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DISCUSSION PAPER SERIES

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Innovation, Firm Survival and Productivity: The State of the Art

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ABSTRACT

Innovation, Firm Survival and Productivity: The State of the Art

We review the theoretical underpinnings and the empirical findings of the literature that investigates the effects of innovation on firm survival and firm productivity, which constitute the two main channels through which innovation drives growth. We aim to contribute to the ongoing debate along three paths. First, we discuss the extent to which the theoretical perspectives that inform the empirical models allow for heterogeneity in the effects of R&D/innovation on firm survival and productivity. Secondly, we draw attention to recent modeling and estimation effort that reveals novel sources of heterogeneity, non-linearity and volatility in the gains from R&D/innovation, particularly in terms of its effects on firm survival and productivity. Our third contribution is to link our findings with those from prior reviews to demonstrate how the state of the art is evolving and with what implications for future research.

JEL Classification: O30, O33
Keywords: innovation, R&D, survival, productivity

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1. Introduction

From an endogenous growth perspective, the effect of innovation on economic growth is mediated through two channels: firm dynamics (entry and exit) and firm productivity. In the first-generation models (Romer, 1990 and 1994; Grossman and Helpman, 1991), the search for new ideas by profit-maximizing firms and the nonrivalry of knowledge are at the heart of the growth in the *productivity* of the resources allocated for the development of new product varieties. In the second-generation models (Aghion and Howitt, 1992 and 1998; Klette and Kortum, 2004; Aghion et al., 2014 and 2015), innovation drives growth through *creative destruction* (*firm entry and exit*) and *productivity gains* secured by successful innovators[1]. Innovation, firm dynamics and productivity are central issues in the evolutionary models of industry evolution too, albeit the emphasis here is on heterogenous effects due to different technological regimes, sources of innovative knowledge, modes of innovating and patterns of innovation diffusion (Nelson and Winter, 1982; Dosi and Nelson, 2013).

Given this theoretical background, the aim of this study is to summarize the theoretical underpinnings of and evaluate the empirical evidence on: (i) how innovation affects firm dynamics; (ii) how innovation affects firm productivity; and (iii) why the effects of innovation on firm survival and firm productivity are inherently heterogeneous. Addressing these questions will enable us to contribute to the economics of innovation literature, particularly to its microeconomic (and mainly empirical) sub-strand, where innovation is the main driver of firm dynamics and productivity.[2]

The attention to heterogeneity in the evidence base enables us to contribute to evidence synthesis along three paths. First, we complement the existing reviews by highlighting the extent of heterogeneity in the reported effect-size estimates and demonstrating that heterogeneity is even more visible in the evidence from recent studies published after 2010. We concur with the existing reviews that the balance of the evidence indicates a positive innovation effect on firm survival and productivity.

[1] In this respect, several empirical studies have confirmed that R&D expenditures and innovation foster aggregate economic growth (Mansfield, 1988; Mankiw et al., 1992; Nelson, 1993; Daveri, 2002; Ortega-Argilés et al., 2014).

[2] Our work is also consistent with the tradition of studying firm survival and firm productivity as indicators of post-entry performance, where the selection process leads productive firms to survive and grow while others to stagnate and ultimately exit (Audretsch and Mata, 1995; see also next section).

However, we argue that the overall effect conceals a high degree of heterogeneity, which needs to be unpacked to arrive at verifiable conclusions about where, why and how innovation may or may not deliver the expected gains in terms of survival and productivity.

Our second contribution is to argue for and suggest future research avenues that can provide *ex ante* theoretical explanations and develop commensurate empirical models for taking account of and quantifying the sources of heterogeneity. Particularly, we call for addressing a range of factors that lead to heterogeneity in the effects of innovation on firm survival and productivity, including time- and industry-specific technological opportunities; innovation types (e.g., product *vs* process innovation; input or output measures of innovation, etc.); innovation intensity and scale; and firm types in terms of age, size, market share, etc. Indeed, we demonstrate that the research effort is evolving in that direction, as reflected in method and modeling developments that highlight the contingent nature of the effects of innovation on firm survival and productivity.

Our third contribution is to argue that the confounding role of the market power needs to be placed under sharper relief in the modeling, estimation and interpretation of the estimates for the effects of innovation on firm survival and productivity. True, the role of market power is already recognized in the existing reviews, particularly in the reviews of the innovation-productivity literature (Hall et al., 2010; Hall, 2011). We acknowledge these efforts, but we go further to call for explicit modeling of market power and the interaction of the latter with innovation intensity in both firm survival and productivity models. This contrasts with the general practice so far, where the issue is usually acknowledged only *ex post* by reviewers, with evidence of slow 'take up' in primary studies.

As mentioned above, this review follows earlier reviews of both research fields published around 2010, which include: (i) Manjón-Antolín and Arauzo-Carod (2008) on innovation and firm dynamics; (ii) Hall et al. (2010) on productivity effects of R&D capital based on knowledge capital models; and (iii) Hall (2011) on the evidence from the Crépon-Duguet-Mairesse (CDM) model of innovation and productivity. We first summarize the theoretical underpinnings (Sections 2 and 4) that inform the empirical models in both research fields. This is followed by a synthesis of the empirical findings in each field (Sections 3 and 5), which consists of combining the conclusions from previous reviews with a more detailed evaluation of the post-2010 works. The choice of 2010 as a demarcation year enables

us to establish whether post-2010 studies pay more attention to heterogeneity, uncertainty and volatility in the aftermath of the global financial crisis.[3] On the other hand, combining the existing review evidence with a synthesis of the recent findings enables us to reflect the cumulation of knowledge over time whilst placing the recent modeling and estimation innovations in sharper relief. The rest of the paper is organized as follows. We first review the literature on the relationship between R&D/innovation and firm survival, from a theoretical viewpoint in Section 2, and empirically in Section 3. Then, we review the literature on the productivity effects of innovation, from a theoretical viewpoint in Section 4, and empirically in Section 5. Finally, in Section 6 we discuss the implications for future research.

2. Innovation and firm survival: theoretical underpinnings

The empirical work on innovation and firm dynamics is informed by three theoretical traditions. The first is the insights from evolutionary theory, originally articulated in the seminal contribution by Nelson and Winter (1982) and updated through so-called history friendly models (Malerba *et al.* 2001 and 2016; Capone *et al.*, 2019). In the evolutionary framework, heterogenous firms operate with bounded rationality and satisficing behaviour and the industry is characterized by uncertainty and out-of-equilibrium dynamics (Dosi *et al.*, 2020). In this setting, a steady-state industry structure may be elusive but the level of profitability (hence that of productivity) is a key determinant of firm survival. Whilst innovative firms realise higher profits, increase their market shares, and survive longer; non-innovative firms realise lower profits, shrinks, and eventually exit. The probability of innovation, in turn, depends on the technological regime in the industry. The probability is higher in un-routinised regimes with higher levels of technological opportunities, but it is lower in routinised regimes where innovation is an incremental or unintended consequence of routinised production. Finally, the positive

[3] We expect such a shift in focus epistemologically – i.e., irrespective of whether the data period in the post-2010 studies cover the post-crisis years. This expectation and the periodisation it informs are based on the observation that there has been an increase in the number of studies that incorporate uncertainty and volatility into their models explicitly (Doraszelski and Jaumandreu, 2013; Peters et al., 2017a; 2017b; and 2018; Andrew, 2020).

effect of innovation on survival is more obvious in good times, rather than in bad times when innovative strategies become riskier (Cefis and Marsili, 2019).

Drawing on Audretsch (1991), we formalise the evolutionary arguments in two equations: a probability of innovation equation (1) and a probability of survival equation (2). The probability that a firm *j* innovates in industry *i* at age *t* is denoted with (I_{it}^{j}) and depends on a constant that defines the asymptotic conditions (*A*) and on whether the firm is in an industry characterised by a routinised (*r*) or un-routinised (*u*) innovation regime. Whereas the un-routinised (entrepreneurial) regime is favourable to innovative firm entry, innovation in a routinised regime is largely undertaken by incumbents. Formally:

$$I_{it}^{j} = A/(1 + re^{-ut}) \qquad (1)$$

For a given constant, the probability of innovation by a young firm (a firm with small *t*) is higher when the industry represents an un-routinised regime - i.e., when *u* is large relative to *r*. In contrast, the probability of innovation declines when age (*t*) increases or when the industry represents a routinised regime – i.e., when *r* is large relative to *u*.[4] Nevertheless, the firm is faced with a positive exit hazard and the probability of its survival depends on the probability of innovation and other factors as stated in (2):

$$\Pr\left(Y_{it}^{j} > 0\right) = f\left\{I_{it}^{j}, [P_i - c(Y_i^*)], [c(Y_i^*) - c(Y_i)]\right\} \qquad (2)$$

Here, *Pr* ($Y_{ij} > 0$) is the probability of firm *j* at age *t* surviving in industry *i*, and it increases if: (a) the probability of firm innovation at age t (I_{it}^{j}) increases; (b) the price-cost margin in the industry (i.e., the market power given by $P_i - c(Y_i^*)$) increases; and (c) the firm is NOT burdened with a size disadvantage due to higher average cost of *c(Y)* relative to the average cost of *c(Y*)* at the minimum efficient scale – i.e., if $c(Y_i) \leq c(Y_i^*)$. If conditions (b) and (c) are determined exogenously in the industry, the probability of innovation in condition (a) is the choice variable that determines the firm's

[4] In Audrestch (1991), the source of the innovative advantage also differs between newly established and incumbent firms. The newly established firms have innovative advantage if information outside of the industry is more important for generating innovative activity. By contrast, the incumbent firms have the innovative advantage if information based on non-transferable experience in the market is more important for generating innovative activity. The source of innovative advantage, however, is not an explicit part of the model. Its effect on the probability of innovation is captured through the relative sizes of the routinised and un-routinised regimes.

survival in, or exit from, the industry. This is because innovation enables the firm to grow, attains the minimum efficient scale (MES) of production, and enjoys the benefits of market power in the industry if exists. Considered in conjunction with equation (1) and recalling that the exit hazard is higher when firm is new and producing below the MES, the firm's probability of survival is higher if it enters an industry with an un-routinised innovation regime and innovates with a higher probability. In contrast, when the firm enters a routinised regime, both the probability of innovation and the effect of the latter on survival are lower.

