting a hypothesis for further research that the aggregate uncertainty tolerance is also what makes the Cambridge area different in firm survival and success from the rest of the UK.

Conclusions

Our analysis of firm survival in the Cambridge Region, inspired by the Audretsch and Dohse (2007) model of firm growth and geographic location, and augmented by Shackle's (1949a) potential surprise function considered at an individual and local level, leads to two important insights. First, uncertainty (captured with independent ownership as compared to any other type of ownership) is found to be a significant predictor of firm survival. And local-context uncertainty, captured by local levels of the psychological trait of neuroticism, also appears to be an important factor conducive to firm survival. Thus, a conceptual extension of the endogenous growth model with individual and local uncertainty seems to find a very good support in the data under analysis in our study. Most importantly, Shackle's original potential surprise function seems to be undeniably present as a factor in firm survival in Cambridge and surroundings.

Specifically, we find that survivors in the Cambridge area are mostly small-sized firms of a daring nature, which also tend to avoid switching sector specialization. The small-size firm survival is actually consistent with some of the findings on the Cambridge Phenomenon presented in earlier studies such as Suma Athreye (2000). Being prone to take decisions with a higher level of uncertainty involved these firms may be expected to exhibit a more open attitude to making choices for which a potential surprise in the outcome exists. Indeed, this Shackle type of daring behavior seems to be important for firm survival, but it seems to also create a paradox: counter-intuitively, a company of a daring type is associated with a higher likelihood of death, but if it survives it tends to have a longer life than a non-daring type of company, which means that overall it is also more stable as a firm.

It is important to note that openness to uncertain options is important and beneficial for the life of an economic enterprise. While it is already found that a higher estimated risk from an undertaking is associated with higher profits, the choice over uncertain options, for which limited information exists, is often still treated in firm practice in terms of the

[16] And the coefficients are not biased indifferent of number of clusters used (Maas and Hox 2005).

mitigation of unwanted and hard-to-estimate risk. Uncertain options are considered to be duly excluded from the list of options as a sign of good management. Our results, put in a general setting, show just the opposite. Undertaking business activities which have highly uncertain outcomes and involve choices for which limited information on the outcome exists may be very beneficial for the company in terms of its survival over time. Even if it naturally increases the hazard of initial perishing, uncertain options for choices still make the survivors stronger in terms of their longevity. These results demonstrates that the Shacklean potential surprise function is not only statistically important but has a very meaningful economic implication for firm survival.

Last, but not least, with regard to the individual role of uncertainty, our results show more specifically that this daring type of feature is dominant among firms in the Cambridge Region, and stochastically explains their survival rates. Therefore, due policy attention should be paid to stimulating, breeding, and harnessing these daring characteristics of firm behavior, as this seems to be the driver that can secure the Cambridge Phenomenon as a sustainable economic process, and avoid the fate of an occasional bubble effect that, over time, loses its entrepreneurial trigger.

Additionally, we find the local environment context, in terms of both spatial distribution and sectoral specialization, to be a significant factor for the survival of a company. In particular, contextual cultural attitudes vis-à-vis uncertainty can further affect individual firm survival, on top of individual factors, while specifically the uncertainty-prone psychological type at the local area level appears to play a significant role in the survival potential of the companies there.

Our findings add, on the one hand, to the existing literature on the importance of location (such as Fritsch and Changoluisa 2017), while on the other hand they contribute to the literature on the importance of the context. The existing literature on endogenous growth models mostly considers context only at the firm level (see for example Huggins, Prokop, and Thompson 2017), but our study adds a new twist to the above two lines of exploration, by suggesting that the geographic locality is a relevant context, in particular in the cultural sense of attitudes to uncertainty, and it can be pivotal for individuals and firms in this locality.

Further research seems worthwhile to address the details behind Shackle's potential surprise function. We have demonstrated here that the main input in Shackle's potential surprise function—the daring type on individual and local levels—seems to be essential for firm survival, as Shackle's concept suggests it is likely to be. Put in a nutshell, our results demonstrate that heterogeneous agents' preferences that are rather irrationally open to uncertainty and are situated in an uncertainty-friendly context help firms survive better. This mixed effect from firm characteristics related to attitudes in handling uncertainty and the surrounding context is what seems to be the rational economic explanation for the survival of companies in the Cambridge area over the past decades, and therefore helps explain the extraordinary economic success known as the Cambridge Phenomenon. If there is a lesson that policy makers can learn from this experience, it is that although promoting entrepreneurship may represent a way to stimulate economic development, successful economic phenomena such as the Cambridge experience are not just the result of a greater endowment of entrepreneurs, but the level of uncertainty they engage with and manage.

