Chapter 2
Statistical Issues in Applied Entrepreneurship Research: Data, Methods and Challenges

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2.1 Introduction

This chapter discusses aspects of the statistical measurement of entrepreneurship, and the use of statistical methods in explaining the role of entrepreneurship in modern economies. The discussion is conducted with reference to topical issues in current entrepreneurship research. The chapter is divided into five sections, the first two sections each containing three components, relating to data measurement, the statistical methods required to analyse the phenomena of interest, and a brief list of issues that remain to be addressed. I first discuss the measurement of entrepreneurship at an aggregate level. Two main classes of measure are in common usage at present. I argue that this is an advantageous situation on balance, as the various measures capture different aspects of what entrepreneurship entails. The econometric methods required to analyse the determinants of international differences in entrepreneurship, and time series variations within countries, are also discussed in this section, as are several outstanding issues that remain to be addressed.

Section 3 discusses interpersonal comparisons in entrepreneurship, in terms of what makes some individuals more likely than others to become entrepreneurs. I argue that panel data sets should be used for this purpose whenever possible. Section 4 treats statistical measurement of entrepreneurship at the regional level, and emphasises the ongoing challenges statisticians face in advancing our core knowledge at this level of analysis. Section 5 offers a brief overview of policy issues, pointing out where progress has been made in the statistical analysis of public policy's interface with entrepreneurship, and where more work is needed. The final section concludes the chapter.

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2.2 International comparisons

2.2.1 Data: How to measure entrepreneurship?

The first question is how to define entrepreneurship for the purposes of making international comparisons. At present, there are broadly two available approaches and data sets. The first defines of entrepreneurship as self-employment, which can be implemented at the aggregate country-level using publicly available OECD *Labour Force Statistics* data. The second approach defines entrepreneurship as the formation and operation of new firms, and is implemented in the Global Entrepreneurship Monitor (GEM), a joint project between London Business School of the UK, and Babson College of the US. Table 2.1 lists some characteristics of the two measures and data sets.

As the table shows, both existing measures and approaches have their merits and demerits. The OECD data go back to the 1960s; useable international comparisons on a large panel of countries go back as far as 1972 (Parker and Robson, 2004); and the series continues to be published. There are some problems of comparability between countries, though algorithms are now being developed by Andre van Stel at Erasmus University in the Netherlands to resolve these problems. In contrast, we currently only have a limited number of years of GEM data, which precludes meaningful time series analyses of entrepreneurship. GEM data have the advantage of greater comparability across countries, and the TEA flow index dovetails with business studies research which equates entrepreneurship with new venture creation. However, a sometimes overlooked drawback of TEA is that by focusing only on new

Table 2.1 Comparison of OECD and GEM data on entrepreneurship

Data set:	OECD(Labour Force Statistics)	GEM
Definition of entrepreneurship	Self-employment	New venture creation (Total Entrepreneurial Activity index, TEA)
Type of measure	Stock	(In)flow: all individuals owning businesses more than 42 months old are discarded from TEA
Advantages	Long time series Includes established as well as new entrepreneurs	Focuses specifically on entry (flow) Considerable cross-country comparability Disaggregate as well as aggregate level data
Disadvantages	Self-employment includes part-time and hobby (non-entrepreneurial) firms Data are not strictly comparable across countries	By omitting older firms, TEA overstates entrepreneurship and is volatile (sensitive to the business cycle) Also includes non-entrepreneurial firms Short time-series

firms, it is overly sensitive to the state of the business cycle. While the movement of countries up and down the TEA "league table" no doubt makes good headlines, it is less clear why firms over 42 months old cease to be entrepreneurial as a matter of course; numerous counter-examples doubtless spring to mind.

In my opinion, the existence of more than one practical entrepreneurship measure is an advantage rather than a limitation. The researcher has greater choice to employ an empirical measure that relates more closely to their theoretical construct, whatever that may be. Unless one adopts an evangelical view that stock or inflow are intrinsically important, both measures contain different information that makes them complements rather than substitutes. Some researchers have recognised this, suggesting that researchers might choose to use a mixture of entrepreneurship measures in their empirical research (Gartner and Shane 1995). Note however that OECD and GEM data the only sources of data that can be used to make international comparisons of entrepreneurship. Other cross-country data sources exist, including the European Community Household Panel (Garcia-Mainar and Montuenga-Gomez 2005).

