THE ELIXIR (OR BURDEN) OF YOUTH?
EXPLORING DIFFERENCES IN INNOVATION BETWEEN START-UPS AND
ESTABLISHED FIRMS

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Abstract

Despite the widely acknowledged role of start-ups in economic development, little is known about their innovative activities compared with those of established firms. Drawing on a sample of 12,209 UK firms, we differentiate between services and manufacturing firms and, using a matching estimator approach, demonstrate that start-ups differ significantly from established firms in their innovation activities. We find that in services, being a start-up increases the likelihood of product innovations. However, in manufacturing, we find no significant differences in the likelihood of product innovation between start-ups and established firms. When examining the returns to innovation, we find that start-ups have a significant advantage both in services and in manufacturing. We explore the implications of these results for theory and policy.

"Microeconomics is plagued by two major gaps: the absence of appropriately full treatment of either the services or of entrepreneurship" (Baumol 2010, p. xviii)

1. Introduction

Start-ups are often viewed as the source of "gales of creative destruction" because they introduce new products that disrupt or overturn the positions of incumbent firms (e.g. Schumpeter 1912/1934). It is frequently assumed that they are more innovative than established firms; yet evidence for this is far from comprehensive. For example, Bhide (2000) found that only 6% of *Inc.* 100 founders claim to have begun their firms with unique products or services, with 58% offering identical or close substitutes to existing products or services. Similarly, Shane (2008) argued that most start-ups begin in "pretty mundane, run-of-the-mill industries" and are not particularly innovative.

In this paper, we compare the innovative abilities of start-ups with those of a matched sample of established firms and posit that only in services do start-ups have an advantage over established firms; in manufacturing, start-ups are less likely to introduce innovative products than established firms. We argue that this is because the nature of innovation in services is substantially different from that in manufacturing (Gallouj and Weinstein 1997; Mills and Marguiles 1980; Tether 2003b). Most service products are intangible, are characterized by a co-terminality of service production and consumption (Amara et al. 2008; Hipp and Grupp 2005; Miles 2005; Sirilli and Evangelista 1998), and have low capital intensity relative to manufacturing (Sirilli and Evangelista 1998). Therefore, we concur with Damanpour (1991), who argued that a distinction between manufacturing and services organizations is needed to

develop "empirically distinguishable theories of innovation," and differentiate between manufacturing and services firms in our analysis of innovative behavior.

In addition, since the ability to generate an innovation does not always translate into economic returns from that innovation, we explore the returns to innovation in these two sets of industries. Building on our discussion of the particular features of innovation in services, we suggest that start-ups are less able than established firms to capture returns to innovation in manufacturing, whereas they will have advantages over incumbents in services.

This study is based on a sample of 12,209 firms from the UK for the period 2002–2004. To compare start-ups – firms under 5 years of age - with established firms, we use a nearest-neighbor matching estimator approach (Czarnitzki 2005; Heckman et al. 1997; 1999) and control for firm size, growth, R&D expenditure, R&D cooperation, organizational autonomy, market orientation, and industry sector in our estimates. Overall, we find that in services, start-ups are more innovative than established firms, while in manufacturing we do not find a statistically significant difference in innovative performance between start-ups and established firms. When examining the returns to innovation, we find that start-ups have a significant advantage in both services and manufacturing.

This research makes the following four contributions. First, it contributes to the limited research that directly compares the innovative activities of start-ups with those of established firms. While previous research only examined the influence of organizational age on innovation in manufacturing (Balasubramanian and Lee 2008; Katila and Shane 2005; Sørensen and Stuart 2000), our study examines whether this conclusion is also valid in the case of services. The study probes the potential context dependency of the effect of age on innovation by comparing services with manufacturing firms. In doing so, we bring together the literatures on age and innovation

with the emerging understanding of the nature of innovation in services, focusing on co-terminality, intangibility and low capital intensity as drivers of differences in performance outcomes (Coombs and Miles 2000; Gallouj and Savona 2009; Tether 2003a, 2005).

Second, previous research used patent-based measures of innovation. However this approach might be unable to fully capture the impact of age on firms' innovative performance because incumbents may be good at developing inventions but not at exploiting the commercial opportunities associated with these inventions. In addition, by focusing on patents rather than on commercialized products, prior research has tended to exclude service industries where obtaining patents is uncommon. By examining whether a firm has introduced a new or significantly improved product we can more directly measure firms' success in commercializing innovations both in manufacturing and services (Leiponen and Helfat 2010).

Third, there has been very little research that examined how the ability to generate rewards from innovation differs between new and established firms and across services and manufacturing industries (Gans and Stern, 2003). The ability to profit from an innovation requires a different set of skills and resources than the ability to introduce innovations. In this paper, we contrast the ability of start-ups to capture the returns from innovations with that of established firms and argue that this ability differs considerably between services and manufacturing firms.

Fourth, we compare the innovative performance of start-ups and established firms using a nearest-neighbor matching estimator. This technique enables direct comparisons between start-ups and established firms in a way that traditional parametric regression techniques do not (Czarnitzki 2005; Heckman et al. 1997; 1999). When the distribution of covariates differs across the two comparison groups, regression techniques produce biased estimates, where the

magnitude of the bias depends on how different the distribution of covariates across the two groups is. In addition, the matching procedure does not require a functional form specification to explain innovative performance patterns, thus further reducing the potential bias in the results.

2. Theoretical development

Start-ups are vital for job generation and economic growth, and they are becoming an increasingly important part of the economic system (Reynolds and White 1997). For example, Kane (2010) shows that in their first year start-ups add an average of 3 million jobs to the US economy. In fact, "without start-ups there would be no net job growth in the US economy" (Kane, 2010, p. 2). Moreover a large number of individuals are involved in entrepreneurship at a given point in time: the Global Entrepreneurship Monitor found that, in the 34 countries surveyed, almost 9.3% of the population either were nascent entrepreneurs or were involved in start-ups (Acs et al. 2004).

Despite the importance of start-ups in economic development and job generation, there is little research that directly compares the innovative activities of start-ups with those of established firms (Balasubramanian and Lee 2008; Katila and Shane 2005; Sørensen and Stuart 2000).[1] This is an important omission as there is evidence to suggest that innovation can shape the survival chances of new firms. Indeed, Cefis and Marsili (2005; 2006) found that by being innovative, firms can greatly increase their chances of survival, suggesting that, for start-ups, innovation may be a matter of life or death. Moreover, there has been a dearth of scholarly work that contrasted the returns to innovation between start-ups and established firms. Appropriating the profits from innovation is critical for new firms who may otherwise be unable to capture the

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[1] There is a related stream of research that investigates whether large firms are more innovative than small firms (e.g. Acs and Audretsch 1987, 1988; Ahuja and Lambert 2001; Jaffe and Lerner 2004; Lerner 2004). The evidence seems to suggest that firms become less innovative as they become larger, even though "there are not many large-sample studies that convincingly document a relationship between firm size and innovation output" (Kuemmerle 2006).

returns to innovation as incumbent firms often control the complementary assets and draw rents from previous innovative efforts.

We contend that in order to compare the innovative activities of start-ups with those of established firms we need to distinguish between services and manufacturing firms as the nature of innovation in services is substantially different from manufacturing (Drejer 2004; Gallouj and Weinstein 1997; Mills and Marguiles 1980; Tether 2003b). An issue that we face is that "innovation theory has been developed essentially on the basis of analysis of technological innovation in manufacturing activities" (Gallouj and Weinstein 1997, p. 537). This is despite services accounting for a larger proportion of gross domestic product than manufacturing in the majority of developed countries (Miles 2005).

Despite the limited research on innovation in services (Hipp 2010), three schools of thought have emerged: assimilation, demarcation, and synthesis (Coombs and Miles, 2000, Tether, 2003, 2005; Gallouj and Savona, 2009). The first school, the assimilation approach, is characterized by an attempt to study innovation in services using the theories and concepts developed for understanding innovation in manufacturing (Salter and Tether 2006). Within this trajectory of research, services play a "subordinate role" in innovation (Djellal and Gallouj 2010) and are just passive adopters of externally produced technologies (Tether and Hipp 2002). The second school of thought, the demarcation approach, argued that innovation in services is different to innovation in manufacturing and that new theories and approaches are needed in order to understand the distinctiveness of services innovation (Tether, 2003; Salter and Tether, 2006; Gallouj and Savona, 2009). This line of work tried to lessen the importance of technology in services innovation and called for new conceptual tools that are more sensitive to the intangibility, high dependence on people and interactivity of services (Salter and Tether, 2006).

The third school of thought, the integrative approach, has argued that services and manufacturing do not follow entirely different approaches and that some aspects of services can also be used to understand the rest of the economy (Droege et al. 2009; Gallouj and Savona 2009; Tether 2003a). This approach has come about from the increasing bundling of services and manufacturing into solutions (Howells 2004) and from some similarities between services and manufacturing that have not been properly conceptualized (Howells 2010).