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Appendix 1: The Culture Based Development (CBD) Model for Firm Survival—Motivation

The CBD reading of the literature review offered in this article could be wrapped up in an ontological model of human thinking. Namely, the human mind as composed of two parts—rational and emotional mind (both grounded in Simon (1955) and Kahnemann (2011). The rational mind is our ability to reason and is responsible for the process of learning and deciding on the basis of what was learned from previous experience, i.e. a probabilistic estimation of risk, so that it benefits the utility that we derive from it. The emotional mind is our ability to feel and it is responsible for the spontaneous reactions which we have to real-world events when we are not equipped with either the time to judge or the knowledge on how to judge (i.e., previous experience with) the event at stake requiring our decision and action, so that we minimize disutility (or failure) equally likely to be ventured. These two processes are distinguished by Kahnemann (2011) as respectively the analytical slow thinking of reason and the heuristic-in-nature fast thinking through our emotions. Both the rational and the emotional mind and their processes, however, are filtered through culture. The reasoning is the mechanism through which we revise our internal preferences and correct and adjust them through a cost-benefit assessment to the norms and formal rules in our social environment (see Sen 1971). The emotional heuristic behavior is influenced by the belief system transmitted from generation to generation in an informal manner (see Bourdieu and Passeron 1977). Only the cultural filter is thus applied to our rational and emotional slow and fast thinking process, an individual reaches a decision (Kahneman 2011). Then, following Williamson (2002), the firm is a group of individuals which all contract and bargain their utilities and dis-utilities from different group choices up to their bargaining power in the group that the firm represents. Then the same applies for the firm as an agent among other firms. Thus, the individual effect and the local effect are always at stake at the same time.

In the context of the above presented model of thinking and cultural bias, there is the role of uncertainty and the cultural-belief biased aspect of decision-making. The mechanism through which human irrational choice operates is the so-called "potential surprise function" (Shackle 1949a). The operation of this function can be best explained through the psychological awareness framework. The mechanism through which knowledge and uncertainty meet in order to influence a decision can be seen as follows. In particular, the awareness divides into four states: known to the others and to oneself, known to the others but not to oneself, known to oneself but not to the others, and unknown to neither oneself nor the others. This idea in terms of knowledge of the world can be translated into: skills, information, intuition and unknown-unknowns (the latter being a term of Shackle, or also the box of Schrödinger's cat)). While skills and information are processed through reason, intuition and fear of the unknown are processed through emotion, and from there through respectively slow and fast thinking and their relevant cultural filter. The impact on choice can respectively be highlighted as follows: skills lead to a clear 0–1 decision based on past experience risk evaluation of the best (optimal) alternative; asymmetric information is the same like the previous, but dealt with under the condition of bounded rationality, i,e. lack of awareness of the imprecision of one's estimation of the optimal alternative; this intuition causes a positive bias towards a choice for which we have an irrational feeling of potentially possible success. The fear of the unknown leads to a negative bias against selecting an idea due to lack of past knowledge on which a probabilistic estimation of the potential outcomes could be based. This latter mechanism of irrational negative bias on choice results in a double negative space of the ideas rejected for R&D investment, i.e. it refuses the implementation of many novel ideas that could generate a Schumpeterian type of innovation. Therefore, the degree of truncation of Schumpeterian innovation through the potential surprise function can be expected to act as a critical factor for the survival of firms.

Appendix 2: The Cambridge Ahead Dataset

Cambridge Ahead is an agency concerned with the long-term growth of the Cambridge cluster of companies. The dataset comprises only companies and limited partnerships (LLPs) (i.e., excluding sole entrepreneurs and other forms of unincorporated businesses). The main source of information is the so-called FAME database produced by Bureau Van Dijk, which includes over 3 million active UK-based companies and a further 6 million firms that are dormant or who have died. The database defines the Cambridge Ahead area as the region within a twenty-miles radius from the center of Cambridge. All postal codes (about 20,000) that fall within this area are selected. Each postal code is next assigned to an electoral ward[17]. The database contains two types of companies according to their origin: Cambridge-based and Cambridge-active. The Cambridge-based companies are those with either their registered office or their primary trading address in one of the Cambridge Ahead postal code areas, without necessarily physically executing their business in this region. The Cambridge-active ones are defined as companies having their registered office or their primary trading address in one of the Cambridge Ahead postal codes, but also operate within the Cambridge Ahead area. The sample of the dataset that we address covers five years (2010–2014) with the survival periods analyzed being: 2013/14; 2012/13; 2011/12 and 2010/2011, thus tracking the duration of four spells.

The information in our dataset about each company includes: name; registered number; registered accounts type; legal form; current market capitalization; trade description; sector according to the Standard Industrial Classification (SIC) 2007; peer group; IPO date; current immediate shareholder information; current domestic and global ultimate owner; registered office address and postcode; primary trading address and employment when provided; and other trading address in Cambridge area and employment when provided. There is also some data on turnover and number of employees, but this is only available for 1,984 and 923 companies, respectively, and therefore we cannot base our analysis on these indicators because of limited representativeness.