2.2.2 Statistical methods

The great advantage of cross-country data sets with a time dimension, such as the OECD *Labour Force Statistics*, is that they facilitate time series analysis. Thus, the researcher can analyse not only static differences between countries, but also trends and cycles in entrepreneurship within countries, as well as cross-country differences in those trends and cycles. Long spans of data are necessary if the researcher is to explain entrepreneurship in terms of slow-changing underlying factors, such as in the economic (e.g., technical change) or policy/institutional (e.g., tax) environment. With time series data for several countries, the statistical power of econometric analysis is enhanced, as both time-series and cross-sectional variations can be harnessed to identify underlying processes (Blanchflower 2000; Parker and Robson 2004). The use of time series data does however require the researcher to abandon the simple ordinary least squares estimator, which generates potentially spurious results when data are non-stationary; superior cointegration methods should be used instead (Parker 1996; Parker and Robson 2004).

2.2.3 Issues that remain to be addressed

There are several ways that the statistical analysis of international comparisons of entrepreneurship can be improved. First, cleaner and more comparable cross-country data are needed. GEM has made a valuable contribution in this regard, albeit from a particular viewpoint; it is to be hoped that the comparable OECD LFS data will also become widely available on an updated basis some day. Second, researchers can do much more to disseminate appropriate econometric (cointegration) techniques, especially those relating to time series data and panels with a large time series dimension. Third, the current literature presently contains numerous reduced form analyses of entrepreneurship and growth; there is ample scope for structural empirical modelling, which recognises that not only might entrepreneurship feed into growth (as some early GEM reports asserted), but also that entrepreneurship might in turn respond positively to more favourable growth conditions. Endogeneity of entrepreneurship is obviously the issue here ? which should not be surprising: presumably that is the reason why we study it! Structural approaches contain the promise of uncovering the causal linkages between entrepreneurship and growth, a topic of growing interest (Acs et al. 2004; van Stel et al. 2005; Wong et al. 2005; and see below).

2.3 Interpersonal Comparisons

2.3.1 Data and Measurement Issues

Studies about individuals' choices to become entrepreneurs can be grouped into three categories, according to the dependent variable used in their empirical analyses. These relate to individual's choice of employment status (self-employed/business owner or employee); the individual‘s choice of whether to start a new venture; and the entrepreneur‘s choice of whether to continue or terminate the present business.

Large-scale micro data sets have been widely available for many years now, fuelling dramatic growth in what is now a vast applied literature on the determinants of entrepreneurship status, entry, and survival (see Parker, 2004, for a review of this literature). Much has now been learned about the salient factors behind these processes; rather than repeat a summary of them here, I will instead concentrate on two limitations of current data sets: the absence of a longitudinal component, and measurement problem in key variables of interest.

Longitudinal surveys, which compile data on individuals by following them through time, are gradually becoming more widely available. The best known longitudinal (panel) data sets in use in applied entrepreneurship research are the National Longitudinal Survey and the Panel Survey of Income Dynamics (both US); the British Household Panel Survey and National Child Development Survey (both UK); and the European Community Household Panel. Several of these data sets, such as PSID and BHPS, are ongoing panels which "top up" respondents who leave the panel with new replacements. It is now becoming clear that panel data sets are essential for understanding the individual-specific factors that drive entrepreneurship as an occupational choice. As well as facilitating the analysis of individual-level career dynamics, panel data enjoy two key advantages over static cross section surveys: they can control for *state dependence* and *unobserved heterogeneity*, both of which appear to be integral aspects of these choices (Henley 2004; Hochguertel 2005). To explain these concepts, consider the following econometric model of occupational choice:

$$s_{it} = X_{it}\beta + \gamma s_{it-1} + \mu_i + u_{it} \tag{2.1}$$

Here, s_{it} represents the decision of individual i about whether to be self-employed at time t: this depends on whether they were self-employed at time t-1 (via the parameter γ); on a vector of observable characteristics at t, X_{it}; and on a person-specific idiosyncratic fixed effect, μ_i. The u_{it} is a random error term. State-dependence is the tendency of individuals to continue what they were doing in the past; this is reflected in the $\gamma\ s_{it-1}$ term. Unobserved heterogeneity is the set of idiosyncratic person-specific factors that make some people innately more likely to be entrepreneurs, for reasons that we cannot measure directly. This is represented by the fixed effect μ_i. When models of this sort have been estimated, these two constructs are found to make important qualitative differences to key parameters of interest, many of which reside in β (see, e.g., Henley 2004; Hochguertel 2005). Put bluntly, without taking account of state dependence and unobserved heterogeneity, the researcher is at risk of generating misleading inferences about the determinants of entrepreneurship.Whether or not panel data are available, statisticians and researchers must pay close attention to measurement error when seeking to understand the individual-level determinants of entrepreneurship. Key to this is obtaining reliable income data for entrepreneurs. For example, in one canonical model of entrepreneurial occupational choice, an important driver of switching propensities is suggested to be relative incomes (Rees and Shah 1986; Taylor 1996; Parker 2003). Yet in conventional sample surveys, self-employed people are known to be reluctant to respond to questions about their income and wealth, and drastically under-report their incomes when they do respond (Pissarides and Weber 1989; Lyssiotou et al. 2004). Statisticians tasked with obtaining individual-level entrepreneurship data need to find better ways of eliciting truthful responses, if at all possible. This is desirable for several reasons, not just for helping researchers identify entrepreneurial selection effects. The levels and inequality of entrepreneurial incomes are of policy interest in their own right (Parker 1997, 1999; Hamilton 2000); and returns to entrepreneurship appear to affect effort and labour supply decisions of entrepreneurs (Bitler et al. 2005; Parker et al. 2005).

High quality asset data are available in the US, where entrepreneurs are observed to play a central role in the accumulation of savings and wealth. Recent calculations reveal that entrepreneurs hold nearly 40% of total net worth in the US (Gentry and Hubbard 2004), while half of the richest 5% of American families own businesses (Quadrini 2000). In addition, entrepreneurial families account for one third of all stockholdings (Heaton and Lucas 2000). Numbers like these suggest that entrepreneurial wealth-holding is important enough to merit serious investment of statistical resources in acquiring better data, especially outside the US where wealth data are patchier. Better data could be used to shed light on issues which are still imperfectly understood, including the "private equity premium puzzle" in business ownership (Moskowitz and Vissing-Jorgensen 2002; Hintermaier and Steinberger 2005); entrepreneurs' investment decisions (Carroll et al. 2000); and entrepreneurs' retirement decisions (Parker and Rougier 2006).

2.3.2 Estimation Issues

There are several statistical estimation issues which crop up when individual-level data are used to analyse entrepreneurial choices. One is endogeneity, especially of human capital and assets. Neither human capital nor assets are random draws; individuals, including entrepreneurs, purposively choose their values; neglecting this can seriously bias regression model parameters purporting to shed light on drivers of entrepreneurship. A good practical example of this is supplied by Parker and van Praag (2006), who show that the inappropriate use of OLS biases substantially downwards rates of return to entrepreneurs' schooling in the presence of borrowing constraints. Other researchers are also recognising the importance of dealing with endogeneity, including Garcia-Mainar and Montuenga-Gomez (2005) in the context of human capital, and Hurst and Lusardi (2004) in the context of wealth. More however remains to be done to spread good practice across the research community, entailing the use of Instrumental Variables (IV) or Generalised Method of Moments (GMM) estimators.

Other statistical estimation issues include the need to control for self-selection into occupations when analysing entrepreneurial outcomes; controlling for tastes (where possible), such as risk aversion; and using non-parametric as well as parametric estimation where this is appropriate. Sample survey data on risk attitudes are potentially valuable, although the accuracy of survey responses to hypothetical questions about gambles is questionable; recent papers that utilise such data in entrepreneurship research include Ekelund et al. (2005) and Kanniainen and Vesala (2005). Non-parametric methods have also become more popular, with Paulson et al.(2006) combining these methods with reduced form and structural parametric estimation in an analysis of borrowing constraints. The advantage of non-parametric methods is to weaken essentially uninteresting assumptions about model structure to generalise the applicability of the researchers' results.