The second strand of the literature models firm dynamics as an endogenous outcome of passive or active learning. This line of work also acknowledges firm heterogeneity but assumes maximising firm behaviour that allows for identification of an equilibrium (steady-state) industry structure. In the passive learning models of Jovanovic (1982) and Hopenhayn (1992), heterogenous firms are subject to idiosyncratic productivity shocks and learn about their efficiency as they operate in the industry. Whilst the efficient firms survive and grow; the inefficient decline and exit when the cost of exiting are lower than the costs of remaining in business. In Jovanovic's noisy selection model, firms are initially endowed with unknown, time-invariant characteristics (*i.e*. *ex-ante* efficiency parameters). *Ex-post*, the prior distribution is updated as evidence comes in and some entrepreneurs discover that they are more (or less) efficient than others. Efficient firms survive and grow, inefficient firms exit. The effect of innovation investment on firm survival, if any, is limited to *ex post* information it provides about the firm's stochastic efficiency draws.

In contrast, in the active learning model of Ericson and Pakes (1995), heterogenous firms are engaged in investment with uncertain outcomes, including R&D investment. New entrants may either adjust in size to the minimum efficiency scale (MES) of the industry "core" or choose/find a niche within which the likelihood of survival is relatively high. Therefore, new entrants that begin with relatively low levels of investment are likely to exit the market, while some more entrepreneurial entrants experience a sequence of initial successes and begin to increase their profits, invest more in strategic assets, and increase their probability of survival. The firm's exit decision is endogenous and depends on whether the efficiency gain from investment in research and development is larger than the increase in the exogenously determined factor price index. Through simulations, the authors demonstrate that their model is successful in predicting several outcomes in industry evolution, including entry and exit rates

in the industry, the correlation between entry and exit rates, and the higher growth rates among small but surviving firms. These properties notwithstanding, the model predicts that the effect of R&D investment on firm survival is indeterminate as it depends on the stochastic outcomes of the investment, the success of other firms, and the competitive pressure from outside the industry.

The third strand builds on Schumpeterian concepts of competition, innovation and creative destruction (Schumpeter, 1934). In formal models (Aghion et al. 2005; 2014; 2015), the effect of product-market competition on innovation follows an inverted-U pattern. When competition increases from a low initial level, it induces firms to escape competition by increasing innovation (the escape competition effect). In contrast, competition reduces the incentive to innovate when it increases from a high initial level where the profit-diluting effects are stronger (the Schumpeterian effect). Ugur et al. (2016a) demonstrate that the Schumpeterian models also imply an inverted-U relationship between innovation and firm survival. Innovation increases the probability of survival when it increases from a low initial level, but it may reduce the probability of survival when it increases from a high initial level due to diminishing scale effects or increased risks.

In Ugur et al. (2016a), survival time is a positive function of the number of innovative product lines that the firm operates (k), the ratio of the firm's output to its initial value (Y/V_0) which captures the firm's growth opportunities, and the average value of the innovative product lines (v) – as stated in (3) below).

$$E[t] \cong \frac{2}{2\mu-\sigma^2}[\ln(k) + lnY_t - lnVo + lnv] \qquad (3)$$

The first term in (3) reflects the relationship between the volatility (σ) and drift (μ) parameters of the firm value. Provided that $\sigma < \sqrt{2\mu}$, equation (3) states that survival time increases with the number of innovative product lines (k), the extent of growth opportunities (Y/V_0), and the average value of the innovative product line (v). [5] Replacing the average value of the innovative product line (v) with its endogenously determined value in Schumpeterian models of innovation, equation (3) can be re-written as:

[5] This assumption is in line with existing evidence on various stock markets including the UK, which indicates that the volatility parameter is usually around one-tenth of the drift parameter (Casas and Gao, 2008).

$$E[t] \cong \frac{2}{2\mu-\sigma^2}\left[\ln(k) + lnY_t - lnVo + ln\frac{\pi - \varsigma w z_i^{\eta}}{\rho + x - z_i}\right] \quad (4)$$

In (4), the numerator of the last term ($\pi - \varsigma w z_i^{\eta}$) is the productivity/profitability of innovation, which is equal to difference between average gross profits (π) and average cost of the R&D investment ($\varsigma w z_i^{\eta}$) in the innovative product line. Because of its addition to costs, the R&D intensity, z_i, in the numerator is negatively related to survival time. However, the R&D intensity in the denominator is positively related to survival time as it mitigates the adverse effects of creative destruction (x) and the discount rate (ρ). Taking the first- and second-order derivatives of the survival time equation, Ugur et al (2016a) demonstrate that this non-monotonic relationship between R&D intensity and survival time is concave – i.e., it has an inverted-U shape.

Despite divergent assumptions about maximising firm behaviour, the three strands of the theoretical literature converge on three predictions concerning firm dynamics and industry evolution: (i) the growth rate in the industry is positively correlated with innovation or creative destruction, both of which imply higher entry and exit rates; (ii) small and new firms exit more frequently (Mata and Portugal, 1994; Mata et al., 1995), but those that survive tend to grow faster (Lotti, Santarelli and Vivarelli, 2001 and 2003); and (iii) firm age and size are positively correlated and both have positive effects on survival time. These predictions enjoy significant support in empirical work, full or partial reviews of which include Geroski (1995); Vivarelli and Audretsch (1998); Caves (1998); Santarelli and Vivarelli (2007); Manjón-Antolín and Arauzo-Carod (2008); Vivarelli (2013); Quatraro and Vivarelli (2015). They are also supported by more recent findings reviewed in Rosenbusch et al. (2011), Hyytinen et al. (2015) and Ugur et al. (2016a).

Nevertheless, the theoretical predictions are less convergent with respect to how innovation affects firm survival. In both active and passive learning models, industry evolution is a stochastic process and the dynamic equilibrium is industry specific. Even in the active learning model, the firms have 'truly idiosyncratic outcomes to even identical investment decisions' (Ericson and Pakes, 1995: 67). Hence, the relationship between investments (including R&D investment) and firm survival is *ambiguous*. This is because the probability of successful investment is determined endogenously by the industry structure that, in turn, is only probabilistically related to its structure in the previous period.

This contrasts with predictions from the evolutionary model, where firms in un-routinised technological regimes are more likely to innovate and innovation is positively correlated with survival. The higher probability of innovation investment in these regimes enables the firms to catch up with technology frontier and attain the minimum efficient scale (MES), while also avoiding the adverse of the industry-wide creative destruction (Audretsch,1991; Audretsch and Mahmood, 1995). The innovation premium may be relevant in routinised technological regimes too, but this premium may not be realised because of lower probability of innovation in such regimes. Overall, more innovative firms are more likely to survive in both regimes, but more innovative firms are more likely to be located in un-routinised as opposed to the routinised regimes.

Somewhere in between lies the prediction from the Schumpeterian models of competition, where the relationship between investment in innovation and firm survival is inverted-U-shaped. This relationship mirrors the hump-shaped relationship between competition and innovation, but it is driven by diminishing returns to investment irrespective of whether firms are neck-and-neck or leader-laggard innovators. Up to a certain threshold, the marginal returns to investment in innovation are higher than marginal costs, the innovative product lines are profitable, and hence the probability of survival is increasing with innovation. After that threshold, however, the marginal benefits of investment fall short of the marginal costs, the new product lines are loss-making, and the probability of survival declines with innovation (Ugur et al., 2016a).

3. Innovation and firm survival: evidence and implications for future research

The discussion above indicates that, *theoretically*, the effect of innovation on firm survival depends on the industry-specific cost and incentive structures that determine the probability of innovation (evolutionary models); the stochastic outcomes of the investment in innovation (active learning models); the extent of creative destruction (innovation intensity) in the industry (evolutionary and

Schumpeterian models); and the risk-return profile of the R&D investment that depends on the firm's innovation intensity (Schumpeterian model). Given these theoretical antecedents, we expect heterogeneity to emerge as a prominent feature of the empirical findings on the relationship between innovation and firm survival.