Appendix 3: Robustness Checks

Table A1. Sensitivity Analysis—Zero Inflated Poisson—Inflation Driven by Daring Type

Note: A zero-inflated model, accounting for the fact that a very large number of the companies are survivors from past periods, preceding the spells under observation and thus biasing towards 0 the number of companies that actually experience the event of interest—company death. Specifications with and without local agglomeration effects and with different degrees of detailed consideration of company age are presented across the three specifications.

Table A2. Sensitivity Analysis—Parametric and Semi-Parametric Tests—Young Companies (up to 25 Years of Age)

Note: Same as Table 2. Only for the sub-sample of young companies that were created, survived or died during the spells under observation.

[17] According to the UK Office of National Statistics, electoral wards/divisions are the key building blocks of UK administrative geography, used to elect local government councilors in metropolitan and non-metropolitan districts. Population counts vary substantially across wards, but the national average ward populations is about 5,500 people. Electoral wards answer to the Eurostat division LAU 2 (Lower tier authorities, tier 2); LAU 1 correspond to "districts" for England; all LAU2 combined under LAU1 and LAU1 form the NUTS3 statistical division of the EUROSTAT nomenclature.

Table 1

Variable	Description	Obs	
spell_survived	duration of being active during 2010-2015	21610	
event_calc	firm experienced death or been dormant during 2010-2015	21610	
total_assets_at_lastyear	total assets in GBP during last available year of life	21404	2
KI_company_dum	dummy variable identifying a knowledge intensive company as = 1	21610	
peer_group_size	number of firms in the same sector and of the same size	21610	1
size_of_competition	being into business with a peer group size lower than the average	21610	
HI	Herfindahl Index for competition between peers in the same industry	21610	1
age	company age (in trems of years between last year of observation and year of being founded)	21610	
d_age25plus	company of age over 25 years	21610	
eyeball_change	change of industry in which the firm operates	21610	
daring	owner of an independent company (as opposed to any other form of ownership)	21610	
Firm size - Financial Analysis Made Easy (FAME) database classification			
d_size1	1 = 1 in FAME	21610	
d_size2	2 = 2-4 in FAME	21610	
d_size3	3 = 5-9 in FAME	21610	

d_size4	4 = 10-49 in FAME	21610
d_size5	5 = >49 in FAME	21610
Location - District		
d_locat1	Bedford	21610
d_locat2	Braintree	21610
d_locat3	Cambridge	21610
d_locat4	Central Bedfordshire	21610
d_locat5	East Cambridgeshire	21610
d_locat6	East Hertfordshire	21610
d_locat7	Fenland	21610
d_locat8	Forest Heath	21610
d_locat9	Huntingdonshire	21610
d_locat10	North Hertfordshire	21610
d_locat11	South Cambridgeshire	21610
d_locat12	St Edmundsbury	21610
d_locat13	Uttlesford	21610
Broad Cambridge Ahead Sector		
ind_1	Construction and utilities	21610
ind_2	Education, arts, charities, social care	21610
ind_3	Information Technology and Telecoms	21610
ind_4	Knowledge Intensive Professional Services	21610
ind_5	Life Science and Healthcare	21610
ind_6	Manufacturing	21610
ind_7	Other Business Services	21610
ind_9	Primary	21610
ind_8	Other Services	21610
ind_10	Property and finance	21610
ind_11	Transport and travel	21610
ind_12	Wholesale and retail distribution	21610