2.3.3 Issues that Remain to be Addressed

There are several ways that improved data can potentially advance our understanding of entrepreneurship. One involves digging deeper inside firms, matching firm-level with individual-level data. We have at present some tantalising evidence about how the inflexibility of incumbent firms' routines can inhibit the development of new ideas inside those firms (see, e.g., Henderson 1993)—requiring new venture creation (entrepreneurship) to exploit those ideas. We are already seeing the emergence of a research agenda which connects firms' decisions with those of employees who quit to pursue new opportunities in entrepreneurship (Gompers et al. 2005). However, this research agenda is still in its infancy, and further development is inevitable. Another area where novel sources of data would be helpful is in relation to credit markets. Some suggestive evidence by Blanchflower et al. (2003) points to the existence of racial discrimination by banks against borrowers; more bank file data are needed to further explore this and related issues, including the relevance and predictive power of conventional theories of credit rationing and asymmetric information (Parker 2002). Ongoing research is also beginning to make more ambitious linkages between hitherto separate topics in entrepreneurship research, for example between human capital, loan decisions and entrepreneurs' performance (Parker and van Praag 2006); and between borrowing constraints and business transfers (Caselli and Gennaioli 2005). Statisticians charged with compiling new entrepreneurial data sets need to recognise the growing demands of researchers for data that break down conventional boundaries in the growing drive for unification of the entrepreneurship field.

What should be clear from the discussion so far is that European researchers are generally less well served than their American counterparts, in terms of their access to high quality data on contemporary issues in entrepreneurship research. There is a case for European statistical agencies to compile more and better European data (preferably in the form of an ongoing cross-country panel data) which bear on the issues we have treated here. As well as obtaining data specifically on wealth accumulation, I would appeal for better data on borrowing constraints (rather than simple measures of asset values, which has been the norm in the literature to date); on business angels and their investments; on high growth firms ("gazelles"); on career histories of entrepreneurs that link firms with workers; and on non-profit entrepreneurs and the nature of their enterprises.

2.4 Regional Comparisons

A lively area of ongoing entrepreneurship research connects aspects of geography, economic growth and entrepreneurship. Work by Acs et al. (2004) and Audretsch and Fritsch (2002) relates spillovers, clusters and growth at the regional level, and evidence is now accumulating that regions with higher levels of new venture creation also have higher average economic growth rates. One possible explanation of this linkage is that entrepreneurs exploit knowledge spillovers in local clusters to generate that growth; an alternative explanation is that small forms are "hothouses", where future entrepreneurs learn from owner-manager "role models" (Wagner 2004).

A statistical (data) problem immediately surfaces: what is the appropriate unit of analysis for which to collect and analyse data? Applies research in this area has tended to work at the level of the firm (small or new) or the province/locality, rather than at the level of the individual. This in turn raises further questions, about the appropriate definitions of small and new firms (e.g., "what is small?"), and where the local boundaries can be drawn. To date, researchers have tended not to worry overly about the sensitivity of their results to these definitions. That may need to change.

As elsewhere in this chapter, some outstanding statistical estimation issues emerge. While the emphasis in the knowledge spillover research has focused on the effects of entrepreneurship on growth, reverse causality is also possible. Indeed, this seems more likely than not, since firm formation activities are known to be more frequent in high-growth periods (Audretsch and Fritsch 1994; Reynolds 1994). This consideration, and the importance of treating lag structures carefully as spillover effects take time to transmit changes in value and employment (Audretsch and Fritsch 2002), again suggest the need for structural modelling; though little of that has been attempted (at least to my knowledge) to date.

Topics deserving further statistical analysis include the effects of local unemployment on the propensity to start new firms and spillover externalities. The available evidence on local unemployment conditions is mixed, with for example Henley (2004) and Acs and Armington (2004) detecting no effects using UK and US data respectively, while Niittykangas and Tervo (2005) report positive effects using a panel of Finnish data. Arguably, finer-grained panel data are needed to resolve this issue. Second, we still lack detailed micro evidence of spillover externalities. The proxies that have been used in the literature have been useful certainly, but rather crude (Audretsch and Feldman, 1996). Third, it is still unclear whether it is better to start up in local rather than national markets, with conflicting evidence coming from Brüderl et al. (1992) and Bhide (2000), among others. These are not issues on which a consensus looks likely to emerge any time soon; greater clarification would however be welcome.