Indeed, effect-size heterogeneity has been acknowledged in a systematic review by Manjón-Antolín and Arauzo-Carod (2008). The authors report a number of contrasting findings on the survival effects of innovation, including: (i) positive and stronger effects of process innovation as opposed to product innovation; (ii) strong and positive effects of process innovation among large firms, but weak or insignificant effect among small firms; (iii) usually positive effects when innovation is measured with R&D investment. However, this review covers only a small set of innovation-survival studies because its focus is on methodological developments in the wider literature on firm survival. Furthermore, the review aims to uncover the range of "firm- and industry-specific covariates that provide largely consistent results across samples, countries and periods." As such, the authors do not engage in a systematic discussion of either the sources of observed heterogeneity or its implications for future research on innovation and firm survival.[6]

We have expanded the set of innovation-survival studies in Manjón-Antolín and Arauzo-Carod (2008) with eight additional studies published in or before 2010. Table A1 in the Appendix provides summary information on the samples, innovation measures and estimators used as well as findings reported in these studies. Examining the evidence from the combined set, we observe that the extent of heterogeneity in summarised findings is now higher than what has been reported in Manjón-Antolín and Arauzo-Carod (2008). Furthermore, the extent of heterogeneity is also higher than what is reported in the literature review sections of most primary studies published until 2010 (e.g. Cefis and Marsili, 2005 and 2006; Esteve-Pérez *et al*., 2004; Esteve-Perez and Manez-Castillejo, 2008).

One source of heterogeneity is the innovation intensity of the industry within which the firm is located. In line with the predictions of the evolutionary models (Audretsch, 1991; Audretsch and Mahmood,

[6] As we indicate below, more recent research pays greater attention to heterogeneity in in the effects of innovation on firm survival. A pertinent example is Hyytinen et al. (2015), who draw attention to the extent of heterogeneity in the related literature before reporting their own findings on the relationship between innovation and start-up survival among Finnish firms.

1995; Mahmood, 2000; and Segarra and Callejón, 2002), a higher level of intra-industry innovation intensity increases exit hazard. This prediction ties in with predictions from Schumpeterian models of innovation (Aghion et al., 2014; 2015), where higher levels of creative destruction in innovation-intensive industries render the firm's existing technology obsolete at faster rates. Hence, firms in innovation-intensive industries face a higher level of exit hazard unless their levels of innovation are high enough to counterbalance the adverse effects of both product-market competition and creative destruction.

Given these theoretical predictions, estimates for the effect of innovation on firm survival would be heterogenous and potentially biased unless researchers control for industry effects. Some studies address the industry-specific effect by including industry dummies in their survival models (e.g., Agarwal and Audretsch, 2001; Agarwal et al., 2002; Mahmood, 2000; Cefis and Marsili, 2005). Nevertheless, the use of industry dummies may not be sufficient to control for cross-industry variation in innovation intensity for two reasons. First, dummy variables are blunt instruments that also control for other sources of inter-industry heterogeneity. Secondly, using industry dummies instead of controlling for observable innovation intensity within the industry can lead to biased estimates if inter-industry variation in innovation intensity is theoretically related to the relationship between firm-level innovation and firm survival.[7]

In the absence of a unified approach to modelling inter-industry variation in innovation intensity, the reported effects of innovation of firm survival tends to be heterogeneous – with the effect depending on the industry composition of the sample and whether industry effects are controlled for or not. Therefore, we identify the first implication for future research as follows: survival or hazard models should control not only for the effect of industry-level innovation intensity but also for the interaction of the latter with the firm's own innovation intensity. Such specification is necessary to minimise the risk of model misspecification and to tease out pertinent information on: (i) the magnitude of the survival premium due to the firm's own innovation effort relative to the creative destruction effect of the intra-industry innovation intensity; (ii) potential non-linearities in the relationship between firm-

[7] A similar concern is raised in Hall et al. (2010) when they discuss the case for and against the inclusion of industry and time dummies in R&D and productivity models.

level innovation and firm survival; and (ii) the optimal level of firm-specific innovation at which exit hazard is minimised given the level of intra-industry innovation intensity.

Another conclusion that can be distilled from the pre-2010 studies in Table A1 is that the effect of the firm-level innovation on firm survival varies in sign between and sometimes within studies. The reported effects are positive in majority (53%) of the studies (Audretsch, 1991; Audretsch and Mahmood, 1995; Cefis and Marsili, 2005; Cefis and Marsili, 2006; Esteve-Perez and Manez-Castillejo, 2008; Esteve-Pérez *et al*., 2004; Fontana and Nesta, 2009; Klepper and Simmons, 2005; and Wagner and Cockburn, 2010). However, the effect is insignificant or mixed in the remaining 47% of the studies. In the set of studies reporting mixed effects, the heterogeneity reflects sectoral variations in Mahmood (2000) and Helmers and Rogers (2011); variation between innovation inputs and outputs in Ortega-Argilés and Moreno (2007) and Wilbon (2002); variation between flow and stock measures of innovation outputs (Buddelmeyer *et al*., 2009); and variation between innovation output types (e.g., patents *versus* trademarks in Jensen et al., 2008).

Effect-size heterogeneity notwithstanding, the evidence from pre-2010 studies indicates a third interesting pattern: the effect on survival is more (less) likely to be positive when the explanatory variable is an output (input) measure of innovation. Positive survival effects are reported when the output measure of innovation is product innovation (Audretsch, 1991; Audretsch and Mahmood, 1995; Banburry and Mitchell, 1995; and Fontana and Nesta, 2009) or intellectual property assets (IPAs) such as patents or trademarks (Buddelmeyer et al., 2010; Helmers and Rogers, 2010; Jensen et al., 2008; Wagner and Cockburn, 2010). This pattern is in line with Rosenbusch *et al*. (2011), who report that output measures of innovation, relative to input measures, are more likely to be associated with higher post-entry firm performance of small and medium enterprises (SMEs).

This pattern can be explained by the argument that product innovation and IPAs reveal innovation successes that enhance firm survival whereas the survival premium due to input measures such as R&D investment is subject to inherent uncertainties and failure risks. This is a pertinent argument, particularly with respect to the effects of innovation on survival among small and medium enterprises (SMEs). However, evolutionary and Schumpeterian models of the innovation-survival relationship offer an alternative explanation, which relies on the positive correlation between market power and the

output measures of innovation. Indeed, output measures of innovation are more likely to indicate firm success in converting innovation investments into innovation outcomes. Successful innovations, in turn, enables firms to grow in the product space as a result of increased efficiency at the supply side and the positive effect of product variety on the demand side. Hence, in the case of output measures of innovation, the efficiency-enhancing and demand-shifting effects of innovation are intertwined; and the survival premium will reflect both efficiency gains and any increase in market power (See the review by Hall, 2011 on the role of market power in the relationship between innovation and productivity). Given this dynamic, an added implication for future research is that it is necessary to control for market power and the latter's interaction with the innovation measures to: (i) isolate the effect of innovation outputs from market power effects; and (ii) verify whether innovation and market power are complements or substitutes in their effects on firm survival.

Moving on to post-2010 studies summarised in Table A2 in the Appendix, we observe that the relationship between innovation and survival is even more heterogenous than the pre-2010 studies. This trend is acknowledged in Hyytinen et al. (2015), who provide an extensive review of the literature before they report their findings on the effects of innovation on start-ups in Finland. The percentage of the post-2010 studies that report a positive relationship between innovation and firm survival is 33%, as opposed to 53% of the pre-2010 studies in Table A1. Furthermore, the sources of heterogeneity include not only innovation types (process *versus* product innovation) or firm size discussed in the context of the pre-2010 studies. In the post-2010 studies, we also observe that the effect of innovation on firm survival differs by the level of R&D intensity (Ugur et al., 2016a; Zhang and Mohnen, 2013); by appropriability of the investment in innovation (between input and output measures (Hall and Sena, 2017); between firms that are single-product and diversified innovators (Colombelli et al., 2016); and by risk appetite (Hyytinen et al., 2015). It is also pertinent to note that the proportion of estimates indicating positive process innovation effects on survival in the post-2010 studies is higher than the pre-2010 set. Finally, the innovation's effect on survival is more likely to be positive when firms engage in both process and product innovations, and when innovation is measured with IPAs (Hall and Sena, 2017; Ortiz-Villaios and Sotoca, 2018).

With respect to R&D intensity as a source of effect heterogeneity, Ugur et al. (2016a) and Zhang and Mohnen (2013) draw on UK and Chinese firm data respectively and report an inverted-U relationship

between innovation intensity and firm survival. The inverted-U relationship holds for R&D in both samples and for R&D and product innovation in the Chinese data. This finding is in line with the prediction from the Schumpeterian model of innovation discussed above. It indicates that both input and output measures of innovation are associated with a survival premium, but the latter is subject to diminishing scale effects due to higher investment risks at higher levels of innovation intensity. When the level of innovation increases beyond an optimal threshold, survival time declines as the profitability of the innovative product lines and the expected value of the firm decline.

A finding in Ugur et al. (2016a) indicates that R&D intensity and industry concentration are complements, with a positive interaction effect on survival. Given the concave relationship between R&D intensity and firm survival, this finding indicates that the survival-increasing effects of R&D intensity is prolonged (i.e., the turning point is pushed to the right) as the level of concentration increases. Stated differently, in more concentrated industries, the positive effect of innovation on survival probability is enjoyed over a longer segment of the R&D intensity distribution. This finding is also in line with Schumpeterian models of innovation, where the firms' desired levels of innovation investment and the effects of the latter on firm survival is a function of an 'escape competition' incentive. It allows for reiterating the case for explicit modelling of market power and the interaction of the latter with the firm's own innovation effort with a view to disentangle the efficiency-enhancing and mark-up effects of innovation on firm survival.