Nevertheless, a complete convergence between services and manufacturing is unlikely to take place (Hipp, 2010). We argue that services are significantly different from manufacturing with three particular characteristics underlying their distinctiveness: intangibility, co-terminality and capital intensity (Miles 2005; Sirilli and Evangelista 1998; Tether and Hipp 2002). We contend that these characteristics are key to understand the innovation differential between start-ups and established firms in services and manufacturing. Next, we examine these characteristics in detail.

Intangibility

Intangibility in services means that "rather than being material products, service products typically involve transformations in such entities as the state of material products, of people…, and in data" (Miles 2008, p. 116). Services do not have an independent physical existence like outputs from manufacturing and are 'invisible' (Tether 2005). Typically, they are hard to record and cannot be stored (Howells 2010). For example, a new management practice, provided by a management consulting organization, will need to be continuously reshaped for each of the organization's customers in order to ensure that it meets the requirements of the specific context in which it is been applied. Manufacturing outputs, on the other hand, have an exteriority relative to their producers and consumers that is, in most cases, not applicable to services (Gallouj and

Weinstein 1997). Because services are intangible they are also harder to protect via intellectual property mechanisms than manufacturing (Amara et al. 2008; Andersen and Howells 2000; Miles 2005). This has implications for innovation as it lowers the entry barriers in services and makes it easier for new entrants to introduce such innovations.

Established firms, instead, are less able to introduce intangible innovations because they suffer from structural inertia (Hannan and Freeman 1984). Researchers have argued that structural inertia limits the ability of established firms to introduce innovations because they cannot easily change their existing ways of doing things (Balasubramanian and Lee 2008; Katila and Shane 2005; Sørensen and Stuart 2000). We argue that structural inertia in established firms influences tangible and intangible innovation in different ways. Structural inertia negatively influences the ability of established firms to introduce intangible innovations because these innovations are relatively instantaneous, not standardized, characterized by attributes that are harder to identify and control and can be produced much more easily when the firm is young. Structural inertia leads established firms to rely on the same previously successful routines inappropriately in all novel situations (Starbuck, 1983) and makes it economically suboptimal to engage even in small adjustments in their capabilities. Because intangible innovations do not follow pre-established routines and have less defined attributes, they are much easier to introduce by new entrants that by established firms. Established organizations are more likely "to act unreflectively and non-adaptively most of the time" (Starbuck, 1983, p. 93) and this is disadvantageous for intangible innovations. As structural inertia is a function of age (Hannan and Freeman, 1984), new entrants continue to be better at intangible innovations even after entry.

The relationship between structural inertia and tangible innovations is less clear. On the one hand, structural inertia may decrease the likelihood that established firms introduce tangible

innovations because they are unable to adjust their activities and structure to incorporate environmental changes, particularly in technologically active areas (Balasubramanian and Lee, 2008). On the other hand, the high degree of reproducibility that is associated with structural inertia (Hannan and Freeman, 1984, p. 154-155) may help established firms be more successful at introducing tangible innovations than start-ups. Because reproducibility and inertia influences reliability and accountability (Hannan and Freeman, 1984) and because tangible products are associated with high levels of reliability and accountability, established firms may be more likely than start-ups to introduce tangible innovations.

Co-terminality

Another characteristic of services that influences the innovation differential between start-ups and established firms is the co-terminality of service production and consumption. Co-terminality means that services require the presence and participation of the client who is often a co-innovator or co-creator of the new service (Edvardsson et al. 2010). This high degree of interactivity between producers and consumers suggests that the origin and attribution of an innovation may not be easy to establish (Tether, 2005) and that the innovation may focus more on this interaction than on the conventional product characteristics (Miles, 2005).

Coterminous innovations need less efforts when introduced because of the high degree of interactivity between producers and consumers. The involvement of customers in design, production, delivery and consumption also makes these innovations easier to introduce as a lot of the information required is often supplied by the customers, so the firms do not need to expend other resources in order to understand the market context. Start-ups are more likely than established firms to introduce coterminous innovations because they do not suffer from inertia and are more flexible than established firms; as a result they find it much easier to coordinate

with consumers on intangible products when this is the case. This would be particularly so when the consumers of new products are outside the incumbent's market domain. Although established firms may have a more extensive network of customer contacts than start-ups they are less able to interact closely and extract the required novelty from them because of their larger repertoires of routines and action generators (Starbuck 1983) – which make them more conducive to conformity and nonadaptability.

In the case of non-coterminous products that are less dependent on the interaction with consumers, established firms have a greater likelihood of introducing such innovations. As the background knowledge required for innovation is cumulative (Cohen and Levinthal 1990), established firms are more likely to have a solid knowledge base and infrastructure required for non-coterminous innovation. As a result, they are more likely than start-ups to bring non-coterminous innovations into the market.

Capital intensity

A third factor that is important in understanding the innovation differential between start-ups and established firms in services and manufacturing is capital intensity. In services innovation costs are a third of those in manufacturing (Sirilli and Evangelista 1998) mostly because service activities are usually characterized by "knowledge and skills embodied in individuals (or teams) …, rather than in physical plant and equipment" (Gallouj and Weinstein 1997, p. 543). Thus product innovations in services require lower levels of capital intensity than in manufacturing.

New firms do not have the capital resources necessary to finance their operations and to avoid a negative cash flow they must obtain additional finance from investors. Obtaining the capital required for a start-up is difficult due to informational asymmetries between investors and

entrepreneurs (Holmstrom 1989). In the case of manufacturing, an established firm will have easier access to capital, either from external funders or their resources and this will provide them with a greater opportunity to meet the capital requirements of development and implementing a new product. This situation is likely to be reversed in services. Since capital requirements are lower in services, start-ups will be able to quickly overcome resource constraints and, in turn, this may give them an advantage over established service firms that have existing assets, which may or may not be well suited to the potential of the innovation. Thus,

> *H1*. *In manufacturing, start-ups are less likely to introduce product innovations than established firms.*

> *H2. In services, start-ups are more likely to introduce product innovations than established firms.*

Although the proceeding discussion explores the advantages and disadvantages of start-ups versus established firms in the generation of innovations, it does not examine the conditions under which firms will be able to profit from these innovations. It is clear that the ability to profit from an innovation requires different skills than the ability to generate an innovation (Teece 1986). Many innovators have found the rewards to their innovations captured by fast followers or the holders of downstream complementary assets (Lieberman and Mongomery 1998; Suarez and Lanzolla 2005). Given this, it may be expected that the ability to capture rewards from innovation is likely to differ between new and established firms in both services and manufacturing.

When compared with established firms, there are two strong reasons to expect that new manufacturing firms will be disadvantaged in capturing the returns to innovation. First, in manufacturing, capturing returns from an innovation requires access to downstream

complementary assets, such as sales and distribution channels and manufacturing facilities. Established firms often have long-term relationships with holders of generic, specialized and co-specialized complementary assets that are required to generate significant sales from an innovation (Teece, 1986). In contrast, start-ups will need to build these relationships from scratch. Second, established firms can draw upon their past products or innovations, whereas new firms are only able to exploit their first generation of products. This means that an established firm may be able to draw rents from prior innovative efforts, whereas a new firm only has the current generation of products to exploit.

In the case of services, however, it is not clear that such patterns prevail. Although established services firms also gain from their experience relative to new firms, the intangibility, co-terminality and low capital intensiveness of services means that such experience is only of modest value on both the supply and demand side. On the supply side, since service products are generally consumed at the point of production, it is challenging for an established firm to draw upon their previous generations of service innovations to develop future innovations. Due to their intangibility, the rate of depreciation of past investments in services is higher than in manufacturing, where past investments can be embodied in physical components. For example, an engineering design consultancy needs to recreate its knowledge for each customer service offering. Indeed, it is clear that developing repeatable service solutions remains a significant challenge for even the most advanced service innovator (Davies et al. 2006; Davies et al. 2010; Miller et al. 2002). On the demand side, a new entrant in services may be successful in convincing a customer to take up its new offering, as this often emerges through co-production between users and producers. This means that when an innovation in services is developed early

adopters are usually at hand since the innovation has been tailored to their specific requirements (Edvardsson, Gustafsson, Kristensson and Witell, 2010).[2] Thus,

> **H3**. *In manufacturing, the level of returns from product innovations captured by start-ups are lower than those captured by established firms.*

> **H4**. *In services, the level of returns from product innovations captured by start-ups are higher than those captured by established firms.*

3. Method

3.1. Data and sample

The analysis is based on the 4th UK innovation survey, which is a publicly available data set, collected in 2005 (see the Appendix for a more detailed description of this survey). The survey was sent by surface mail to more than 28,000 business units in the UK in April 2005, and a response rate of 58% was obtained. Data collection was administered by the ONS, though responses were voluntary (Robson and Ortmans 2006). The final sample consists of 10,528 established firms and 1,401 start-ups, where start-ups are identified as firms established after January 1, 2000.[3]

The sample of firms in the UK innovation survey includes only firms with more than 10 employees and therefore is not representative of the entire spectrum of start-ups. Given that most start-ups fail or remain small, the new ventures within the 4th CIS represent firms that have been relatively successful, growing rapidly to 10 full-time employees in less than five years (Cefis and Marsili 2006). Therefore, it would be unwise to generalize the experience of these firms as relevant to all start-ups. Indeed, many of these firms had overcome many of the most significant

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[2] In the case of credence goods (e.g. brokerage, surgery, car repairs etc.), the reputation of established firms can be very important in capturing the returns from innovations. We believe, however, that this is unlikely to override the benefits that start-ups derive from co-creation with users.