Table 2

	ALL Companies				DARING Companies				NON-DARING C	
	Parametric		Semi-parametric		Parametric		Semi-parametric		Parametric	
	Exponential		Cox		Exponential		Cox		Exponential	
_t	Haz. Ratio	Z-test	Haz. Ratio	Z-test	Haz. Ratio	Z-test	Haz. Ratio	Z-test	Haz. Ratio	Z-test
total_assets_lastavyear	1.00	-0.28	1.000	-0.30	1.00E+00	-1.20	1.00E+00	-1.19	1	0.39
HI	5.18E-06	-1.65	9.30E-06	-1.57	0.000	-1.72	0.000	-1.65	126397.7	0.49
eyeball_change	0.607	-2.83	0.623	-2.68	0.610	-2.67	0.626	-2.52	0.678	-0.63
d_age25plus	0.000	-0.03	0.000	0.00	0.000	-0.05	0.000	0.00	0.000	-0.02
daring	1.401	2.86	1.377	2.72						
d_size1	1.484	2.90	1.446	2.71	1.263	1.44	1.233	1.28	2.013	1.85
d_size2	0.808	-1.44	0.814	-1.39	0.698	-2.09	0.705	-2.03	0.757	-0.58
d_size3	0.720	-1.94	0.732	-1.84	0.596	-2.68	0.609	-2.56	1.176	0.34
d_size4	0.587	-3.01	0.596	-2.92	0.522	-3.28	0.532	-3.18	0.533	-1.20
d_locat1	0.638	-2.09	0.651	-2.00	0.664	-1.91	0.677	-1.82	0.000	-0.01
d_locat2	0.418	-1.94	0.430	-1.88	0.342	-2.13	0.354	-2.07	2.732	0.86
d_locat3	1.062	0.92	1.056	0.84	1.060	0.88	1.054	0.80	1.321	0.50
d_locat4	1.086	0.96	1.080	0.89	1.080	0.88	1.073	0.81	1.855	0.87
d_locat5	0.933	-0.93	0.935	-0.90	0.926	-1.02	0.928	-0.99	1.489	0.63
d_locat6	0.565	-3.10	0.564	-3.11	0.567	-3.08	0.566	-3.09	0.000	0.00
d_locat7	0.695	-2.00	0.708	-1.90	0.699	-1.97	0.712	-1.87	0.000	0.00

d_locat8	1.007	0.07	0.999	-0.01	1.006	0.06	0.998	-0.02	1.024	0.03
d_locat9	0.983	-0.28	0.980	-0.31	0.979	-0.33	0.977	-0.37	1.287	0.44
d_locat10	1.102	1.13	1.091	1.01	1.097	1.07	1.086	0.95	1.432	0.50
d_locat11	0.984	-0.26	0.978	-0.36	0.987	-0.22	0.981	-0.31	0.915	-0.16
d_locat12	1.008	0.07	1.005	0.05	0.999	-0.01	0.998	-0.02	1.577	0.51
ind_1	0.669	-6.15	0.689	-5.69	0.676	-5.95	0.696	-5.50	0.398	-1.71
ind_2	0.944	-0.76	0.953	-0.62	0.946	-0.72	0.955	-0.59	0.694	-0.53
ind_3	0.717	-5.39	0.737	-4.95	0.722	-5.23	0.742	-4.79	0.480	-1.58
ind_4	0.797	-2.24	0.813	-2.05	0.814	-2.02	0.829	-1.84	0.287	-1.55
ind_5	1.052	0.33	1.065	0.41	1.085	0.51	1.098	0.58	0.618	-0.77
ind_6	0.577	-6.33	0.597	-5.93	0.580	-6.17	0.601	-5.77	0.408	-1.58
ind_7	0.738	-5.55	0.757	-5.10	0.742	-5.42	0.761	-4.97	0.500	-1.43
ind_9	1.011	0.09	1.026	0.21	1.027	0.22	1.041	0.33	0.315	-1.03
ind_10	0.503	-9.24	0.524	-8.67	0.495	-9.29	0.517	-8.72	0.785	-0.50
ind_11	0.671	-3.42	0.689	-3.19	0.678	-3.32	0.696	-3.10	0.000	0.00
ind_12	0.703	-5.02	0.723	-4.62	0.704	-4.94	0.724	-4.55	0.542	-1.17
_cons	0.048603	-17.15			0.079853	-14.47			0.043395	-4.37
N subjects	19866		19866		19045		19045		821	
N failures	3803		3803		3725		3725		78	
Time at risk	66774		66774		63736		63736		3038	
LR chi2(31)	1336.31		1235.38		1213.31		1120.71		78.69	
Log likelihood	-12028.2		-36605.9		-11735.0		-35732.7		-281.2	

Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000

Table 3

speed of death	0	1	2	3	n firms
average	64.42	14.96	9.39	11.23	21,610
Bedford	73.17	13.17	7.32	6.34	205
Braintree	79.17	11.11	4.17	5.56	72
Cambridge	63.54	15.14	8.67	12.65	3,541
Central Bedfordshire	61.43	14.39	10.77	13.42	1,133
East Cambridgeshire	66.46	14.29	7.97	11.27	2,120
East Hertfordshire	67.88	13.58	10.26	8.28	302
Fenland	71.94	11.07	7.11	9.88	253
Forest Heath	65.59	14.49	8.86	11.05	959
Huntingdonshire	64.3	15.7	9.45	10.55	4,076
North Hertfordshire	62.87	15.41	10.33	11.4	1,123
South Cambridgeshire	63.73	15.61	9.79	10.86	5,228
St Edmundsbury	64.42	14.1	9.94	11.54	624
Uttlesford	64.94	13.73	10.39	10.94	1,974