Pooling both pre- and post-2010 studies, we identify three method-related issues in the empirical research on innovation and firm survival. The first concerns the paucity of the attempts at modelling frailty. Although the causes and consequences of frailty have been discussed at length in survival analysis (Aalen, 1994; Wienke, 2010; Mills, 2011), two-thirds of the empirical studies reviewed here do not control for frailty or unobserved heterogeneity. Furthermore, most of the studies that do control for frailty are in the post-2010 set in Table A2. The neglect of frailty is a potential source of bias, which is highly likely given the emphasis on firm heterogeneity in the theoretical models that inform the empirical models. To the extent that firms are heterogenous in terms of management quality or quality of the firm's R&D personnel, it is necessary to augment the survival (or hazard) models with frailty as unobserved random effect (see, Mills, 2011). Statistical theory predicts that the effect of the covariates on the population hazard diminish in favor of the frailty effect as time increases (Gutierrez, 2002).

Stated differently, models without control for frailty may yield upward-biased estimates for the effects of the covariates in the survival model, including the covariate(s) capturing innovation.

We think the evidence on frailty indicates three implications for future research. First, it is good practice to verify if frailty is significant and report the findings explicitly. Secondly, it is necessary to report not only whether frailty is significant, but also to comment on whether a significant frailty effect is associated with stronger or weaker effects of innovation on survival.[8] A third implication is that it is necessary to test whether frailty (unobserved heterogeneity) is correlated with the covariates in the model and to take account of endogeneity that results from the correlation.[9]

The summary information in Tables A1 and A2 allows for two further method-related observations. One concerns the choice between proportional hazard (PH) and accelerated failure time (AFT) estimators.[10] Because there is no clear guidance about which approach is more appropriate, empirical studies choose one or the other. This is acceptable, but good practice requires sensitivity checks based on alternative specifications. Whilst some studies report such sensitivity checks and justify the preferred model on the basis of model fit criteria (e.g., Ortega-Argilés and Moreno, 2007; Cefis and Marsili, 2012; Fernandes and Paunov, 2015; Ugur et al., 2016a), this is not the case across the board. Therefore, we suggest that future research conduct sensitivity checks and justify their preferred estimators based on model-fit diagnostics. Such diagnostics include the Schoenfeld (1982) residuals test to decide between the semi-parametric and parametric baseline hazard models; and the Akaike and Bayesian information criteria (AIC/BIC) and the Cox-Snell residuals plots to choose between PH and AFT specifications of the parametric baseline hazard.

[8] It must be noted that the studies that control for frailty tend to pay attention only to whether the sign of the estimated coefficients on innovation remain the same between models with and without frailty.

[9] This issue arises irrespective of whether frailty is modelled as a multiplicative or additive term in the baseline hazard. If exists, such correlation is a cause of endogeneity. Researchers can address the letter through Mundlak (1978) corrections, which involve augmenting the survival model with time averages the covariates correlated with frailty to ensure mean independence.

[10] This issue arises because the shape of the hazard function is unknown and economic theory provides information only about the relevant covariates and their expected effects on the likelihood of firm exit. Stated differently, survival studies tend to estimate a reduced-form hazard model where the logarithm of the hazard is a linear function of two arguments: the baseline hazard function and the covariate function that includes innovation and other covariates suggested by the theory. The PH estimators assume that the baseline hazard function depends on time only whereas AFT estimators assume that it depends on time and the function of the covariates. Hence, the baseline hazard is the same in both estimators only if the covariates are assumed to be zero. Furthermore, the interpretation of the coefficient estimates differs. In the PH models, the coefficients are semi elasticities of the hazard with respect to the covariates, whereas they measure the effect of the covariates on the length of the predicted time until the failure event is likely to occur in the AFT models.

The final method-related observation concerns to the choice between continuous and discrete-time hazard models. This issue again arises from the absence of theoretical guidance on which conception of time is more appropriate for firm survival data (see, Manjón-Antolín and Arauzo-Carod, 2008). On the one hand, duration time (i.e., the time to exit) is theoretically continuous. On the other hand, firms are observed only at some intervals, usually every year in annual surveys or in accounting data. The data constraint makes the discrete-time models more appropriate but discrete-time models estimate the odd ratio instead of the hazard rate for exit to occur by time *t*. A possible extension for future research would be to compare the performance of both discrete and continuous time models and choose the best-performing model on the basis of predictive power indicators such as the area under the receiver operating characteristic curve (AUC), as demonstrated by Gupta et al. (2018) in the context of financial distress hazard estimations.

4. Innovation and firm productivity: theoretical underpinnings

In early endogenous models, innovation drives economic growth through spillover effects that sustain investment in physical and human capital by raising the latter's marginal product above the discount rate (Romer, 1986; Lucas, 1988). In later models (e.g., Romer, 1990; Aghion and Howitt, 1992; Aghion et al., 2015), innovation drives productivity growth through technological change that reduces production costs[11] or increases product quality or both. One line of empirical research that follows from the endogenous growth theory investigates what came to be known as the spillover (or standing-on-the-shoulders) effect of the knowledge stock on the production of new knowledge (i.e., on the production of innovation outputs).[12] This empirical strand has been reviewed in a recent meta-analysis by Neves

[11] The most common case being through labour-saving innovation (Freeman and Soete, 1987; Simonetti, Taylor and Vivarelli, 2000; Piva and Vivarelli, 2018).

[12] The metaphor "standing on the shoulders of giants" is attributed to Isaac Newton and used in work on the economics of innovation to refer to spillovers from investment in innovation. Innovation spillovers play a central role in endogenous growth models, where investors in innovation benefit from ideas embedded in the existing stock of knowledge.

and Sequeira (2018), who report that the average spillover (standing-on-shoulders) effect is positive but smaller than one.

The empirical literature on innovation and productivity we review below constitutes the second line of empirical research that resonates with but also predates the theoretical endogenous growth models. This line of research builds on a Cobb-Douglas production function augmented with knowledge capital, which is constructed from investment in innovation. Here knowledge capital is an additional input and has separable effects on output by affecting the level of total factor productivity (TFP). Stated differently, knowledge capital (i.e., investment in innovation) enables the firm to obtain a higher level of output with given levels of physical capital and labour as conventional inputs. This formulation ties in with the first-generation endogenous growth models, where innovation is growth enhancing because it increases the productivity of the resources used in the production of goods and ideas. It is also compatible with second-generation models, where innovation is a source of creative destruction (i.e., higher entry and exit rates) and technological change that increase firm productivity.

Following the seminal contribution by Griliches (1979), empirical work based on knowledge capital has flourished and expanded in several directions. One strand, which came to be known as the *primal approach* because of its reliance on a production function, estimates a Cobb-Douglas production function augmented with R&D capital stock. Assuming perfect competition in factor markets and separability of the knowledge capital (K) form conventional inputs capital (C) and labour (L), the production function can be stated as follows:

$$Q_{it} = Ae^{\lambda t} C_{it}^{\alpha} L_{it}^{\beta} K_{it}^{\gamma} e^{u_{it}} \qquad (5)$$

Here, Q_{it} is real output of firm or industry i at time t. C_{it} is deflated physical capital stock; K_{it} is deflated R&D capital; L_{it} is labour (number of employees or hours worked); and $Ae^{\lambda t}$ is technological progress with a rate of disembodied technological change λ. Using lower case letters to denote logged values, the model is:

$$q_{it} = \alpha c_{it} + \beta l_{it} + \gamma k_{it} + \eta_i + \lambda_t + u_{it} \quad (6)$$

The logarithm of technical progress yields a firm- or industry-specific effect (η_i) and a time effect (λ_t). Following Mairesse and Griliches (1988), the empirical work adopts various assumptions about the intercept (η_i) and the slope coefficient of interest (γ). Some studies assume that both the intercept and the slope coefficient are constant across firms/industries and hence use pooled OLS for estimation (e.g., Adams and Jaffe, 1994; Mairesse et al., 2005; Ortega-Argiles et al., 2010). Some others assume random intercepts drawn from the same distribution and constant slopes. Then the parameters are estimated with a between estimator that consists of a cross-sectional (total) OLS with data averaged over time for each cross-sectional unit (Griliches, 1980 and 1998c; Schankerman, 1981; Bartelsman et al., 1996; Ortega-Argiles et al., 2010) . Elasticity estimates from pooled OLS or between estimators are referred to as *elasticity estimates in the level dimension*.

Some studies assume that the firm-specific effects are constant over time and utilise a *within* estimator, where all terms in the model are either first-differenced or expressed as deviations from the within-firm mean (Griliches and Mairesse, 1991; Mairesse and Hall, 1996). Productivity estimates from time-differenced or within estimators are referred to as *elasticity estimates in the temporal dimension*. Estimates from the *level* and *temporal* dimensions will be consistent if model (6) is specified correctly and the covariates are not subject to mismeasurement.

