



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



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ABSTRACT

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

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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”.

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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 small¹. 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 decline 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.

Table 1

Replicating Table 1 in Derbyshire and Garnsey (2014) with the data in Coad et al (2013). Decline (“d”) corresponds to growth strictly lower than the 33.3333th percentile for each year (for the subsample of firms that survive until the end of year 5), growth (“g”) corresponds to growth strictly above the 66.6667th percentile, and stasis (“s”) is the category in between (with strict inequalities).

Growth path	No. of firms	Percent	Growth path	No. of firms	Percent
dddd	32	1.47	gggs	30	1.38
dddg	42	1.93	ggsd	20	0.92
ddds	19	0.87	ggsg	24	1.10
ddgd	37	1.70	ggss	25	1.15
ddgg	40	1.84	gsdd	27	1.24
ddgs	30	1.38	gsdg	23	1.06
ddsd	11	0.51	gsds	19	0.87
ddsg	20	0.92	gsdgd	24	1.10
ddss	36	1.65	gsgg	28	1.29
dgdd	44	2.02	gsds	26	1.19
dgdg	40	1.84	gssd	23	1.06
dgdg	21	0.97	gssg	25	1.15
dggd	46	2.11	gsss	30	1.38
dggg	28	1.29	sddd	37	1.70
dggg	26	1.19	sddg	32	1.47
dgsd	20	0.92	sdds	16	0.74
dgsd	25	1.15	sdgd	35	1.61
dgsd	31	1.42	sdgg	17	0.78
dsdd	20	0.92	sdgs	18	0.83
dsdg	28	1.29	sdsd	17	0.78
dsds	16	0.74	sdsg	13	0.60
dsgd	14	0.64	sdss	36	1.65
dsgg	15	0.69	sgdd	20	0.92
dsgs	15	0.69	sgdg	31	1.42
dssd	17	0.78	sgds	20	0.92
dssg	21	0.97	sggd	21	0.97
dsss	31	1.42	sggg	16	0.74
gddd	38	1.75	sggs	15	0.69
gddg	33	1.52	sgsd	21	0.97
gdds	17	0.78	sgsg	15	0.69
gdgd	34	1.56	sgss	23	1.06
gdgg	32	1.47	ssdd	24	1.10
gdgs	24	1.10	ssdg	21	0.97
gdsd	18	0.83	ssds	21	0.97
gdsg	22	1.01	ssgd	22	1.01
gdss	18	0.83	ssgg	18	0.83
ggdd	35	1.61	ssgs	33	1.52
ggdg	22	1.01	sssd	27	1.24
ggds	26	1.19	sssg	55	2.53
gggd	41	1.88	ssss	103	4.73
gggg	40	1.84	Total	2176	100.00

2. Sales are a poor measure of temporal performance of a new/small firm because they are so volatile.

We acknowledge “there is no way of measuring an amount of expansion, or even size of a firm, that is not open to serious conceptual objection” (Penrose, 1959, p. 199) but make the case that changes in sales are a better indicator for NVs than employment headcounts for three reasons.

The first is because the latter is too coarse-grained to pick up variations. The second is that it is a much more clearly articulated objective of the NV owner(s) to raise sales than to raise workforce size (Achtenhagen et al., 2010). The third is that sales volatility has been shown to be a major influence on the survival/non-survival of NVs (Frankish et al., 2013), reflecting the well-established observation that greater volatility requires greater access to finance to even-out fluctuations in cash-flow. NVs with sales volatility, but limited access to finance, are therefore high risk.

3. Entrepreneurship is about uncertainty and not risk, so the coin-flipping analogy in which probabilities are known in advance is not appropriate.

We do not agree with D&Gs discussion of risk and uncertainty. The seminal article by Jovanovic (1982, p. 651) discusses how entrepreneurs may know the distribution of outcomes even if they don't know their individual random draw (i.e. risk). However, a gambler in a casino may be uncertain about their total night's winnings (i.e. uncertainty). We consider that the semantics of risk vs uncertainty is not helpful here.

4. If growth paths are close to random then “there is little to be gained by further research effort.”

We don't take our observation that growth paths are close to random to imply that “there is little to be gained by further research effort” (their Section 5). Far from it! What we do believe is that, given our current state of knowledge, the greater risk is making inferences that key relationships are in place when the evidence to support them is thin. One example is the

inference that entrepreneurs learn – defined as those with more experience in a prior business – and therefore perform better than those without that experience. This “finding” has led to a range of questionable changes – such as policies making it easier for bankrupts to re-start – that are likely to be costly to implement and yet, in our view, will have minimal impact.

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