Table 4

dep.var.					speed of death			
	coef.	z-alue	[95% Conf. Interval]		coef.	z-alue	[95% Conf. Interval]	
total_assets_gbp_lastavyear	-6.63E-10	-0.01	-1.28E-07	1.26E-07	-6.78E-10	-0.01	-1.28E-07	1.26E-07
HI	-0.934	-0.50	-4.5701	2.7018	-0.934	-0.50	-4.5702	2.7017
eyeball_change	-0.150	-2.75	-0.2569	-0.0432	-0.150	-2.75	-0.2569	-0.0432
age	-0.043	-75.91	-0.0436	-0.0414	-0.043	-75.91	-0.0436	-0.0414
d_size1	-0.073	-1.77	-0.1539	0.0079	-0.073	-1.77	-0.1539	0.0079
d_size2	-0.215	-4.86	-0.3011	-0.1281	-0.215	-4.86	-0.3011	-0.1281
d_size3	-0.217	-4.39	-0.3139	-0.1201	-0.217	-4.39	-0.3139	-0.1201
d_size4	-0.117	-2.41	-0.2115	-0.0216	-0.117	-2.41	-0.2115	-0.0217
ind_1	-0.145	-5.63	-0.1951	-0.0944	-0.145	-5.63	-0.1951	-0.0944
ind_2	-0.025	-0.78	-0.0891	0.0384	-0.025	-0.78	-0.0891	0.0383
ind_3	-0.127	-5.07	-0.1767	-0.0781	-0.127	-5.07	-0.1768	-0.0782
ind_4	-0.052	-1.28	-0.1304	0.0273	-0.052	-1.28	-0.1304	0.0273
ind_5	-0.071	-1.21	-0.1862	0.0438	-0.071	-1.21	-0.1862	0.0438
ind_6	-0.087	-2.90	-0.1455	-0.0282	-0.087	-2.90	-0.1455	-0.0282
ind_7	-0.156	-6.83	-0.2011	-0.1114	-0.156	-6.83	-0.2011	-0.1114
ind_9	0.263	6.33	0.1817	0.3446	0.263	6.33	0.1818	0.3446
ind_10	-0.109	-4.05	-0.1618	-0.0562	-0.109	-4.05	-0.1618	-0.0562

ind_11	-0.122	-2.84	-0.2065	-0.0378	-0.122	-2.84	-0.2065	-0.0378
ind_12	-0.073	-2.66	-0.1262	-0.0192	-0.073	-2.66	-0.1262	-0.0191
_cons	1.295	28.06	1.2048	1.3857	1.295	28.06	1.2047	1.3856
Random-effects:								
Location_district								
sd(_cons)	0.026		0.0097	0.0680	0.000		0.0000	2.72E+71
sd(mean_neuroticism)					0.009		0.0028	0.0267
sd(mean_conscienciousness)								
sd(Residual)	0.899		0.8901	0.9072	0.899		0.8901	0.9071
Number of observations		21404				21404		
Number of groups		13				13		
Obs per group (min)		72				72		
Wald chi2(19)		6958.34				6958.28		
Log likelihood		-28087.032				-28087.015		
Prob > chi2		0.0000				0.0000		