[3] We excluded firms from the construction sector because this industry exhibits very different patterns of innovation from either services or manufacturing (Reichstein et al. 2004). We also excluded firms in mining and utilities.

problems that new firms face before completing the survey. Thus, in the empirical analysis, we control for differences in growth rates between new ventures and established firms to reduce the danger of selection bias based on the nature of the sample.

3.2. Econometric approach

To compare new ventures and established firms directly, we use a non-parametric matching method. Matching estimators are usually applied to evaluate the effect of a policy intervention (treatment) on the sub-population of individuals or firms exposed to the treatment (treated) and/or on the sub-population not exposed to it (non-treated) (see for example Heckman et al. 1997; Heckman et al. 1999). In this study, we follow Czarnitzki's (2005) econometric method to improve balance (i.e., the degree to which the covariate distribution is similar across the two groups of firms) and to separate the differences between start-ups and established firms according to observable characteristics from the gaps in innovative performance due to unobservable firm characteristics. Therefore, in our study the 'treatment' is the characteristic dimension on which the two groups of firms differ – age – and not a policy intervention that has affected only a set of firms in our sample.

The idea of the matching estimator is to match each new firm with established firms with similar observable characteristics and to compare the average innovative performance outcome for these two sets of firms. The matching estimator is based on the following formulation: let D be the treatment, an indicator denoting whether a firm is a start-up; let $Y_i(1)$ be the outcome for the treated firm (i.e., the likelihood of introducing a new product that would be observed if the firm were a start-up); and let $Y_i(0)$ be the outcome of the non-treated firm (i.e., the likelihood of introducing a new product for the same firm if it were not a start-up). What we want to measure

is the mean effect on the likelihood of a product innovation for a start-up, that is, the sample average treatment effect (SATT) on the treated firm:

(1) $SATT = E[Y_i(1) - Y_i(0)|D = 1] = E[Y_i(1)|D = 1] - E[Y_i(0)|D = 1].$

A problem arises because it is impossible to observe the value of $Y_i(1)$ and $Y_i(0)$ for the same firm. So, although we can estimate $E[Y_i(1)|D = 1]$, we cannot estimate $E[Y_i(0)|D = 1]$. The matching estimator approach use the average outcomes for similar firms that were not treated. The basic idea is to find other established firms with similar observable characteristics for each start-up. Let X be a vector of the observed covariates. Then, we can condition on a set of covariates such that

(2) $SATT = E[Y_i(1)|D = 1, X] - E[Y_i(0)|D = 1, X].$

In this study, we apply the matching estimator as Abadie et al. (2001) implemented in the Stata program, *nnmatch*. This program runs a nearest-neighbor matching procedure, which matches each new firm to the nearest established firms. For each new firm *i*, there are two potential outcomes, in which one is observed and the other needs to be estimated. The observed outcome is its own estimate, while the unobserved outcome is estimated by averaging the outcome of the other most similar established firms. We opted for this non-parametric matching technique over the propensity score matching method (Rosenbaum and Rubin 1983) because the control group (i.e., the number of established firms) is significantly large and also because the neighbor matching procedure does not require us to specify and estimate a model describing the selection mechanism.

Let N_1 be the number of start-ups, and let $w(i,j)$ be the weight placed on the *j*th observations of established firms used to construct the counterfactual (i.e., the nearest neighbors) for the *i*th

new firm. This weight is constructed using the distance from the vector of covariates of the start-up i, X_i, to that of the j nearest established firms (see Abadie et al. 2001 for details). However, the weight $w(i,j)$ can be set equal to 1 for a sub-set of covariates, which implies that the start-up and the matched established firms show exactly the same value for that particular covariate.

The SATT will then be equal to the following:

$$(3) \ \text{SATT} = \frac{1}{N_1} \sum_{i \in (D_i = 1)} \left[Y_i(1) - w(i,j)Y_j(0) \right]$$

This method requires us to choose the vector of the covariates X used to match start-ups with established firms. We describe these measures subsequently. The matching estimator also requires us to choose how many nearest neighbors we want to use (i.e., how many established firms we want to match with a particular start-up). Matching one start-up with only one established firm will minimize the bias because we are matching the new firm with the most similar established firm. However, using more than one matched established firm will decrease the variance because more information is used to derive the counterfactual for each start-up. Therefore, we report the results of the matching estimator using both one match and two matches. This approach ensures that we have robust information that does not incorporate observations that are not sufficiently similar. Finally, we use the bias-corrected matching estimations as Abadie et al. (2001) implemented and correct for heteroskedasticity (Abadie and Imbens 2006).

Traditional regression analysis could also be applied to estimate the differences between new firms and established firms with respect to their innovative performance. For example, if we were using the likelihood of introducing a new product as a measure of a firm's innovative performance, we could estimate a logit model in which the dependent variable equals 1 if the firm is a product innovator and zero if otherwise; we could also use as independent variables the

set of observed covariates and the dummy variable, *D*, which captures whether the firm is a start-up. A significant coefficient estimate of *D* would suggest that start-ups and established firms have different propensities to innovate. However, when the distribution of covariates differs across the two groups of firms, regression techniques produce biased estimates, and the magnitude of this bias depends on how different the distribution of the covariates across the two groups is (Rubin 1973). There are likely to be regions in the space of the covariates in which there are start-ups but not established firms, and therefore the parametric model estimation would involve extrapolation beyond what the data would support. Moreover, such extrapolations are often sensitive to changes in the regression model (King and Zeng 2007). Matching can overcome these problems by creating a group of start-ups and established firms that have similar observable characteristics to enable comparison of their innovative performance. This process can be considered a way to drop observations from the group of established firms so that the remaining data show a good overlap in distribution densities of the covariates. In addition, the matching procedure has the advantage of not depending on a functional form specification to explain the propensity of innovation and the appropriability from innovation and, therefore, of reducing the potential for bias in the estimates.

3.3. Measures

In this study we use two measures to capture firms' innovative performance: the likelihood of introducing a product innovation and the returns from new products. These measures allow us to assess different aspects of the outcome of firms' innovative efforts. While the first measure is a simple indicator of the presence or absence of a product innovation, the second measure captures the intensity of product innovations, i.e. it is a proxy of both the quantity and quality of new products launched into the market.

3.3.1. Outcome variables. Product innovation is measured by asking firms whether during the three-year period (2002–2004), they introduced new or significantly improved products (goods or services) (Cassiman and Veugelers 2006; Cefis and Marsili 2006; Laursen and Salter 2006; Leiponen and Helfat 2011). The variable is equal to 1 if the firm introduced a new product and 0 if otherwise. In a previous wave of the survey (UK innovation survey 2001), firms were asked to provide a written description of their product innovations. The following are examples of product innovations in services: "introduction of a next-day pallet delivery service" (sic=60); "legal advice and assistance to asylum seekers" (sic=74), "online stock broking services" (sic=65); and these are some examples in manufacturing: "digital imaging paper" (sic=24); "use of plastic corrugated as returnable shipping boxed" (sic=21); "super silent ultra compact diesel generators for mobile cell phone masts" (sic=31). While these examples are far from being representative of the wide variety of product innovations in these industries, they do highlight the intangibility, lower capital intensity and underlying co-terminality of new products in services.

Although this variable is self-reported, prior research has shown that measures of innovation reported in the CIS are highly correlated to other measures of innovative outputs, such as patents (Duguet and MacGarvie 2005; Hall and Mairesse 2006). Research has also shown that CIS-based innovation measures have predictive validity for explaining a range of performance outcomes, including firm survival (Cefis and Marsili 2005), productivity (Mairesse and Mohnen 2002), sales growth (He and Wong 2004; Lööf and Hesmati 2002), and exports (MacGarvie 2006).

Returns from product innovations. Following prior studies (Mairesse and Mohnen, 2002; He and Wong, 2004; Cassiman and Veugelers, 2006; Laursen and Salter, 2006), we derive this variable exploiting two items in the questionnaire. One item asked firms what percentage of total turnover

did products, introduced between 2002 and 2004 which were *new to the market*, account for in 2004. The other item asked firms what share of total turnover did products, introduced between 2002 and 2004 which were *new to the firm*, account for in 2004. We sum these two proportions for the set of innovative startups and established firms – those that have introduced a new product - to derive a measure of *share of sales from innovative products*.

3.3.2. Matching variables. To control for the differences between start-ups and established firms related to their structural characteristics, we used several variables. First, we matched firms according to whether they are part of a wider enterprise group. This accounts for the different innovative performance that firms belonging to a corporate group are likely to show with respect to independent new ventures because they are able to draw on ideas and knowledge from the wider corporate enterprise. This dummy variable, which we call 'organizational autonomy' is based on a survey question that asked whether the firm is independent or part of a wider group.