In elasticity models, the elasticity of output with respect to knowledge capital, γ, is assumed constant across firms or industries. If firms operate with different factor shares depending on the competitive equilibria they are faced with (Hall et al., 2010), it is more appropriate to assume *rate-of-return* rather than *elasticity* equalisation. Then, the change in R&D capital stock (Δk_{it}) is transformed into R&D intensity, assuming that the annual depreciation rate is close to zero. This transformation allows for rate-of-return estimations, where the coefficient of interests is ρ in the output model (7a) or its total factor productivity (TFP) equivalent (7b) below.[13]

[13] Elasticity and rate-of-return estimates based on the knowledge capital model have become known as the *primal approach*, in contrast to the *dual approach* based on cost or profit functions. This review excludes the dual-approach studies as the

$$\Delta q_{it} = \Delta\lambda_t + \alpha\Delta c_{it} + \beta\Delta l_{it} + \rho\frac{R_{it}}{Q_{it}} + \Delta u_{it} \quad (7a)$$

$$\Delta TFP_{it} = \Delta\lambda_t + \rho\frac{R_{it}}{Q_{it}} + \Delta u_{it} \quad (7b)$$

A second variant of the knowledge capital model has been proposed by Crépon, Duguet and Mairesse (1998). The model, which came to be known as the CDM model for short, extends the Griliches-type knowledge capital model along two dimensions. [14] First, it takes account of potential selection in the firm's decision to innovate and how much to invest in innovation. Secondly, it controls for endogeneity that may arise from mismeasurement of the innovation variables and/or from simultaneity in the relationship between inputs and outputs in the production function. The model consists of a system of four equations: (a) usually two research equations (8a and 8b) that model the firm's decision to innovate (y_{0i}) and/or its choice of the level of innovation intensity (y_{1i}); (b) an innovation output equation (9) that models the effect of innovation investment on innovation outputs (y_{2i}) such as process or product innovation, patents, sales revenue from innovative products, etc.; and (c) a labour productivity equation (y_{3i}) augmented with predicted innovation outputs (10).

$$y_{0i} = \begin{cases} 1 \; if \; y_{0i}^* = X_{0i}\beta_0 + \varepsilon_{0i} > 0 \\ 0 \; if \; y_{0i}^* = X_{0i}\beta_0 + \varepsilon_{0i} \leq 0 \end{cases} \quad (8a)$$

$$y_{1i} = y_{1i}^* = X_{1i}\beta_1 + \varepsilon_{1i} \;\; if \; y_{0i} = 1 \quad (8b)$$

$$y_{2i} = \alpha_{21}y_{1i} + \alpha_{23}y_{3i} + X_{2i}\beta_2 + \varepsilon_{21i} \;\; if \; y_{0i} = 1 \quad (9)$$

$$y_{3i} = \alpha_{32}y_{2i} + X_{3i}\beta_3 + \varepsilon_{3i} \;\; if \; y_{0i} = 1 \quad (10)$$

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latter are small in number and their model specifications are more varied than the primal-approach studies. A review of the dual-approach studies is provided in Hall et al. (2010).

[14] The CDM model has inspired a large volume or empirical research after its publication in the *Economics of Innovation and New Technology* (*EINT*) in 1998. A recent special issue of the *EINT* (vol. 26, no. 1-2, 2017) celebrates the twenty years of research informed by the CDM model. The special issue features bibliometric and epistemological reviews that locate the CDM model in the wider field of research on innovation and productivity as well as research articles reflecting the state-of-the-art in the specification and estimation of the CDM model.

Vectors X_{0i}, X_{1i}, X_{2i} and X_{3i} are covariates that explain the innovation decision, innovation input, innovation output and labour productivity; and the ε terms are idiosyncratic errors with multi-variate normal distributions. The predicted inverse Mills' ratio (Heckman, 1979) is usually included in (9) and (10) to correct for possible selection bias. Finally, the α's and β's are the vectors of unknown parameter to estimated. vectors. [15]

In the original study by Crépon, Duguet and Mairesse (1998), the effect of R&D capital intensity on labour productivity from the preferred asymptotic least squares (ALS) estimation is 0.119. As indicated by Mairesse et al. (2005), this is very close to the OLS estimate from Griliches-type production function estimated with the same dataset. Does this mean that the more structured CDM model that is supposed to correct for selectivity and endogeneity is promising too much but delivering too little? Not necessarily. The CDM delivers more reliable estimates in the presence of selection and when the innovation variable is mis-measured. This is more likely to be the case when the innovation measures consist of indicator variables that capture the firms' yes/no responses to innovation surveys; or the firm's self-assessment of what is 'new' to the market and what is new to the firm itself. Other examples of innovation indicators that may suffer from selection and mismeasurement problems include indicator variables for organisational innovation or so-called non-technological innovation. It is in these situations that the CDM model delivers on its promises by correcting for downward bias in the productivity-effect estimate when the innovation measure is mis-measured. It also corrects for the simultaneity bias that may be upward or downward, depending on whether efficient or inefficient firms select into becoming innovation-active in any of these innovation types.

Nevertheless, it must be noted that the quality of the CDM model's correction for selection or mismeasurement depends on whether the innovation decision and input equations (equations 8a and 8b above) and the innovation output equation (equation 9) are specified correctly. In Crépon, Duguet and

[15] Crépon, Duguet and Mairesse (1998) estimated the model in two steps using asymptotic least squares (ALS) or minimum distance estimators. In the first step, the reduced-form (auxiliary) coefficients in each equation are estimated separately, taking account of error correlations. In the second step, the information about the auxiliary parameters is used to estimate the structural parameters of interest – mainly the effects of innovation outputs on productivity. When the innovation output measure is continuous, the coefficient estimate is the elasticity of productivity (usually labour productivity) with respect to the innovation output. When the innovation output is measured with an indicator variable, the coefficient estimate indicates the productivity difference between innovative and non-innovative firms.

Mairesse (1998), model specification has been informed by Schumpeterian perspectives on innovation. The authors control for firm size, market share, diversification indicators, demand conditions and technological opportunities and a range of industry and time dummies. In later applications, a wider range of explanatory variables are controlled for and the theoretical justification for selection is theoretically more eclectic. Considering Lööf and Heshmati (2006) as an example, we can see that physical capital per employee, R&D personnel, indicators of obstacles to innovation, product life cycle, and growth rate in the firm's main market, etc. are added to covariates measuring firm size or demand conditions. The downside of this modeling flexibility is increased risk of model misspecification. Given the absence of a commonly agreed theoretical framework that informs model selection, the added structure in the CDM model can deliver two outcomes working at cross purposes: correction for selection and mismeasurement on the hand and heterogeneity and perhaps bias on the other, depending on which covariates are included in or excluded from the innovation equations.

5. Innovation and firm productivity: evidence and implications for future research

The two variants of the knowledge capital model introduced above - the Griliches-type knowledge capital model and the CDM model with a richer structure that controls for selectivity and endogeneity – have underpinned a long-lasting research effort for modeling and estimating the effects of innovation on firm productivity. In a content and bibliometric review, Broström and Karlsson (2017) document how this academic endeavour developed through methodological and estimation innovations and careful attention to the conceptual linkages between theoretical underpinnings and empirical effort aided with the emergence of rich datasets. The authors also demonstrate that the interest in this line of research has been associated positively with increased interest in the diffusion of innovation as a research theme in 2000s. In what follows below, we take stock of the evidence reported in the research field, paying particular attention to sources of heterogeneity in the evidence base and to the boundary-

pushing methodological contributions that have emerged so far and are likely to inform future developments.

5.1 The Griliches-type knowledge capital model

The evidence from the Griliches-type knowledge capital model until 2010 has been evaluated by several narrative reviews (Hall et al., 2010; Mairesse and Sassenou, 1991; Mairesse and Mohnen, 1994; Hall, 1996). The latest and most comprehensive narrative review (Hall et al., 2010) reported that the effect of R&D capital on productivity are positive and economically significant. The median elasticity estimate is approximately 0.08 and the median private rate of return on R&D investment is between 20% and 30%. These summary measures, however, conceal a high degree of heterogeneity.

The narrative reviews identify several sources of the heterogeneity in the evidence base, including variations in measurement, model specification and estimation methods. One measurement issue is the absence of firm-level prices in the data. This missing data problem implies that the firm-level price indices may be different than the industry-level price indices used to deflate the inputs and outputs in the model.[16] Given that quality improvements are higher in the products of innovation-intensive firms, the absence of firm-level prices is conducive to higher (lower) elasticity estimates if innovation-intensive firms are (are not) represented in the sample. Hence, the estimates will reflect both 'true' productivity improvements and revenue gains due to market power when innovation-intensive firms are included in the sample (see, Hall et al., 2010; Griliches, 1998b; Hanel, 1994).

A second measurement issue is double counting, which occurs when R&D expenditures on capital and R&D personnel are not deducted from the observed measures of physical capital and labour in the production function. Hall et al. (2010) report that the elasticity estimates would be biased downward if physical capital and labour are not corrected for double counting. Downward bias is also reported in some studies that estimate elasticities in the temporal dimension or rates of return using time-differenced data, albeit the bias is less clear cut (Harhoff, 1994; Hall and Mairesse, 1995).

[16] It must be indicated that lack of firm-level price data is an issue in both Griliches-type and CDM-type knowledge capital models.