Appendix 3 – Robustness Checks

Table A.1

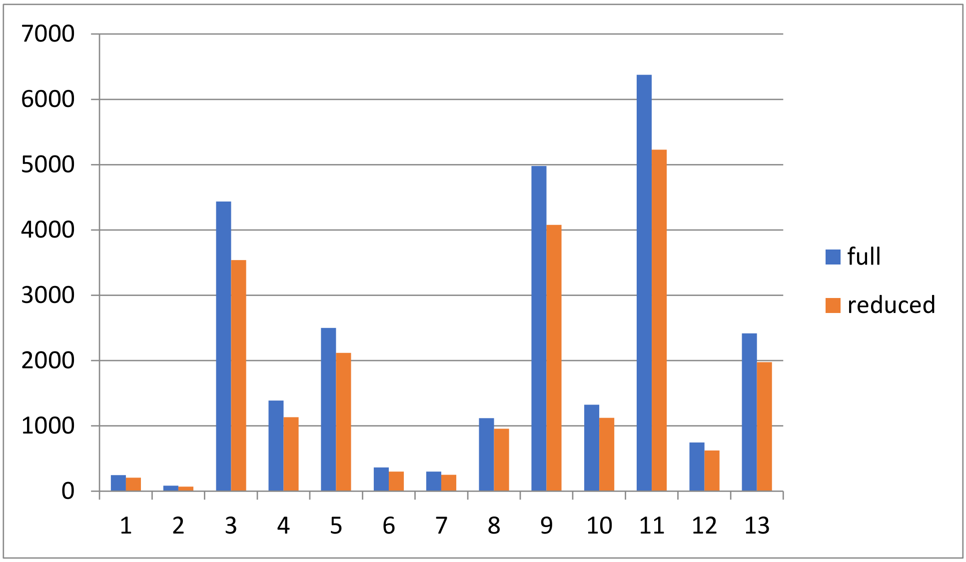
	Cambridge Ahead -YOUNG Companies (below 25 years)					
	Parametric					
	Exponential		Weibull		Gompert	
_t	Haz. Ratio	Z-test	Haz. Ratio	Z-test	Haz. Ratio	Z
total_assets_gbp_lastavyear	1	-0.28	1	-0.25	1	
HI	0.000	-1.21	0.000	-1.40	0.000	
eyeball_change	0.634	-2.57	0.564	-3.22	0.575	
daring	1.374	2.68	1.436	3.06	1.428	
d_size1	2.526	6.71	2.975	7.87	2.894	
d_size2	1.371	2.11	1.410	2.30	1.404	
d_size3	1.064	0.36	1.046	0.26	1.049	
d_size4	0.628	-2.60	0.604	-2.81	0.608	
d_locat1	0.721	-1.52	0.686	-1.75	0.692	
d_locat2	0.537	-1.38	0.552	-1.32	0.545	
d_locat3	0.973	-0.42	0.972	-0.43	0.970	
d_locat4	0.982	-0.21	1.005	0.06	0.994	
d_locat5	0.932	-0.94	0.924	-1.06	0.924	
d_locat6	0.463	-4.11	0.438	-4.41	0.443	
d_locat7	0.827	-1.04	0.808	-1.17	0.807	
d_locat8	0.836	-1.91	0.805	-2.31	0.811	
d_locat9	0.924	-1.23	0.915	-1.40	0.916	
d_locat10	0.888	-1.38	0.874	-1.56	0.876	
d_locat11	0.907	-1.58	0.905	-1.62	0.906	
d_locat12	0.926	-0.69	0.926	-0.69	0.923	
ind_1	0.796	-3.49	0.741	-4.57	0.751	
ind_2	1.040	0.51	1.022	0.28	1.025	
ind_3	0.930	-1.18	0.905	-1.62	0.908	
ind_4	0.774	-2.53	0.718	-3.27	0.727	
ind_5	1.252	1.46	1.267	1.53	1.263	
ind_6	0.563	-6.59	0.502	-7.92	0.511	
ind_7	0.954	-0.86	0.930	-1.33	0.936	

ind_9	0.619	-3.96	0.564	-4.72	0.569	
ind_10	0.489	-9.59	0.420	-11.63	0.430	-
ind_11	0.677	-3.34	0.615	-4.16	0.626	
ind_12	0.773	-3.65	0.724	-4.57	0.731	
_cons	0.084384	-13.79	0.033631	-18.63	0.040299	-
N subjects	8390		8390		8390	
N failures	3797		3797		3797	
Time at risk	20876		20876		20876	
LR chi2(31)	827.81		1163.44		1085.99	
Log likelihood	-7857.0		-7175.2		-7535.8	
Prob > chi2	0.0000		0.0000		0.0000	
/lnp or /gamma			0.567	41.65	0.3816	
p			1.763	1.72		
1/p			0.567	0.55		

Table A.2

	Zero Inflated - Poisson				
	Spec 1 - without regional effect		Spec 2 - with regional effect - dummy age25plus		
	Coef.	Z-test	Coef.	Z-test	
d_spell_deathspeed					
total_assets_gbp_lastavyear	6.12E-08	0.80	5.17E-08	0.70	2
HI	-2.173	-0.58	-1.858	-0.48	
eyeball_change	-0.376	-2.57	-0.380	-2.62	
d_age25plus	-24.821	- 801.86	-24.822	- 801.33	
age					
d_size1	0.304	2.83	0.304	2.84	
d_size2	-0.140	-1.20	-0.144	-1.24	
d_size3	-0.330	-2.33	-0.329	-2.32	
d_size4	-0.420	-2.88	-0.424	-2.91	
d_locat1			-0.160	-1.17	
d_locat2			-0.410	-1.58	
d_locat3			0.046	1.25	
d_locat4			0.096	2.15	
d_locat5			-0.029	-0.69	
d_locat6			-0.084	-0.97	
d_locat7			-0.133	-1.20	
d_locat8			0.012	0.23	
d_locat9			-0.026	-0.72	
d_locat10			0.050	1.09	
d_locat11			-0.011	-0.31	
d_locat12			0.050	0.83	
ind_1	-0.158	-4.62	-0.153	-4.44	
ind_2	0.037	0.98	0.037	0.98	
ind_3	-0.097	-3.25	-0.108	-3.57	
ind_4	-0.057	-1.12	-0.058	-1.15	
ind_5	0.074	0.84	0.070	0.81	
ind_6	-0.242	-4.83	-0.244	-4.85	