Second, because firm size is a significant factor in shaping innovative activities, it is important to compare firms of similar sizes (Cohen 1995). This reduces the effects of the liability of smallness from our analysis, while focusing directly on the liability of newness. We measure firm size as the number of employees in 2004.

Third, we match start-ups with established firms of similar growth rates. As Geroski (2000) and a more recent study by Mason et al. (2009) showed, fast growing firms are likely to be more innovative. In addition, because our sample includes start-ups who have survived for up to five years reaching at least a size of 10 employees, it might be biased toward young firms, which have experienced relatively high growth rates.[4] Comparing our population of start-ups with

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[4] It is worth pointing out that, contrary to what one would expect on the basis of the growth rates of few successful start-ups in high-technology sectors, most new ventures do not growth very fast and few start-ups experience a significant change in their size after 6 (Kirchhoff 1994) or 10 years from inception (Anyadike-Danes et al. 2009). This is consistent with the theory of early growth firms put forward by Garnsey (1998), who postulates the presence

established firms who have experienced a similar growth rate helps mitigate this problem. To execute this match, we followed Imai and van Dyk (2004) and classified firms into six growth bands based on a baseline of average growth rate for the two-digit industry and taking half a standard deviation as the scale. This approach ensures that we compare high-growth start-ups with high-growth established firms.

Fourth, firms that invest in R&D are likely to have a superior capacity to innovate. R&D enables firms to develop new products and processes and to absorb knowledge from outside the firm more effectively (Cohen and Levinthal 1990). We calculate the measure of a firm's R&D intensity by dividing the total R&D expenditure in 2004 by sales in the same year (Kleinknecht 1996).

Fifth, we matched the observations on the size of the perceived product market to account for firms operating in the international market being more likely to be innovative (MacGarvie 2006; Sterlacchini 1999). We measure this variable using an item on the questionnaire that asked firms to indicate which of four markets (local, regional, national, or international) they perceived to be the largest for their products. This variable takes the value 1 if the firm is oriented toward the international market and 0 if otherwise.

Sixth, prior research has found that firms that engage in R&D cooperative agreements are more innovative (Belderbos et al. 2004; Stuart 2000). We measured this using an item in the survey that inquired whether firms collaborated with other firms and institutions for their innovative activities. This matching covariate is equal to 1 if firms have a R&D cooperative agreement and 0 if otherwise.

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of an early growth plateau stage where young firms, which have achieved an acceptable return of their assets, do not display positive growth rates.

Finally, we include 46 industry dummy variables to account for different propensities to innovate across industries (Klevorick et al. 1995). By matching new ventures with established firms operating in the same two-digit industry, we can control for industrial conditions, such as appropriability strategies, technological opportunities, market conditions, level of concentration, and growth rates, all of which can profoundly shape a firm's ability to create new products and/or new processes (Breschi et al. 2000). Table 1 presents the variables used in the analysis.

-- Insert Table 1 about here --

In summary, the nearest-neighbor matching procedure allows us to compare the innovative performance of a start-up with that of one or two established firms with the same organizational autonomy; with the same market orientation (national vs. international); with similar size, growth rate, R&D investment, and co-operative engagement; and operating in the same industry.

The set of matching variables for the comparison of innovative sales between new ventures and established firms partially overlap with the one described above. Two matching variables R&D Cooperation and Organizational Autonomy were not included in this supplementary analysis because there is good overlap in the distribution of these two variables across the sample of new ventures and established firms.

4. Results

Table 2 presents the number of established firms and new ventures, the proportions of product innovators in each group of firms and two-sample z-tests on the equality of proportions in each 2-digit sic code manufacturing sectors.[5] Table 3 shows the corresponding information for services firms.[6] The sample includes 395 new ventures and 3,919 established firms in manufacturing and 1,006 new ventures and 6,609 established firms in services. In manufacturing,

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[5] Because in some sectors the number of product innovators is less than the recommended number of observations (n=10) in each group we calculated the Fisher exact tests which confirmed the findings obtained using the z-test.
[6] Some sectors in manufacturing were dropped from the analysis because of the lack of start-ups companies.

more than 40% of new ventures are product innovators. However, contrary to our expectations, a basic test of means suggests that the innovative performance of new ventures does not differ from that of established firms. Although the difference in the proportion of product innovators in the two groups of firms is not significant in any sector, with the exception of recycling, in some sectors (Recycling and Chemicals & Chemical Products) new ventures are considerably more innovative than established firms, while in others (Office Machinery & Computers and Wearing Apparel) the incidence of product innovations is greater among established firms than in start-ups. In services, start-ups are more likely than established firms to be product innovators. Certain sectors appear to be driving this result: Wholesale Trade & Commission Trade, Inland Transport, and Other Business Activities, which include professional services firms.

- Insert Tables 2 and 3 about here -

When we focus on the sample of product innovators and we compare the percentage of sales from innovative products by start-ups (n=170) and established firms (n=1,737) in manufacturing, we find that there is a statistically significant difference between their average innovative sales (t = -4.42): startups have, on average, 29.3% of their turnover from new products while the corresponding figure for established firms is 19.3%. Also among the sample of product innovators in services, we find that start-ups (n=347) report, on average, a higher proportion of sales from innovative products than established firms (n=1,892). The difference in this sector is even more pronounced than in manufacturing: the fraction of turnover from new products is, on average, 32.9 for startups and 19.8 for established firms (t = -6.99). Thus, contrary to our expectations, manufacturing start-ups appear to be able to either develop more innovative products or new products that generate higher proportion of sales than established firms.

Before reporting the results of the matching procedure, we examine the extent to which start-ups and established firms differ with respect to the matching variables. Tables 4 and 5 report descriptive statistics for the matching variables before and after matching. We find considerable differences between the two groups of firms in both services and manufacturing: start-ups are significantly smaller, grow faster, and invest a larger proportion of their sales in R&D activities than established firms. Size differences are particularly evident in services, in which the average established firm is twice as large as the average start-up, though start-ups in this industry grow five times faster than established firms on average. These three variables—size, growth rate, and R&D intensity—have standardized differences that are larger than 10%, and their means are all statistically different. This lack of balance in covariates that have a large effect on innovation (i.e., size, growth, and R&D intensity) would introduce significant bias in our estimates if we were to compare the innovative performance of start-ups and established firms using a traditional regression technique.

--- Insert Tables 4 and 5 about here ---

As the *p*-values of the *t* and χ^2 tests reported in the last columns of Tables 4 and 5 demonstrate, the matching estimator achieves a good balance of the covariates. This means that the neighbor matching procedure allows us to compare start-ups with the sub-population of established firms that are relatively small in size, but R&D intensive, and that have grown rapidly. The Kolmogorov–Smirnov equality-of-distributions test confirms the similarity in firm size and R&D intensity distributions across the two groups of firms.[7] The improved balance in firm size and R&D intensity can be assessed further by comparing the quantile–quantile (Q–Q) plots before and after matching. Figs 1 and 2 depict the results for the manufacturing sample, and

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[7] For the sample of manufacturing (services) firms, the *p*-value for equality of distribution of size is 0.977 (0.428) and of R&D intensity is 0.959 (0.174).

Figs 3 and 4 depict the results for services. The Q–Q plots before matching for firm's size distribution, displayed on the left-hand side of Figs 1 and 3, are consistently below the 45-degree line, which indicates that the size distribution of start-ups is substantially different from that of established firms. As the plots on the right-hand side of Figs. 1 and 3 show, the sizes of start-ups and established firms are identical for almost every quantile (i.e., the dots are concentrated along the 45-degree line). Similarly, in the Q-Q plots for the R&D intensity distribution before the matching procedure, reported on the left-hand side of Figs 2 and 4, the points lay above the 45-degree line indicating that there is a considerable imbalance in the distribution of this variable. As shown in the right-hand side of Figs 2 and 4, the matching procedure leads to R&D intensity of startups and established firms to be similar for most quantiles of the distribution. These results suggest that matched firms can be considered sufficiently similar to the start-ups in the sample, and therefore we can proceed to estimate the SATT.

------- *Insert Figures 1 and 2 about here* -------

------- *Insert Figures 3 and 4 about here* -------

We also performed a similar battery of tests to assess the balance in the distribution of the matching variables before and after the matching procedure when we use as outcome variable the share of sales from innovative products. Although not reported, these tests indicate that while there is considerable difference between these two groups of firms in the distribution of size, growth, R&D intensity and market orientation before the matching, after this procedure we achieve a good balance in the distribution of these covariates.

Table 6 presents the estimates for the SATT of being a start-up on product innovation, when we match each start-up with one or two established firms. We find no significant differences between new ventures and established firms in the incidence of product innovation in

manufacturing. Therefore, we do not find support for our *Hypothesis 1*. In services, instead, we find that, consistent with our *Hypothesis 2*, start-ups are more likely than established firms to introduce a product innovation. In particular, the likelihood of introducing a new product is 5% higher for new ventures than for established firms when we use one match.

