Journal of Business Venturing Insights 3 (2015) 5–8

Contents lists available at ScienceDirect

Journal of Business Venturing Insights

journal homepage: www.elsevier.com/locate/jbvi

Are firm growth paths random? A reply to “Firm growth and the illusion of randomness”

Alex Coad [a,*], Julian S. Frankish [b], Richard G. Roberts [c], David J Storey [a]

[a] University of Sussex, BMEc, University of Sussex, Jubilee Building, Falmer BN1 9SL, UK
[b] Barclays Bank, UK
[c] University of Birmingham, UK

ARTICLE INFO

Article history:
Received 20 November 2014
Accepted 28 November 2014
Available online 25 February 2015

Keywords:
Firm growth
Growth paths
Autocorrelation
Randomness
Gambler's Ruin
Gibrat's Law

ABSTRACT

We respond to Derbyshire and Garnsey's article "Firm growth and the illusion of randomness", adding theoretical and methological clarifications as well as some new empirical evidence.

1. Introduction

We much appreciate the interest in our paper shown by Derbyshire and Garnsey. The latter authors' work, based on a deep knowledge of individual businesses over a long period of time, is an example to all wishing to understand temporal volatility of new and small enterprises. Indeed, we view the paper by Garnsey and Heffernan (2005), which demonstrated the scale, nature and diversity of temporal volatility, as a key intellectual building-block for our 2013 paper.

2. The D&G critique

1. What looks like randomness actually reflects the methods used – specifically the binary distinction between growth and decline. The inclusion of the more nuanced concept of stasis or stability produces very different results.
2. Sales are a poor measure of temporal performance of a new/small firm because they are so volatile.
3. Entrepreneurship is about uncertainty and not risk, so the coin-flipping analogy in which probabilities are known in advance is not appropriate.
4. If growth paths are close to random then “there is little to be gained by further research effort”.

* Corresponding author.
E-mail addresses: A.Coad@sussex.ac.uk (A. Coad), Julian.frankish@barclays.com (J.S. Frankish), r.roberts.1@bham.ac.uk (R.G. Roberts), D.J.Storey@sussex.ac.uk (D. Storey).

http://dx.doi.org/10.1016/j.jbvi.2014.11.001
2352-6734/

3. Clarifying what we say

Our data constitute a random sample of New Ventures (NVs) in England and Wales. This is important for two reasons. The first is that we make no claims that our results necessarily apply to established firms – large or small[1]. The second is that, as we show elsewhere (Coad et al., 2014), almost all prior work on NVs has been based on convenient samples of firms that are subject to up to 10 forms of bias. For this reason alone it is unsurprising that our emphasis on temporal volatility differs from that of others, because this issue cannot be quantified in existing NV databases.

Our analysis is of 2814 NVs that survive until the end of the fifth year (not fourth). Since the first annual growth rate is measured from year 1 to year 2 (i.e. $\log(\text{sales})_{it} - \log(\text{sales})_{it-1}$ for firm i in year t), and in order to calculate four consecutive annual growth rates, we need data until the end of the fifth year. Then we examine survival into the sixth year on the basis of the first four consecutive growth periods. In our baseline analysis we don't exclude any firms on the grounds that they do not grow.

We calculate growth rates in the usual way (Tornqvist et al., 1985, see also Coad, 2009 for a survey) by taking log-differences (see Coad et al., 2013, p. 621).

So, to be absolutely clear; we do not argue that NV growth paths are entirely random, but that they are *close to* random, and that randomness is a considerably better approximation than determinism. Specifically we say:

> "We therefore suggest that it is an acceptable heuristic to consider that growth paths occur in approximately random fashion, even if we observe some departures from a purely random benchmark that are significant in statistical terms." p. 623.

We have some reservations about the data used by Derbyshire and Garnsey. Their TBM database is only just a bit larger than the Value-Added Tax (VAT) stock, and so disproportionately covers larger starts and probably captures them later after 'start-up'. It excludes the very smallest firms. The Barclays data covers a wider slice of the start-up population (only excluding the very smallest starts that do not even bother to open a business current account). This might be an important distinction (although the authors do not challenge the unpredictability of outcomes per se).

4. Responding to Derbyshire and Garnsey

1. What looks like randomness actually reflects the methods used – specifically the binary distinction between growth and decline. The inclusion of the more nuanced concept of stasis or stability produces very different results.

   All organizations change over time but perhaps nowhere is that change so radical or rapid as in the NV. We are therefore not comfortable with concept of stasis for two reasons.

   The first is that it uses metrics that are too "clunky" to identify the scale of change that is actually occurring. So surely the results presented by D&G for "S-S-S-S", that 56.40% of NVs do not change over five years is counterintuitive?

   The second is a measurement problem. Using their methods, D&G could easily increase the number of firms in the 'stasis' category by grouping firms into size categories of 1–9, 10–49 and 50+ employees. Movement between the categories would then be minimal. Alternatively they could reduce the number of 'stasis' firms by using the number of work tasks, or hours worked as shown on employee timesheets as a metric that would show a negligible number of firms are in 'stasis'.

   In our 2013 paper we had only two categories of firm performance in order to keep the analysis manageable (see also Chan et al., 2003)[2]. Moving from 2 to 3 categories increases the number of categories from 16 to 81. We agree it is interesting to move from 2 to 3 categories, provided this is done in a rigorous way. However, if the difference between the three categories depends on an employment change of greater than 1 employee in magnitude, this makes it more difficult for a single employee firm than for a 100 employee firm to leave the stasis group, which distorts the analysis. Instead we prefer to define growth as the bottom third of sales growth, stasis as the central third, and growth as the top third, so as to have three equi-populated groups. This analysis is carried out on our Barclays dataset, and the results are presented below in Table 1. Each of the 81 possible growth paths is observed in our data. We see that the most highly-populated category is "ssss", four consecutive periods of stasis, which is observed for 103 firms. The relatively large number of observations in "ssss" might perhaps be influenced by the fact that growth rate variance is lower for some groups of firms such as larger firms (see e.g. Sutton, 2002; Bottazzi and Secchi, 2006), such that larger firms are less likely to be found in the categories of relatively fast rates of decline or growth. The three next most populated categories are "sssg" (55 firms), "dggd" (46 firms) and "dgdd" (44 firms). Meanwhile, the three least populated categories are "ddsd" (11 firms), "sdsg" (13 firms) and "dsgd" (14 firms).

   So, despite being the focus of so much entrepreneurship scholarship, there are only 40 surviving NVs that exhibit prolonged growth ("gggg"). These constitute 1.8% of all surviving NVs and their numbers only slightly exceed the 32 surviving NVs that exhibit prolonged decline ("dddd").

[1] The recent paper by Anyadike-Danes and Hart (2014) clearly makes the point that the scale and nature of performance in the first five years of life of an NV is radically different from their performance in the next 10 years.

[2] We only became aware of Chan et al. (2003) after our JBV paper was accepted, which is unfortunate given the similarities.