	ind_7	-0.113	-4.20	-0.112	-4.16
	ind_9	0.241	3.87	0.246	3.91
	ind_10	-0.195	-4.73	-0.196	-4.77
	ind_11	-0.179	-2.94	-0.168	-2.77
	ind_12	-0.117	-3.15	-0.115	-3.09
	_cons	0.188	1.72	0.182	1.61
inflate					
	daring2	-0.814	-7.05	-0.817	-7.08
	_cons	0.675	5.87	0.673	5.85
Wad (chi2)		(19) = 893814.27		(31) = 891565.02	
Prob > chi2		0.0000		0.0000	
N of Zeros		13887		13887	
N		21404		21404	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6000
5000
4000
3000
2000
1000
0
1 2 3 4 5 6 7 8 9 10 11 12 13
full
reduced

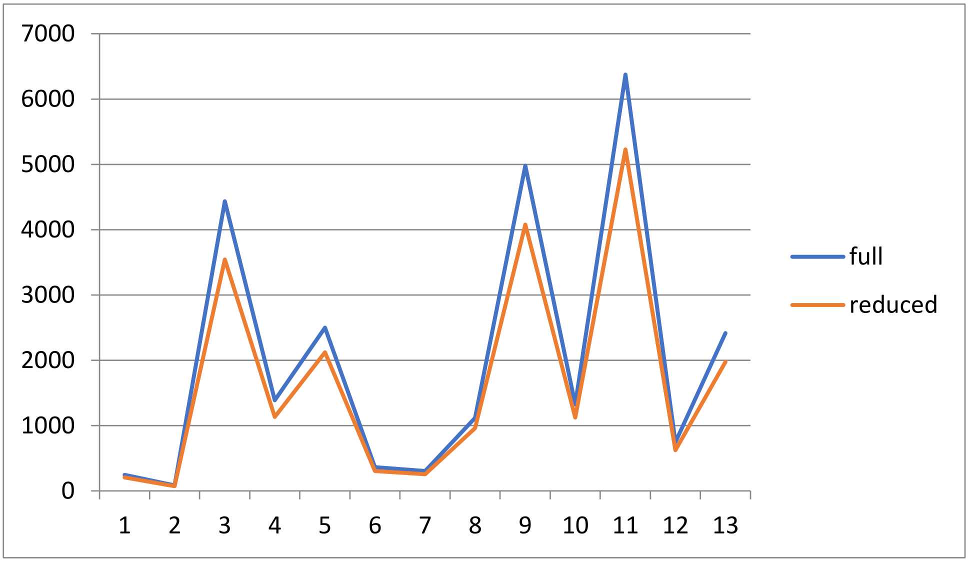
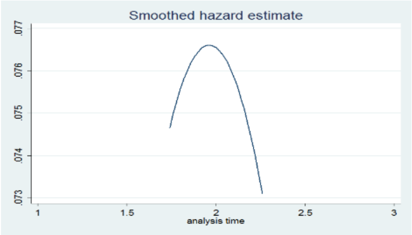

7000
6000
5000
4000
3000
2000
1000
0
1 2 3 4 5 6 7 8 9 10 11 12 13
full
reduced

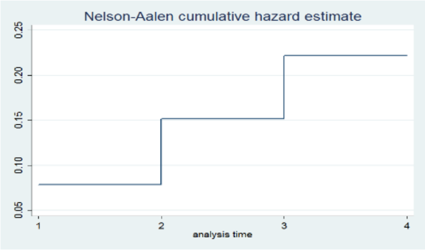
Figure 1

Beg. Time	Total	Fail	Net Lost	Survivor Function	Std. Error	[95% Conf. Int.]	
1	20072	1573	853	0.9216	0.0019	0.9178	0.9253
2	17646	1295	735	0.854	0.0025	0.849	0.8589
3	15616	1093	602	0.7942	0.0029	0.7884	0.7999
4	13921	0	1.40E+04	0.7942	0.0029	0.7884	0.7999

Graph of Hazard Ratio



Graph of Cumulative Hazard Ratio (Nelson-Aalen Cumulative Hazard Curve)



*Graph of Survival Function (Kaplan-Meier Survival Curve)

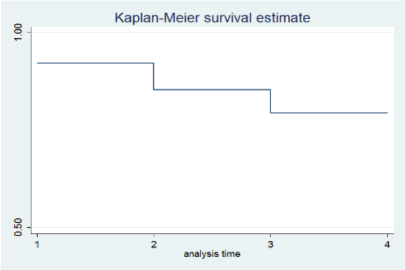
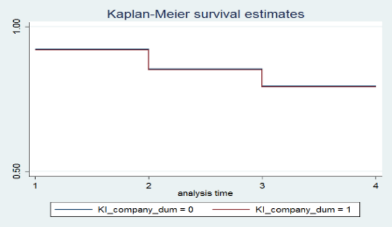