The third source of heterogeneity relates to model specification. Some studies report smaller elasticity estimates when the labour input in the production function is disaggregated by skill levels (Mairesse and Sassenou, 1991; Crépon and Mairesse, 1993). Hall et al. (2010) indicate that this is due to positive correlation between skilled labour and R&D, which suggests that skilled labour and R&D capital may be complements. The elasticity and rate-of-return estimates also tend to be smaller when the knowledge capital model controls for R&D spillovers (Ugur et al., 2016b).[17]

The fourth source of heterogeneity relates to the estimators used. On the one hand, elasticity estimates in the temporal dimension are usually smaller than the elasticity estimates in the cross-sectional dimension.[18] On the other hand, Ugur et al. (2016b) report that the elasticity estimates are smaller when the generalised method of moments (GMM) or other instrumental variable (IV) methods are used to correct for endogeneity, but this is not the case with respect to rates-of-return estimates. A fifth source of heterogeneity is the variation in the R&D intensity of the firms/industries in the sample. Hall et al. (2010) report that the elasticity estimates are larger when the sample consists of high-R&D-intensity firms, but this is more likely to be the case when the estimates are based on the cross-section dimension.

Ugur et al. (2016b) builds on the existing reviews until 2010 and updates the evidence synthesis. Drawing on meta-analysis tools, they establish where the balance of the evidence lies and what explains the heterogeneity in the reported estimates. The average of the *elasticity* and *rate-of-return* estimates after controlling for publication selection bias are positive (0.06 and 14%, respectively), but heterogenous. The median estimate across primary studies ranges from 0.008 to 0.313 for elasticities at the firm or industry level; and from 8% to 68% for rates of return at the firm level or industry level. Strongly consistent evidence is reported on additional sources heterogeneity, as summarised below.

[17] Stated differently, the elasticity estimates may be upward biased if the knowledge production does not take account of the knowledge spillovers from external R&D or cooperative R&D (Cassiman and Veugelers, 2002; Piga and Vivarelli, 2003).

[18] One reason is the mismeasurement of the R&D capital, which is exacerbated when the growth rates of the R&D capital or its deviation from the mean are used. Another explanation is potential multicollinearity between the time effects reflecting autonomous technological change and the growth rates of R&D capital. A third explanation relates to missing data on cyclical variables such as capacity utilisation or person-hour worked instead of headcount employment (Hall et al., 2010). A fourth explanation is that R&D investment is less responsive to business cycle conditions or policy interventions compared to physical capital. Finally, Bloom (2007) demonstrates that the persistence of the R&D investment series increases as uncertainty increases. Therefore, the within-firm variation in R&D capital is smaller than the between-firm variation; and the explanatory power of the R&D stock series is reduced when the elasticity estimates are based on within estimators.

1. The use of perpetual inventory method (PIM) for constructing the R&D capital is associated with relatively larger estimates compared to other methods where the R&D capital accumulation is a multiplicative rather than additive process. This is because the PIM accords the same weight to additional units of R&D investment in year (t) irrespective of the R&D capital stock in year (t-1). This may be a source of upward bias if the contribution of an additional unit of R&D investment to R&D capital is a positive function of the latter in the preceding year(s). Hence, there is a case for sensitivity checks involving the use of logarithmic methods of R&D capital capital construction, as suggested earlier in Klette (1994).
2. Small-firm data is associated with smaller elasticity estimates of productivity at the firm level. This may be due to high failure rates among young and small firms or lower market power or both – as predicted Schumpeterian models of innovation and firm performance (Aghion et al., 2014). However, it may be also due to higher incidence of measurement error or selectivity in the data on small firms, which the knowledge capital model, unlike the CDM model, does not address explicitly (Pellegrino and Piva, 2020).
3. Elasticity estimates for R&D-intensive firms or industries are larger than non-R&D-intensive or mixed firms/industries. This finding is in line with Hall et al. (2010) and indicates that that R&D-intensive firms/industries are better placed to exploit the benefits of innovation as a result of either enhanced efficiency or increased market power or both.
4. Publicly funded R&D (i.e., an R&D subsidy) is associated with smaller productivity estimates at the firm or industry level. One reason is that public support for business R&D may be concentrated in firms/industries that generate higher levels of R&D (knowledge) spillovers and hence lower levels of appropriability (e.g., health and defence). Secondly, public funds may be concentrated in industries with lower returns due to large scales at the capacity building phase (e.g., aircraft and communications sectors). Finally, firms may be less efficient in the use of public subsidies in general, or subsidies may be misdirected (Hall et al., 2010). The implication for future research is that it may be necessary to decompose the R&D capital into public and private components to establish whether both types are complements (substitutes) and enter the production function separately (or in total).

5. Finally, instrumental variable estimators such as generalized method of moments (GMM) two-stage least squares (2SLS) yield smaller elasticity estimates compared to OLS estimators. This finding suggests that R&D investments and productivity may be responding to unobserved shocks in the same direction, leading to upward bias in OLS estimates of the innovation investment's productivity effects.

We follow Ugur et al (2016b) and draw attention to two methodological innovations in the research field evaluated above: the adoption of a common factor framework to estimation of the Griliches-type model with spillovers (Eberhardt et al., 2013) and the modelling of productivity as an endogenous outcome in Doraszelski and Jaumandreu (2013).[19] Eberhardt et al. (2013) argue and demonstrate that the conventional knowledge capital model yields upward-biased productivity effects of own R&D capital at the industry level – mainly because of its failure to take account of the cross-sectional dependence driven by spillovers as an unobserved common factor. On the other hand, Doraszelski and Jaumandreu (2013) model productivity as an unobservable endogenous outcome. They are able to account for uncertainty, non-linearity, and heterogeneity in the productivity effects of R&D. The productivity estimates from their model are *smaller* than the 'average' of 0.08 reported in the reviews discussed above. However, their estimates are *larger* than those derived from a Griliches-type knowledge capital model applied to the same dataset. They also report that the productivity effects of R&D are non-linear – with the effect increasing in the level of R&D intensity and hence indicating increasing returns to scale in R&D investment. These studies provide added evidence on heterogeneity in the productivity effects of innovation; and herald further searches for methodological innovations in the studies to follow.

We provide a summary of the recent studies where the search for methodological innovation is evident (Table A3 in the Appendix). Of these, Belderbos et al. (2015) test for non-linear returns to R&D and for complementarity between the firm's own R&D and the R&D conducted by its foreign subsidiaries. They report that returns to own R&D investment reflect diminishing scale effects (and own R&D and foreign subsidiary R&D are complements) among firms in low-tech industries. Among firms in high-

[19] A judicious review of the methodological developments until the cut-off year of 2010 is not feasible here due to space limitations. However, we refer the reader to excellent discussions in Griliches and Mairesse (1995) and Hall et al. (2010) on model specification, identification and estimations issues in the research field until 2010.

tech industries, there are neither diminishing scale effects nor complementarity between own and foreign-subsidiary R&D. Non-linear returns to R&D (with some evidence of diminishing returns to scale) are also reported in Kancs and Silerstovs (2016), who utilize the endogenous productivity model of Doraszelski and Jaumandreu (2013) and treatment-effect estimators based on propensity score balancing. Their findings indicate that the returns to R&D investment are about 15% on average, ranging from −2% for low levels of R&D intensity to 33% for high levels of R&D intensity. Furthermore, firms in high-tech sectors both invest more in R&D and secure higher returns. Nevertheless, the returns to R&D increases at smaller rates as R&D intensity increases, indicating the existence of an optimal threshold beyond which the innovation's effect on firm productivity may become smaller than its effect on the firm's average costs.

The evidence from this recent work enables us to make two observations about implications for future research. The first is about the need to endogenize productivity – in line with the approach in Doraszelski and Jaumandreu (2013). This approach utilizes a dynamic model where the firm invests in R&D to improve productivity over time. However, productivity is also a determinant of investment in R&D and other types of investment (e.g., investment in physical capital) as well as subsequent decisions on static inputs such as labour and materials. Furthermore, the evolution of productivity is subject to random shocks that reflect uncertainties related to investments in both physical capital and R&D investments.

Following this line of modeling, Andrew (2020) offers two methodological contributions: taking account of the firm's life cycle and using age as an argument in the Markov process for productivity; and estimate the productivity effects of R&D with a conditional heteroskedasticity estimator, which captures the effects of innovation on the mean and variance of total factor productivity (TFP). This study reports three novel findings that lend support to our call for identifying and quantifying the sources of heterogeneity, non-linearities and uncertainty in the innovation-productivity relationship: (i) R&D investment has non-linear effects on both the *level* and *volatility* of the TFP in the next period; (ii) older firms are more efficient in converting R&D spending into productivity gains and in undertaking R&D investment with more uncertain returns / success rates; and (iii) productivity is persistent in that firms with higher productivity are also more efficient in converting R&D inputs into future productivity gains.

The second implication is about the potentially confounding effect of market power in the innovation-productivity relationship. This issue is addressed in Máñez et al. (2015), who extend the Olley and Pakes (1996) method of estimating production functions with endogenous inputs in two directions. On the one hand, and similar to Doraszelski and Jaumandreu (2013), they assume that productivity evolves in accordance with an endogenous rather than exogenous Markov process. On the other hand, they estimate two production functions jointly – one with labour input and an inverse demand function for materials; and one with labour and capital inputs and inverse demand functions for materials and capital. In both models, the demand for materials and capital is assumed to be heterogenous, depending on the firm's R&D and export status. The total factor productivity (TFP) obtained as the residual from the joint estimation is then regressed on the firm's R&D and export status using OLS and system GMM estimators. Their findings indicate that R&D-active firms have higher levels of productivity, and R&D and exporting status are complements. They also control for market power and report that the positive effect of R&D on productivity remains positive but becomes slightly smaller when market power is controlled for. This finding ties in with our argument above that the innovation's effect on firm productivity (or survival) is due to improved efficiency and enhanced market power at the same time. The finding in Máñez et al. (2015) indicates that this is the case with respect to R&D investment as an input measures of innovation. Market power is likely to be a confounding factor even when output measures of innovation (e.g., product innovation or IPAs) are used, as long as the firm's output is not deflated with firm-specific deflators.