------- Insert Table 6 about here -------

To test whether outliers, either firms or industries, might be driving our results we ran a number of supplementary analyses. We eliminated from the sample of startups firms in the 99th percentile of the size distribution and obtained new estimates for the SATTs. We also repeat a similar analysis dropping startups companies in the 99th percentile of the R&D intensity distribution. In addition, we excluded firms in industries where there are a higher proportion of product innovators among established firms than among startup companies, but this does not affect the results.[8] Similarly, we removed firms in sectors where the number of product innovators among new ventures is higher than among established firms[9]. The sign and the significance value of these SATTs are consistent in all of the above tests with the ones calculated using the entire population of startups.

In Table 6, we report also the results of the matching procedure when we apply it to the sample of product innovators and compare their performance in terms of percentage of innovative sales. In line with what we found by examining the average value of this outcome variable, the estimates for the SATT of being a start-up on innovative sales show that new ventures in either manufacturing or services exhibit a higher proportion of sales from innovative

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[8] This means excluding firms in "Office Machinery & Computers" (SIC 30) and in "Wearing Apparel" (SIC 18) from the manufacturing sample and firms in "Air Transport" (SIC 62) and in "Insurance and Pension Funding (SIC 66) from the services sample.
[9] This implies eliminating firms in "Chemicals & Chemical Products" (SIC 24) and in "Recycling" (SIC 37) from the sample of manufacturing firms and firms in "Wholesale Trade & Commission Trade" (SIC 51) and "Water Transport" (SIC 61) from services.

products. Thus our *Hypothesis 3*, which stated that new ventures in manufacturing are less able to reap greater returns from innovation is not supported, while our results are consistent with *Hypothesis 4*. The gap between established firms and startups in their returns from innovation is higher in services, where new ventures report an average proportion of sales from innovative products, which is 8% higher than that displayed by established firms.

To probe these results, we explore whether an industry's appropriability regime shapes the returns to innovation for manufacturing and services firms. To do this, we classify different two-digit SIC code industries in manufacturing and services into two groups according to whether they are characterized by a strong and weak appropriability regime. For this classification, we draw on a question on the survey that asks firms to report the importance of five legal methods to protect their innovations: 'patents', 'copyrights', 'confidentiality agreements', 'registration of designs' and 'trademarks'. Each of the five items is measured on a four point scale (0, 1, 2, and 3) where 0 indicates 'not used' and 3 represents 'high degree of importance'. To classify an industry as been characterized by a weak or strong appropriability regime, first we calculated the cumulative use of legal protection methods at the firm-level, then we derived the industry-level average and finally we assigned industries with an above (below) mean use of legal protection methods to a strong (weak) appropriability regime.[10] Using this approach, we can derive estimates of the SATTs for both manufacturing and services under a strong and a weak appropriability regime.

Table 6 shows that start-ups in both manufacturing and services industries with a strong use of legal appropriability methods are able to achieve higher returns for their product innovations than established firms. Thus, although our initial results suggested – contrary to our hypothesis 3 –that start-ups in manufacturing industries had an advantage over incumbents, it

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[10] For a list of industries in each category see footnote Table 6.

appears that this result might be explained by the importance of strong appropriability regimes in manufacturing industries for start-up innovators. This suggests that the strength of the appropriability regime in manufacturing significantly shapes the distribution of rewards from innovation between new and established firms, a finding that is consistent with the existing literature on start-ups in manufacturing industries (Gans and Stern 2003; Shane 2005).

5. Discussion and conclusions

Our analysis demonstrates that start-ups differ considerably from established firms in their innovative activities. Drawing on information from the UK innovation survey, we find that in services, start-ups have a higher likelihood of generating product innovations than established firms, while, in manufacturing, there are no significant differences between start-ups and established firms in the generation of product innovations. In addition, we find that start-ups in both manufacturing and services have a higher proportion of sales from innovative products than established firms and that these advantages are greatest in industries with strong appropriability regimes. If we assume that the proportion of sales from innovative products is a proxy for the quality of innovation, our results for manufacturing are consistent with prior studies using patent citation rates, including Sørensen and Stuart's (2000) study of the US semiconductor and biotechnology sectors and Balasubramanian and Lee's (2008) work on a sample of firms from a wide range of manufacturing sectors.

There are four main implications of our findings for the literature on innovation. First, our analysis of services breaks new ground in understanding the ways industrial conditions can shape the advantages and disadvantages of start-ups versus established firms in terms of innovation. The results demonstrate that it would be unwise to generalize about the advantages of start-ups on the basis of manufacturing studies only. Moreover, given the overwhelming size of the

services sector in modern industrial economies, focusing on manufacturing industries only leaves a significant portion of economic activity outside the purview of theory and research on the innovative advantages of new ventures versus established firms, possibly leading to mistaken notions of the relationship between age and innovation. Bringing together the literature on service innovation with the discussion of age and innovation, this paper has helped to invoke a set of factors – intangibility, co-terminality and low capital intensity – that might help to explain the relative advantages of start-ups versus established firms, enriching our understanding of the advantages of age for innovation.

Second, the current literature on innovation focuses on the relative advantages of *small* versus *large* firms for different types of innovation. For example, the industry life-cycle approach highlights the advantages of size for process innovation. Other authors have highlighted the problems large firms face in attempting to innovate, especially inertia, myopia, and rigidities that may lead such firms to be risk averse and conservative in relation to innovation activities (Dougherty and Hardy 1996; Hannan and Freeman 1984; Leonard-Barton 1992; Levinthal and March 1993). Although this literature provides insights into the conditions under which size may shape innovativeness, especially at different stages of the industry life cycle, it does not focus on the advantages or disadvantages of new firms versus established firms in terms of innovation, when the effects of size and industry conditions are held constant. The majority of firms in the economic system are neither large nor new. Although traditional discussions on the role of start-ups in the economic system predict a model of high-growth start-ups (usually located within a technology-based industry) challenging large, possibly slow-to-innovate incumbents, they may obscure large economic patterns. Indeed, most industries are relatively stable (McGahan 2004) and populated by numerous and established SMEs. Moreover, most

start-ups are modest in scope and scale, and tend to compete with other SMEs rather than launching ambitious attacks on large incumbents. For example, Bhide (2000) found that 78% of *Inc.* 100 founders indicate that they compete against other start-ups and SMEs. Thus, the focus in the literature explaining the rivalry between high-growth start-ups and established firms in technology-based industries tends to ignore the common nature of the competition between start-ups and established SMEs.

Third, our analysis suggests that established SMEs in services may be doubly disadvantaged in lacking both financial and human resources, as well as the market presence of large established firms. They may also face many of the behavioral and contextual disadvantages suffered by large firms. The results also suggest that start-ups in manufacturing face high barriers to innovation, and established firms, with their existing capital investments and access to markets, are liable to hold sway in this sector.

Fourth, by focusing on the commercialization of new technology rather than inventive outputs, we show that the organizational–environment fit related to start-ups and innovation differs across industries and degrees of innovation. Sørenson and Stuart (2000) argued that studies using patent data tend to understate the adverse consequences of age on innovation because they focus on inventions rather than commercialized products. They suggested that although established firms may be able to develop inventions, they may lack the motivations and skills required to exploit the commercial opportunities associated with these inventions. In focusing on commercialized products, this research extends our understanding of how innovative returns are distributed across different cohorts of firms. Our work suggests that start-ups act as "carriers of novelty" in the services economy, an environment that provides rich opportunities for the coupling of novelty in technology and organizational forms. This finding opens up a new

avenue for research and theorizing on the life cycle of industries to account for the uniqueness of services with regard to innovation (Barras 1986). Our study shows that the services sector provides fertile ground for innovative start-ups because of intangibility, low capital intensity, and an intimate producer–user relationship conducive to the creation of new products (Gallouj and Weinstein 1997). In contrast, in manufacturing numerous hurdles must be overcome by start-ups to successfully develop and commercialize a product innovation, a challenge that can only be achieved in the shadow of a strong appropriability regime. This may explain in part why start-ups are more likely to become established and grow more quickly in services than in manufacturing (Shane 2008).

Our findings have implications for policy makers, who may operate on the simple model that equates newness and innovation. Our research shows that newness may or may not beget innovativeness and that it is important to consider the industry conditions under which new firms operate. In designing policy to support new firms, efforts to support manufacturing firms will need to differ significantly from services, and therefore policy instruments must be sensitive to the industrial conditions. Such an approach would put in place programs to help new firms lower the liabilities associated with newness in manufacturing and help develop policies to support established service SMEs to upgrade their skills to meet the competition posed by new firms.

There are significant limitations to our study. We were unable to compare firms of different ages directly (e.g., some new firms may have been better established than others at the time of the survey). We also had no information on the age of firms other than that they had been established for at least five years. In addition, given that the population only includes firms with more than 10 employees, our sample is not representative of the entire range of start-ups in the UK. Moreover, given that responses were from single informants at one moment in time, we

were unable to test whether our measures of innovation are completely reliable; we do not know whether managers' assessments of their own innovative prowess are subject to systematic error. However, it is difficult to see how or why managers of start-ups or established firms would overstate their innovative activities in a government-run, voluntary survey and how the patterns of these errors would systematically differ across manufacturing and services. We have also not attempted to measure the nature or type of innovations developed by start-ups versus established firms. A further limitation of our study is that our findings may be driven by alternative theoretical explanations, which we are unable to rule out. For example, an alternative explanation for why start-ups are more innovative than established firms in services and less innovative in manufacturing is that the perceived importance of innovation for survival is greater in manufacturing than in services. In manufacturing, innovations are of vital importance for established firms to compete with new entrants, while, in services, established firms may have other more effective ways of competing, such as maintaining close customer relationships.