Figure 2

Number of subjects	20072
Time at risk	67255
Failures	3961
Incidence rate	0.06

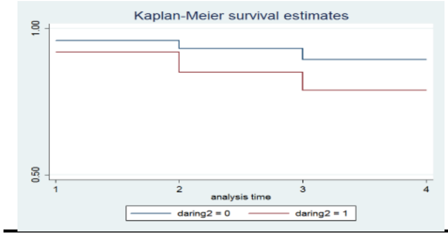
Kaplan-Meier for Two Groups

Knowledge Intense vs Non-Knowledge Intense Companies



Log-rank test for equality of survivor functions		
KI_company_dum	Events observed	Events expected
0	3163	3171.87
1	798	789.13
Total	3961	3961
chi2(1)	=	0.13
Pr>chi2	=	0.7138

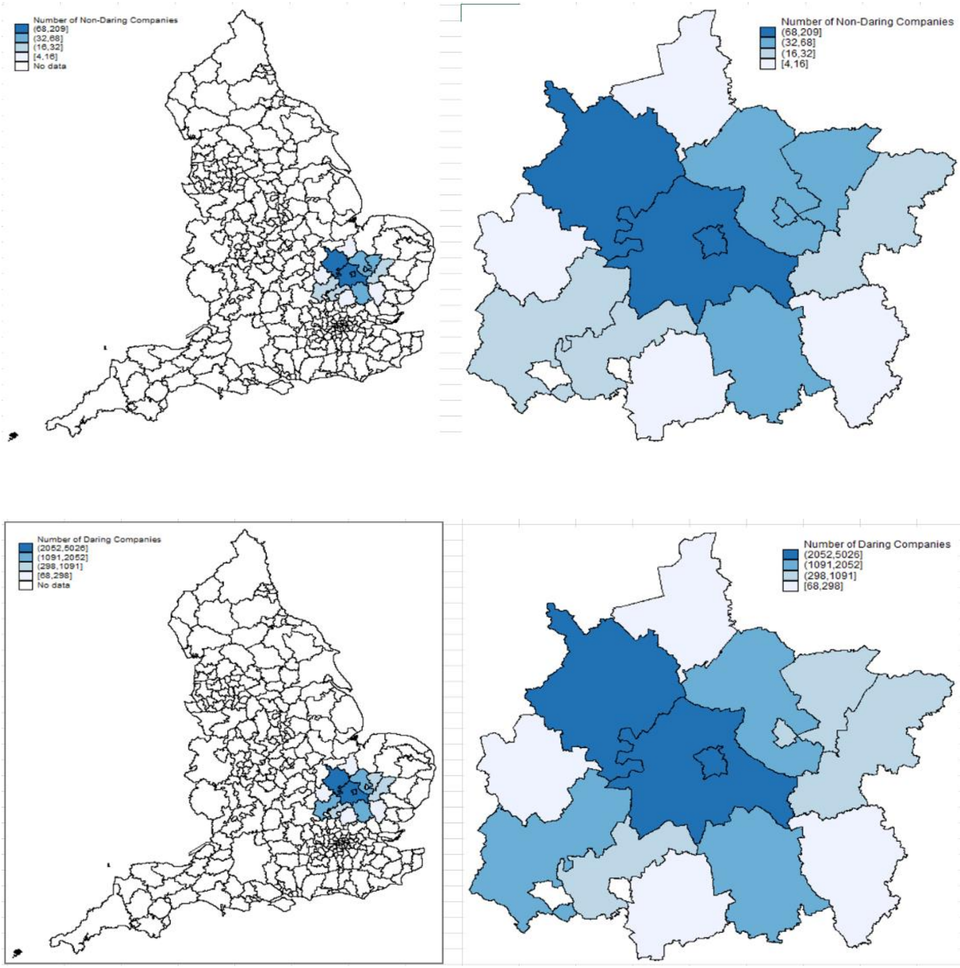
Daring vs Non-Daring Companies



Log-rank test for equality of survivor functions		
daring	Events observed	Events expected
0	86	174.44
1	3875	3786.56
Total	3961	3961
chi2(1)	=	50.67
Pr>chi2	=	0.0000

Figure 3

Figure 4


Number of Non-Daring Companies
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(32,68]
(16,32]
[4,16]
No data
Number of Non-Daring Companies
(68,209]
(32,68]
(16,32]
[4,16]
Number of Daring Companies
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(1091,2052]
(298,1091]
[68,298]
No data
Number of Daring Companies
(2052,5026]
(1091,2052]
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