2.5 Policy Issues

While theoretical models of entrepreneurship proliferate policy recommendations, rigorous quantitative analyses of government interventions are scarcer. Fortunately, robust policy evaluation methods are beginning to emerge, and disseminate through the literature. One example is matching approaches which compare outcomes for program participants and members of control groups. For instance, Meager et al. (2003) used this approach to assess a British business support scheme for youths called the Prince's Trust, while Almus (2004) also used one to evaluate start-up loan assistance programmes in Germany in the 1990s. Another example is to control for selection bias into government programmes, as in Wren and Storey (2002) in the context of the UK's Enterprise Initiative scheme. However, despite the welcome improvement in the rigour of statistical evaluation methods, further work remains to be done to develop and disseminate these methods in the wider scholarly community. Some intrinsically difficult problems remain, including evaluating the true additionality of programs, such as loan guarantee schemes (Riding and Haines 2001); and estimating the externalities generated by entrepreneurs—although there have been some ambitious efforts along these lines (Nordhaus 2004).

On a positive note, solid progress is now being made on several empirical fronts in the policy domain. For example, it is becoming clear that courts play a central role in enforcing loan contracts, which has important direct effects on the efficiency of entrepreneurship (Jappelli et al. 2005; Zazzaro 2005). Also, less draconian bankruptcy laws do seem to promote entrepreneurship (Fan and White, 2003; Berkowitz and White 2004). Research using time series data have detected generally negative effects from government regulations on entrepreneurship (Kanniainen and Vesala 2005; Torrini 2005). The evidence on taxation and entrepreneurship is reviewed in another chapter, by Herb Schuetze;[1] here again, empirical work seems to be clarifying the role of policy in practice.

2.6 Summary

To summarise, it is clear that progress has been and continues to be made in many areas of statistical data collection and analysis in applied entrepreneurship research. Throughout the chapter, I have tried to balance a generally favourable view towards this progress with an attempt to identify areas where further improvements are needed. There are certainly some cases where theory has overtaken the current state of the art in statistical measurement, and where the latter needs to catch up, including competing theories of entrepreneurial start-up finance; social capital of entrepreneurs; and the distinction between productive and unproductive entrepreneurship. I would expect to see individual researchers rising to some of these challenges, by compiling their own data suited to the particular task at hand. It is not practical to expect statistical agencies to obtain these data themselves, though they may in the future play a greater role in commissioning and distributing novel large scale data sets, to promote their more widespread utilisation.

What of the future for statistical methods in applied entrepreneurship research? I would expect to see greater use of experimental methods in entrepreneurship research, rather than continued almost exclusive reliance on questionnaire-based instruments; a recent example of this is Coelho et al (2004). There are several areas where experimental evidence could help to distinguish between rival theories, including models of credit markets, and entrepreneurial learning frameworks. Future researchers might also want to control empirically for individuals' measured preferences and cognitive biases, as exemplified by Landier and Thesma (2003), for example. However, I hope that future researchers rein back efforts to model entrepreneurs' attitudes and perceptions; the danger here is of "cheap talk", whereby entrepreneurs give systematically misleading responses to survey interviewers.

Another statistical method I see becoming more popular in applied entrepreneurship research in the future is the use of simulation and calibration methods. As theories of entrepreneurship become more complicated, and broader linkages are made between previously disparate topics, tractable structural modelling will become more complex and maybe even impossible. We have already seen several examples of simulation and calibration methods in the economics of entrepreneurship, including the evaluation of government credit programs (Gale 1991; Li 2002); the optimal taxation of entrepreneurs (Parker 1999); entrepreneurs' life cycle savings

[1] Chapter 10

and investment decisions (Quadrini 2000; Meh 2005); and entrepreneurs' asset portfolio decisions (Polkovnichenko 2003; Hintermaier and Steinberger 2005). This trend looks set to continue. Finally, for the reasons outlined throughout in this chapter, I foresee greater usage in applied entrepreneurship research of panel data and more sophisticated statistical estimators, such as instrumental variables and policy evaluation methods. What seems certain is that future researchers operating at the empirical frontiers of this field will need superior statistical training as never before.

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