Several questions that require investigation emerge from this study. For example, it would be useful for future research to determine more accurately the birth dates of firms and to compare cohorts of firms of different ages (e.g., firms established for three, seven, and twelve years). It would also be worthwhile exploring the sources and determinants of innovation among the population of start-ups and to examine how industry conditions, such as rates of entry and exit, shape the innovative behavior of new firms. In addition, researchers should examine differences in the 'radicalness' of innovation developed by start-ups and established firms across different sectors. Probing deeper the nature of innovation and (dis)advantages of start-ups in its production and exploitation will help us to better understand the elixir or burden of age for innovation.

APPENDIX

The UK innovation survey

The UK innovation survey is based on the broader harmonized European Community Innovation Survey (CIS) (Robson and Ortmans 2006). The motivations and methods used in innovation surveys are described in the Organisation for Economic Co-operation and Development's (OECD 2005) Oslo Manual. The innovation survey approach is based on a long tradition of research on innovation that attempts to measure the level and types of innovations in the economic system (for examples, see Cohen and Levinthal 1990; Levin et al. 1987; Smith 2005), while CIS data have been used in a range of empirical studies (see for example Cassiman and Veugelers 2006; Laursen and Salter 2006; Leiponen 2000; Tether and Tajar 2008).

The survey was addressed to the firms' representative for recording economic information for the Office of National Statistics (ONS). Although the database does not provide information on the roles of respondents, the ONS reports that the survey is usually completed by the managing director, chief financial officer, or R&D manager of the firm. When comparing firms of similar or equal sizes, especially small firms, it is likely that the respondent is the managing director, who would be knowledgeable about key aspects of the firm's activities.

The sample was designed to ensure adequate regional and industry response rates. The ONS conducted a census of firms with more than 250 employees and a stratified sample of firms with less than 250 employees. Small and medium-sized enterprises (SMEs) were sampled from 23 industries and 12 regions, using information from the ONS Inter-Departmental Business Register (DTI 2005). The response rates for different sectors, regions, and size classes are consistent with the overall sample (Robson and Ortmans 2006). Because the survey was carried out in one wave, it is not possible to compare early and late respondents to check for non-response bias. However, because the best way to avoid non-response bias is to achieve a high response rate (Armstrong and Overton 1977), the 58% response rate should be sufficient.

The validity of the CIS questionnaire was established by piloting and pre-testing in a range of European countries and with firms from a variety of industry sectors, including services, construction, and manufacturing (Smith 2005). In addition, the UK government supported two

further pilots and a round of cognitive testing. The first was performed by the ONS and the second by Cambridge University (Bullock et al. 2004). To help avoid common method bias and habitation, the questionnaire includes a diverse range of question types, including Likert scales, yes/no questions, percentages, and questions about expenditure. To test directly for common method bias, we performed Harman's one-factor test on the items included in our models. We found multiple factors and that the first factor did not account for the majority of the variance (the first factor accounted for only 3% of the variance). This suggests that the problems associated with common method bias do not appear to be present in our study (Podsakoff and Organ 1986).

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TABLE 1
Variables used in the matching estimator

Matching variables	Description
Firm size	Number of employees in 2004
Employment growth rate bands	1: < Industry Mean –std.dev. 2: (Industry Mean - std.dev; Industry Mean – 1/2 std.dev] 3: (Industry Mean – 1/2 std.dev; Industry Mean] 4: (Industry Mean; Industry Mean + 1/2 std.dev] 5: (Industry Mean + 1/2 std.dev; Industry Mean + std.dev] 6: > Industry Mean + std.dev
R&D intensity	R&D spending in 2004 over turnover in the same year
Market orientation	Dummy equals to 1 if a firm operates on the international market
R&D cooperation	Dummy equals to 1 if a firm engages in a R&D co-operative agreement
Sector	2 digit sic code (38 industries)
Organizational autonomy	Dummy equals to 1 if a firm is part of an enterprise group
Outcome variables	
Product innovation	Equals to 1 if a firm introduced a product innovation
Share of sales from innovative products	Percentage of total sales from products new to the market and from products new to the firm introduced between 2002 and 2004

Table 2. Differences in innovative performance between new ventures and established firms in manufacturing

SIC Code	Sector	Established firms		New Ventures		z-test[*]	p-value
		Number	Proportion of product innovators	Number	Proportion of product innovators		
15	Food & Drink	381	0.470	32	0.375	1.033	0.302
17	Textiles	106	0.368	14	0.500	-0.955	0.339
18	Wearing Apparel	67	0.343	12	0.167	1.211	0.226
20	Wood & Products of Wood	126	0.262	14	0.357	-0.760	0.447
21	Pulp, Paper & Paper Products	113	0.407	9	0.333	0.434	0.664
22	Publishing & Printing	335	0.343	39	0.359	-0.195	0.845
24	Chemicals & Chemical Products	163	0.663	9	0.889	-1.410	0.158
25	Rubber & Plastic Products	282	0.479	24	0.542	-0.592	0.554
26	Non-Metallic Mineral Products	149	0.416	8	0.500	-0.468	0.640
27	Basic Metals	74	0.311	9	0.333	-0.138	0.891
28	Fabricated Metal Products	526	0.310	42	0.381	-0.954	0.340
29	Machinery & Equipment	356	0.500	26	0.346	1.515	0.130
30	Office Machinery & Computers	35	0.686	3	0.333	1.235	0.217
31	Electrical Machinery & Apparatus	214	0.435	14	0.429	0.044	0.965
32	Radio, TV & Communication Equipment	114	0.754	12	0.583	1.282	0.200
33	Medical, Precision & Optical Instruments	186	0.677	16	0.563	0.937	0.349
34	Motor Vehicles	216	0.454	27	0.481	-0.273	0.785
35	Other Transport Equipment	92	0.435	15	0.600	-1.191	0.234
36	Furniture	341	0.463	60	0.383	1.148	0.251
37	Recycling	43	0.186	10	0.600	-2.674	0.008
Total Manufacturing		3919	0.443	395	0.430	0.490	0.624

[*]Two-sample z-test on the equality of proportions

Table 3. Differences in innovative performance between new ventures and established firms in services

SIC Code	Sector	Established firms		New Ventures		z-test[*]	p-value
		Number	Proportion of product innovators	Number	Proportion of product innovators		
50	Sale, Maintenance & Repair of Motor Vehicles & Motorcycles	343	0.207	40	0.150	0.851	0.395
51	Wholesale Trade & Commission Trade, exc. Motor Vehicles & Motorcycles	721	0.300	59	0.475	-2.787	0.005
52	Retail Trade, exc. Motor Vehicles & Motorcycles; Repair of Personal & Household Goods	1096	0.173	125	0.184	-0.297	0.766
55	Hotels & Restaurants	544	0.176	136	0.228	-1.378	0.168
60	Inland Transport	451	0.186	51	0.294	-1.835	0.067
61	Water Transport	19	0.211	1	1.000	-1.777	0.076
62	Air Transport	18	0.500	4	0.250	0.908	0.364
63	Supporting & Auxiliary Transport Activities; Activities of Travel Agencies	274	0.292	26	0.192	1.078	0.281
64	Post & Telecommunications	197	0.406	68	0.426	-0.294	0.768
65	Financial Intermediation	120	0.508	14	0.429	0.565	0.572
66	Insurance & Pension Funding	59	0.508	7	0.000	2.554	0.011
67	Activities Auxiliary To Financial Intermediation	312	0.340	49	0.286	0.746	0.455
70	Real Estate Activities	267	0.243	37	0.324	-1.060	0.289
71	Renting of Machinery & Equipment	219	0.265	30	0.300	-0.407	0.684
72	Computer & Related Activities	314	0.650	62	0.661	-0.175	0.861
73	Research & Development	157	0.554	25	0.560	-0.055	0.956
74	Other Business Activities	1596	0.291	282	0.397	-3.573	0.000
Total Services		6609	0.286	1006	0.344	-3.800	0.000

[*] Two-sample z-test on the equality of proportions

TABLE 4

Comparison between matching covariates of start-ups and established firms in manufacturing before and after the matching

| | Before Matching | | | | | Standardized Differences (%)** | After Matching | | | | |
| | New Ventures | | Established firms | | | | New Ventures | | Established firms | | |
Matching variables	Mean	St.Dev	Mean	St.Dev	p-value*		Mean	St.Dev	Mean	St.Dev	p-value*
Size	148.435	344.110	195.723	609.044	0.018	-9.560	135.310	328.337	137.757	330.918	0.913
Growth	0.282	1.185	0.033	0.337	0.000	28.569	-	-	-	-	-
R&D intensity	0.019	0.112	0.009	0.064	0.100	10.330	0.013	0.063	0.107	0.017	0.459
	Proportion		Proportion		p-value*	Differences (%)	Proportion		Proportion		p-value*
Growth Bands											
1	0.010		0.065		0.000	-5.460	0.049		0.051		0.998
2	0.020		0.149			-12.850	0.146		0.139		
3	0.030		0.407			-37.720	0.373		0.380		
4	0.040		0.235			-19.530	0.162		0.169		
5	0.050		0.075			-2.530	0.104		0.097		
6	0.060		0.069			-0.920	0.167		0.164		
Organizational Autonomy											0.944
No	0.612		0.594		0.490		0.639		0.637		
Yes	0.387		0.405			-1.800	0.361		0.363		
Market Orientation											
No	0.478		0.403		0.004	7.500	0.505		0.456		0.153
Yes	0.521		0.596				0.495		0.544		
R&D Cooperation											
No	0.823		0.802		0.321	2.100	0.838		0.866		0.250
Yes	0.177		0.198				0.162		0.134		
Sector dummies					0.000						0.992

*Two-sample t-test with unequal variance for continuous variables and χ_2 test for categorical variables.