5.2 CDM model

The empirical work based on the CDM model has also been reviewed several times. Hall and Mairesse (2006) provide an early synthesis in their introduction to a special issue of the *Economics of Innovation and New Technology* (vol. 15, no. 4-5) titled: Empirical Studies of Innovation in the Knowledge Driven Economy. This is followed by further reviews, including Hall (2011), Mohnen and Hall (2013), Lööf, Mairesse and Mohnen (2017) in a new special issue of the *EINT* (vol. 26, no. 1-2, 2017), and Mohnen (2019). In the paragraphs below, we first identify the range of convergent and divergent findings from the reviews and from the empirical studies published until around 2010 (Table A4 in the Appendix).

Then we focus on more recent primary studies (Table A5 in the Appendix) to verify the extent and sources of heterogeneity in the evidence base identify the range of methodological developments with implications for future research.

The reviews by Hall and Mairesse (2006), Hall (2011), and Mohnen and Hall (2013) identify several convergent patterns in the findings of the studies published until around 2010. First, the elasticity with respect to innovative product sales per employee is usually between 0.09 and 0.13. Secondly, the typical elasticity estimates from the CDM and Griliches-type models are similar when the estimates are based on continuous rather than dichotomous measures of innovation. For example, the average CDM estimates based on the intensity of innovative product sales is around 0.10 and this is well within the confidence interval for the average estimate of 0.08 from the Griliches-type knowledge capital model based on R&D capital. A third convergent pattern is that the productivity effects are significantly larger when the sample consists of high-innovation-intensity firms (0.23 - 0.29) or the innovation measure is an indicator variable (with effect-size estimates ranging from 0.17 to 0.45). Finally, the largest effects on productivity seem to be due to organizational innovation, defined as innovation in business processes and work practices. This is the case in two out of three studies (Polder *et al*., 2009; Raffo et al., 2008; and Siedschlag *et al*., 2010) that report estimates for organisational innovation until 2010.[20]

One conclusion we derive from these findings is that the selection and mismeasurement issues that the CDM model is designed to address are less severe when the innovation measure is continuous. In contrast, they are quite severe when innovation is measured with an indicator variable; and the indicator variable refer to newer types of innovation (e.g. organization innovation or non-technological innovation) captured in recent innovation surveys. As such, the CDM model appears to be delivering on what it is designed to achieve. As indicated above, however, the reliability of the correction for selection and mismeasurement error depends on whether the innovation equations in the CDM model (equations 8a and 8b and 9) are specified correctly. If not, model misspecification can be a new source of heterogeneity and perhaps bias, depending on which covariates are included in or excluded from the innovation decision equations. Therefore, the consistently larger productivity gains due to new types of

[20] The issue of organizational innovation will be discussed at more length below, where we review the recent contributions.

innovation (e.g., organizational innovation, non-technological innovation, etc.) require further scrutiny of whether the CDM model's correction for selection and mismeasurement is sufficiently robust and consistent.

A second conclusion follows from the relatively larger productivity effects associated with output measures of innovation. This empirical pattern raises the question of whether market power is a confounding factor for the estimates based on product innovation dummies and/or on samples of highly innovative firms. The role of market power in the innovation-productivity modeling is discussed at some length in Hall (2011), where two channels are identified for the effect of innovation on productivity. One is the 'efficiency of production' channel whereby the innovating firm's productivity increases directly as a result of producing a higher level of output with the same level of inputs. The second is the 'demand-shift' channel whereby the increases its revenue (hence its productivity) because of increased demand for the firm's innovative products. If the industry is perfectly competitive, the firm does not respond to increased demand by increasing its price-cost margin. However, the firm can increase its price-cost margin (and its revenue productivity) if industry-level competition is imperfect. Indeed, the demand-shift (i.e., the market-power) effect of innovation on the firm's measured productivity is larger, the less elastic is the demand for the firm's innovative products (Hall, 2011).

This confounding effect is more likely when innovation is measured with 'outcome' variables such as product innovation or IPR assets, which cause an outward shift in the firm's demand curve. It is also more likely when the sample is restricted to high-innovation-intensity industries. In such industries, incumbents undertake innovation due to a Schumpeterian 'escape-competition' motive, which increases entry costs for new firms and enable incumbents to increase their market shares at the same time. The richer set of innovation types included in the CDM model and the larger effect-size estimates associated with outcome measures of innovation increase the need for disentangling the direct productivity effects of innovation from indirect market-power effects. Yet the focus in the research filed so far has been on celebrating the discovery of a wider set of innovation types (including organizational innovation) with ever larger effects on productivity rather than addressing the question of whether the reported productivity-effect estimates are confounded by market power.

More recent studies that estimate a CDM model are summarized in Table A5 in the Appendix. We observe five directions in which the CDM model has been extended, four of which reflect methodological innovations and one reflects an important attempt at investigating the role of appropriability (intellectual property rights protection - IPRP) choices made by the firms.

One methodological development has been the use of Heckman selection models (Heckman, 1976; 1979) to correct for selectivity in the research and innovation equations (Halpern and Muraközy, 2012; Aboal and Garda, 2016; Aboal and Tascir, 2018; and Tello, 2015). We observe that the heterogeneity in the reported effect-size estimates is higher after the increase in the use of Heckman selection procedure. In some studies, for example in Aboal and Garda (2016) and Aboal and Tascir (2008), the elasticity estimates are large (between 1.5 and 5); and the magnitude is larger when firms engage in non-technological as opposed to technological innovation. In contrast Tello (2015) reports insignificant effects. In between, Halpern and Muraközy (2012) report that the effect is insignificant when the productivity model is estimated with one innovation type at a time; but the effect is positive and larger than the average reported in Hall's (2011) review when both technological and non-technological innovation are included in the model.

We are of the view that these variations may reflect the limitations of the Heckman selection routine in correcting for selectivity. The model can yield unbiased estimates for the auxiliary coefficients in the research and innovation equations if two conditions are satisfied (see Puhani, 2000). First, there must be a sufficient number of exclusion restrictions - i.e., a sufficient number of covariates in the innovation output equations that are excluded from the research equations. Secondly, the assumption made about the distribution of the error terms in the selection equation must be valid. Given these conditions, we suggest that researchers using Heckman-type selection in the context of the CDM model should report evidence on whether these conditions are satisfied; and how the productivity estimates based on Heckman-type selection differ from those based on ALS or maximum likelihood estimations proposed by the proponents of the CDM model.

The second method-related contribution is due to work by Bettina Peters and her co-authors (Peters et al., 2017a; 2017b; and 2018), who build on the stochastic productivity specification proposed by Doraszelski and Jaumandreu (2013) and incorporate the market power dimension discussed above. In

their models, the firm operates in a monopolistically competitive market and maximizes its short-run profit by setting its product price at a mark-up over marginal cost. Given this price-setting behaviour, and for a given age and level of capital stock, innovation has heterogenous effects on the firms' revenue productivity. Two sources of heterogeneity are variation in the firms' innovation intensity and financial strength. The authors report that innovation benefits constitute a larger proportion of the firm's market value when the firms are more innovation intensive and have higher financial strength. The authors also report that the productivity gains from innovation are larger when the estimation depends on marketing innovation. The evidence of larger effects at high levels of innovation intensity and when the innovation measure is marketing innovation strengthens the case for disentangling the efficiency and market power effects of innovation. The case for disentangling the market power and efficiency effects of innovation also finds support in recent findings by Baum *et al*. (2017). The authors adopt a Generalized Structural Equation Model (GSEM) approach to estimating the CDM model, which corrects for selectivity, mismeasurement and endogeneity problems and offers the added value of allowing for feedback effects from productivity to future R&D investment. The authors report that the effect of product innovation (innovative product sales intensity) has a positive effect on productivity, and the effect is larger among knowledge-intensive firms.

Despite the apparent case for taking account of market power and the interaction of the latter with innovation intensity, only Castellaci (2011) address the issue by augmenting the innovation output and productivity equations of the CDM model with market concentration and the interaction of the latter with product innovation intensity. They report that firms in concentrated industries invest more in innovation, but firms in such industries secure smaller productivity gains. This finding is puzzling because it implies that firms that benefit less from innovation undertake higher levels of innovation! Furthermore, their estimate of the productivity effect becomes negative when the Herfindahl index of market concentration is 0.15 or greater. This empirical issue notwithstanding, the findings in Castellaci (2011) lend further support to our argument that market power is a likely confounding factor in the relationship between innovation and productivity.

The third methodological innovation is due to Damijan *et al*. (2011), who compare the evidence from the CDM with 'treatment effect' evidence based on propensity score matching. The elasticity estimate from the CDM model is large (0.98) when the innovation variable is the probability of undertaking a

product or process innovation. However, the average treatment effect on the treated (ATT) is insignificant when estimated non-parametrically and using propensity score matching of innovative and non-innovative firms. The discrepancy between parametric and non-parametric estimation results raises the question of whether researchers should use treatment-effect estimations methods for verifying the robustness of the parametric estimates from the CDM model or other models of innovation and productivity. The advantage of the treatment-effect methods is that they allow for inference of causal effects if the matching or balancing quality is good. The disadvantage is that the results remain highly sensitive to the selection or matching models used to ensure matching or balancing quality. Overall, we are of the view that treatment-effect estimators can be used to address the selection and simultaneity issues that the CDM model is designed to address.