**The standardized percentage difference is defined as the mean difference between new ventures and established firms as a percentage of the standard deviation: $[100(x(1) – x(0))]/[(s^2(1) + s^2(0))/2]^{1/2}$, where $x(1)$ and $x(0)$ are the sample means in the two groups and $s^2(1)$ and $s^2(0)$ are the corresponding sample variances.

TABLE 5

Comparison between matching covariates of start-ups and established firms in services before and after the matching

Matching variables	Before Matching						After Matching				
	New Ventures		Established firms		p-value*	Standardized Differences (%)**	New Ventures		Established firms		p-value*
	Mean	St.Dev	Mean	St.Dev			Mean	St.Dev	Mean	St.Dev	
Size	167.568	554.961	396.665	2079.347	0.000	-15.055	87.635	385.932	91.155	399.728	0.770
Growth	0.539	1.749	0.132	0.614	0.000	31.020					
R&D intensity	0.031	0.286	0.012	0.123	0.003	8.946	0.014	0.181	0.015	0.197	0.863
	Proportion		Proportion		p-value*	Differences (%)	Proportion		Proportion		p-value*
Growth Bands											
1	0.020		0.022		0.000	-0.170	0.013		0.012		0.999
2	0.082		0.089			-0.780	0.053		0.054		
3	0.423		0.604			-18.180	0.632		0.634		
4	0.238		0.203			3.480	0.179		0.179		
5	0.092		0.045			4.760	0.049		0.049		
6	0.146		0.037			10.890	0.074		0.072		
Organizational Autonomy											
No	0.659		0.627		0.049	3.210	0.821		0.821		0.968
Yes	0.341		0.373				0.179		0.179		
Market Orientation											0.779
No	0.761		0.718		0.004	4.330	0.875		0.878		
Yes	0.239		0.282				0.125		0.122		
R&D Cooperation											0.451
No	0.843		0.842		0.932	0.100	0.921		0.927		
Yes	0.157		0.158				0.079		0.073		
Sector											
					0.000						0.989

*Two-sample *t*-test with unequal variance for continuous variables, χ2 test for categorical variables.
** The standardized percentage difference is defined as the mean difference between new ventures and established firms as a percentage of the standard deviation: $[100(x(1) – x(0))]/[(s^2(1) + s^2(0))/2]^{1/2}$, where x(1) and x(0) are the sample means in the two groups and $s^2(1)$ and $s^2(0)$ are the corresponding sample variance.

FIG. 1
Q–Q plots of firm size in manufacturing before (left-hand side) and after (right-hand side) matching
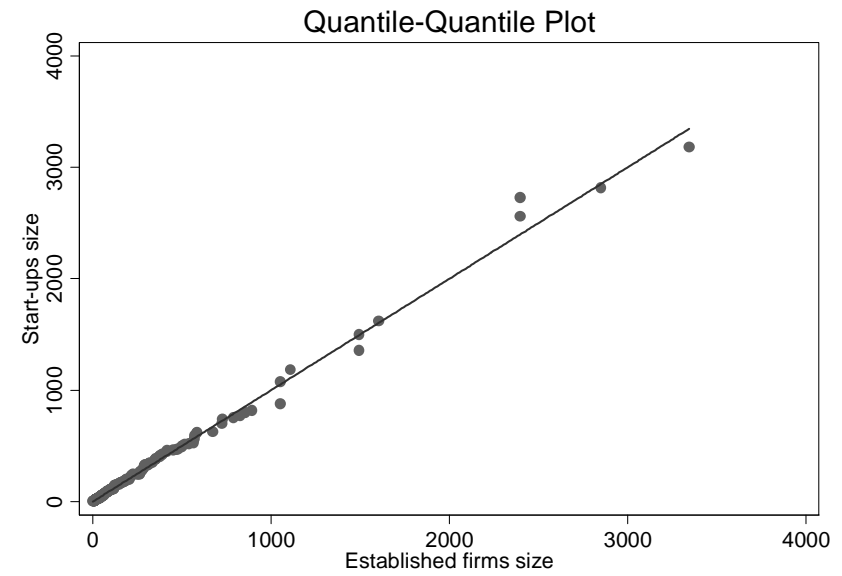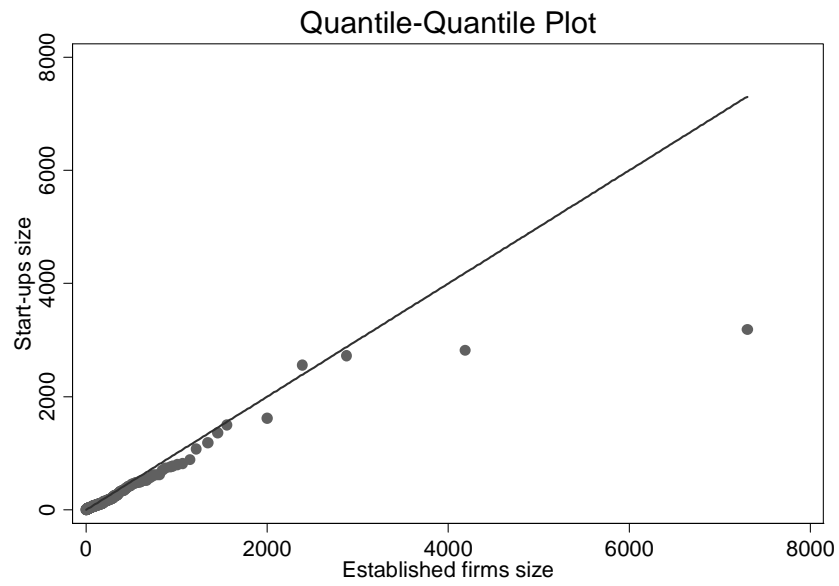
FIG. 2
Q–Q plots of firm R&D intensity in manufacturing before (left-hand side) and after (right-hand side) matching
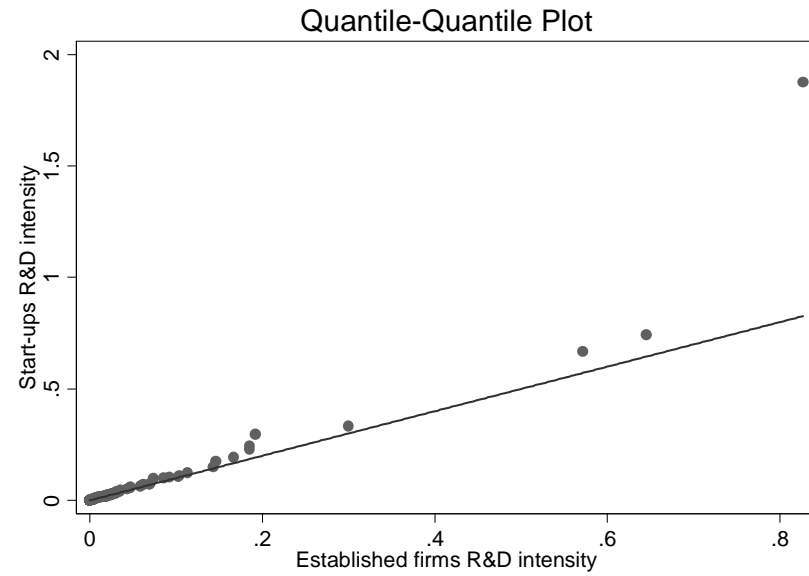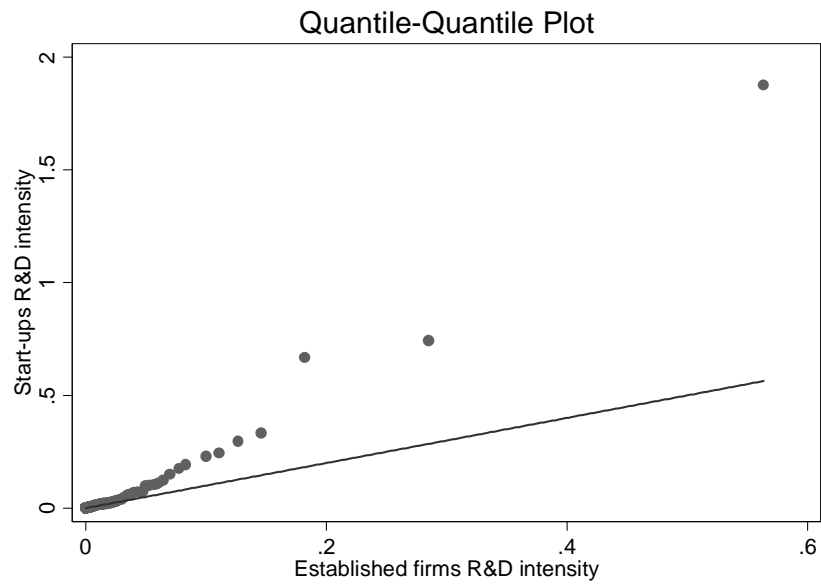
FIG. 3
Q–Q plots of firm size in services before (left-hand side) and after (right-hand side) matching
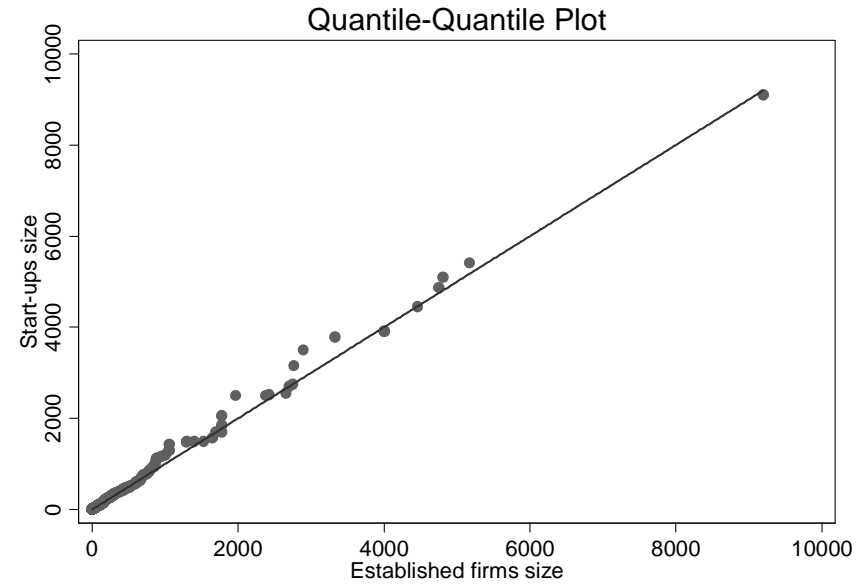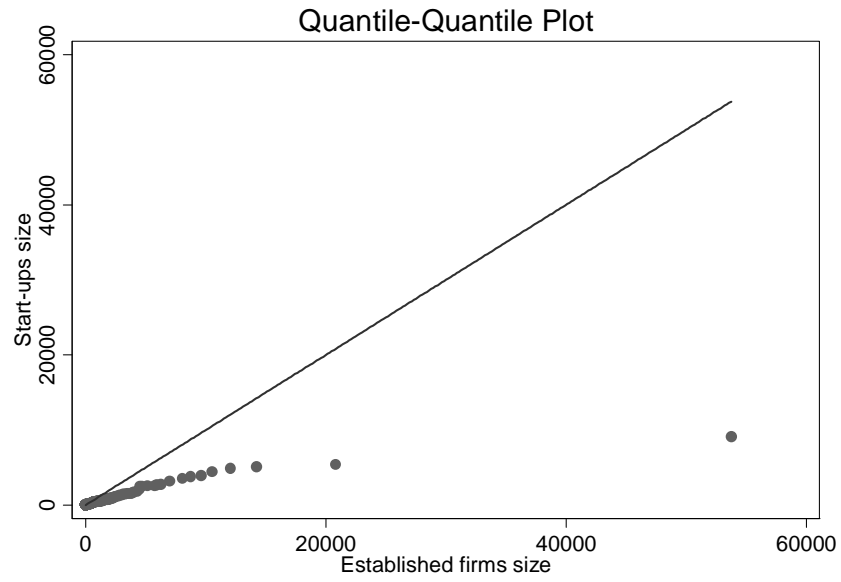
FIG. 4

Q–Q plots of firm R&D intensity in services before (left-hand side) and after (right-hand side) matching
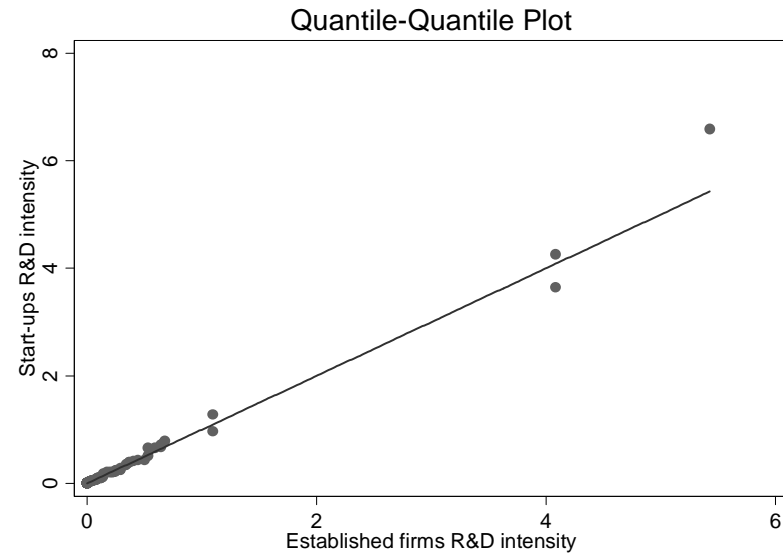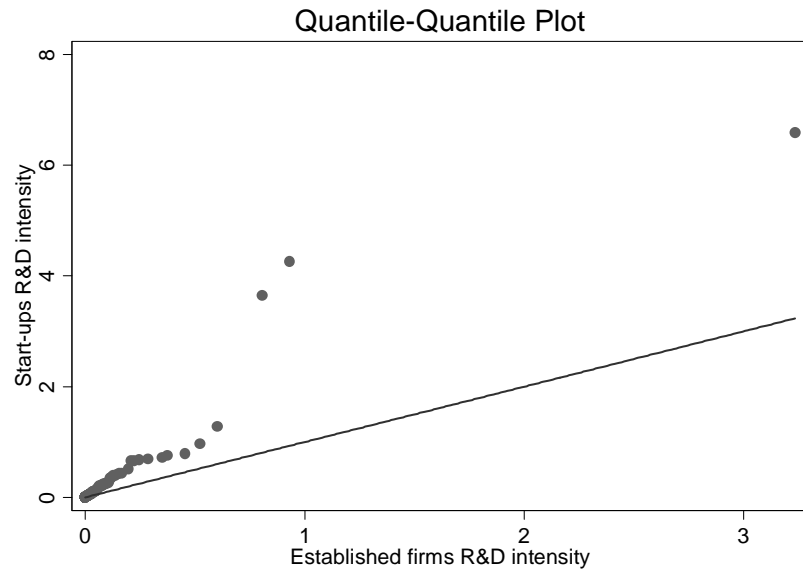
TABLE 6

Matching estimates of the SATT of being a start-up

	N Start-ups	N Established firms	One match			Two matches		
			SATT	Std. Err.	p-value	SATT	Std. Err.	p-value
Manufacturing								
Product Innovation	395	3,919	-0.038	0.033	0.241	-0.031	0.028	0.257
Share of Sales from Innovative Products[†]	170	1,737	6.383	2.898	0.028	6.871	2.842	0.016
Strong appropriability[†1]	75	888	7.876	3.763	0.036	5.792	3.442	0.092
Weak appropriability[†2]	95	849	4.295	4.616	0.352	5.736	3.805	0.132
Services								
Product Innovation	1,006	6,609	0.050	0.020	0.014	0.040	0.018	0.029
Share of Sales from Innovative Products[†]	347	1,892	8.566	2.308	0.000	8.774	2.100	0.000
Strong appropriability[†3]	118	647	10.073	3.953	0.011	9.323	3.775	0.014
Weak appropriability[†4]	229	1,245	8.780	2.791	0.002	9.433	2.526	0.000

Note: Matching variables: market orientation, R&D cooperation, organizational autonomy, R&D intensity, size, growth bands, and sector dummies.
[†] Matching variables: market orientation, R&D intensity, size, growth bands, and sector dummies
[1] Includes firms in industries (SIC codes): 24, 25, 29, 30, 31, 32, 33, 34, 35.
[2] Includes firms in industries (SIC codes): 15, 17, 18, 20, 21, 22, 26, 27, 28, 36, 37.
[3] Includes firms in industries (SIC codes): 51, 64, 65, 72, 73.
[4] Includes firms in industries (SIC codes): 50, 52, 55, 60, 61, 62, 63, 66, 67, 70, 71, 74.