The fourth innovation in the post-2010 research based on the CDM model is that of Hall and Sena (2017). This study enhances the specification of the innovation and productivity equations in the CDM model by linking the CDM research agenda with the economics literature on intellectual property rights protection (IPRP). It estimates the effects of innovation output on productivity, conditional on whether firms protect their innovation through formal or informal IPR methods. It reports that firms that innovate and use formal IPRP methods are more productive than other firms. With respect to informal IPRP methods, the authors find that only large firms are more productive when they innovate. Thirdly, the authors find that both process and product innovations have positive and significant effects on productivity only when firms use both formal and informal IPRP methods to protect their innovation. These findings are highly informative in that both innovation and IPR protection are closely related to market power. As such, it provides further support for taking account of and the interaction of the latter with innovation activity in both CDM and Griliches-type models.

The final observation from Table A5 in the Appendix relates to the wider range of innovation measures used in the estimations of the CDM model. In addition to organizational innovation that has been investigated in the pre-2010 studies, the recent studies estimate the productivity effects of marketing innovation (Aboal and Garda, 2016; Aboal and Tascir, 2018; Peters et al., 2018); firm's broadband connectivity (Bartelsman *et al*., 2019); and innovations in resource planning, customer resource management and supply chain management (Bartelsman et al., 2017). Interestingly, the productivity effects of these 'non-technological' innovation types are larger compared to the effects of process or

even product innovation, which requires sustained investment in research and development. One question that arises from these findings is that why firms secure higher levels of productivity gains when they engage in narrowly defined innovations instead of more encompassing innovation types? The second question is whether these 'non-technological' innovation types are introduced as a result of investment in R&D (which is a predictor of the innovation output in the CDM model) or they represent external consultancy inputs that do not necessarily reflect the innovativeness of the purchasing firm. Therefore, we are of the view that future research must pay more attention to how we can reconcile the flexibility that the CDM model offers for modelling the innovation-productivity relationship with the need for further theorisation about the relevance of the expanding range of 'non-technological' innovation types.

6. Conclusions and implications for future research

The evidence from the extant literature indicates that the effect of innovation on firm survival and productivity is positive. It also indicates that the research effort in both fields has made significant contributions by pursuing novel research questions and engaging in boundary-pushing methodological innovations. As such, our review lends added support to similar findings from prior reviews. Nevertheless, we identify three *issue areas* that have received inadequate attention in prior reviews: (i) a high degree of heterogeneity in the evidence base and the exacerbation of the latter by the proliferation of innovation variables used in empirical research; (ii) potentially confounding effects of market power in the relationship between innovation on the one hand and survival and productivity on the other; and (iii) the need for more systematic decision-making with respect to methodological choices. In what follows, we take each issue in turn and identify tentative implications for future research.

The *first issue area* is heterogeneity in the evidence base, which has been acknowledged but not problematized in prior reviews. We observe that heterogeneity in the reported effects of innovation on

firm survival or productivity has increased as the innovation variables have become more varied in both research fields. In addition to input and output measures of innovation, we observe the emergence of what we tentatively describe as 'non-technological' innovation types such as organisational innovation, marketing innovation, human resources management innovation, logistics innovation, etc. These 'non-technological' innovation types are compatible with the updated innovation definition in the third edition of the Oslo Manual (OECD, 2005). However, there is little or no theoretical explanation for the high level of variation in their estimated effects on productivity or other measures of post-entry performance. Heterogeneity in the evidence base is also observed in relation to different levels of innovation intensity in the industry. Whilst the innovation-productivity research tends to report larger productivity effects among more innovative firms, some innovation-survival studies report decreasing survival times at higher levels of innovation intensity.

Given these empirical patterns, we identify three questions that need to be addressed more systematically than what has been acknowledged in the literature. The first is the extent to which the 'non-technological' innovations are funded through the firms' R&D budgets. This is important because the concept of innovation in the theoretical models presupposes a knowledge production function in which R&D investment is a major input. This is even more explicit in the CDM model, where the predicted levels of innovation output are functions of R&D investment. Given this backdrop, the inclusion of 'non-technological' innovation types in productivity or survival models would constitute model misspecification if 'investment' in such innovations is part of the operating expenditures rather than R&D expenditures. The second question is about reconciling the ever expanding range of innovation measures used in the empirical research with the absence of theoretical explanations as to why the 'newer' innovation types affect survival or productivity; and why their effects can be expected to be larger (or lower) than those of 'older' innovation types. The third question is about whether the effects of innovation of firm survival or productivity are subject to increasing or decreasing scale effects; and how to reconcile the larger productivity effects reported at high levels of innovation intensity with relatively shorter survival time (or higher hazard rates) reported by some survival studies focusing on firms with higher innovation intensity.

To address the first two questions, we recommend better engagement with the emerging literature on heterogeneous innovations (Akcigit and Kerr, 2018) and on the differential effects of innovation and

imitation at different levels of proximity to the technology frontier (Aghion *et al.*, 2014). Such engagement helps in addressing the disjuncture between data and theory. It may also inform the development of a new innovation typology, where innovations are classified on the basis of funding source, the knowledge frontier in the industry, and the relative weights of innovation (discovery) and imitation (standing on the shoulders of innovators) inherent in the innovation measures. From this perspective, coexistence of findings indicating larger productivity effects but shorter survival times at higher levels of innovation intensity are consistent and complementary. This is because larger productivity effects of innovation among innovation-intensive firms are necessary to compensate for higher risks that, in turn, constitute a source of higher exit hazard that reduces the average survival time. Given our review findings, we recommend controlling for the initial level of R&D/innovation intensity through non-linear specifications of both productivity and survival models.

The *second issue area* concerns the potential correlation between innovation and market power, which is again indicated but not problematized in prior reviews. We demonstrate that it is necessary to disentangle the efficiency-enhancing effects of innovation from the demand-shifting effects on both survival and productivity. This is justified by the evidence indicating that innovation types more likely to be associated with market power (i.e., innovation types with strong demand-shifting effects such as product innovation, marketing innovation of intellectual property assets) tend to have relatively stronger positive effects on firm survival and productivity. It is also justified by the evidence of larger productivity effects of innovation among innovation-intensive firms, which may also enjoy a higher level of market power if their investment in innovation is driven by a Schumpeterian 'escape-competition' motive.

We are aware of the difficulties involved in disentangling the efficiency-enhancing and demand-shifting effects of innovation in the absence of firm-specific cost and price data and demand conditions. Nevertheless, it is feasible to control for market power in both productivity and survival models by utilising Lerner indices when profit data are available or industry-level concentration indices when such are unavailable. The existing evidence indicates that the effect of innovation on productivity is slightly smaller when market power is controlled for. There is also evidence indicating that innovation and market power may have complementary effects. Therefore, correct identification and estimation of the market structure and the interaction of the latter with the innovation activity of the

firm are important both in terms of academic research and in terms of evidence-based innovation and competition policies.

The *third issue area* is methodological. Our review acknowledges the boundary-pushing methodological innovations in both research fields. However, it also identifies a need for a systematic approach to methodological choices and robustness analysis. Starting with the innovation-survival models, we recommend taking account of frailty in a systematic manner and correcting for any endogeneity due to correlation between frailty and the regressors. We also recommend model-performance- and statistical-test-based selection between proportional hazard and accelerated failure time models; and between continuous and discrete-time hazard models. With respect to innovation-productivity analysis, we acknowledge the innovations that endogenize productivity, take account of its persistence and capture the effect of innovation on both the level and volatility of productivity. Nevertheless, we argue that further work is required for strengthening the economic and statistical theoretical framework that underpins the innovation equations in the CDM model.

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APPENDIX: SYNOPSIS TABLES

Table A1: Studies on innovation and firm survival published until 2010

Study	Sample	Innovation measure	Estimator	Effect on survival[#]	Control for frailty
Audretsch (1991)	US firms	Small firm innovation output rate, industry innovation output rate	Discrete time logit	Small firm innovation rate positive; industry innovation rate negative	No
Audretsch and Mahmood (1995)	US firms	Small firm innovation output rate, industry innovation output rate	Discrete time logit	Small firm innovation rate positive; industry innovation rate negative	No
Banburry and Mitchell (1995)	Implantable cardiac pacemaker firms (US)	Product innovation	Discrete time logit	Insignificant after controlling for market share	No
Buddelmeyer et al. (2010)	Australian firms	Patent applications and stocks; trade-mark applications and stocks	Piece-wise constant exponential hazard model	Patent applications negative; patent stocks and trademarks positive	Yes
Cefis and Marsili (2005)	CIS: Dutch manufacturing firms	Innovator/non-innovator dummy; Process/product innovation dummies	Continuous time, parametric duration model	Positive	No
Cefis and Marsili (2006)	CIS: Dutch firms	Innovator/non-innovator dummy; Innovation expenditures; R&D Exp.	State transition probabilities	Positive	No
Esteve-Perez et al. (2004)	Spanish manufacturing firms	R&D and export	Continuous-time Cox proportional hazard model	Positive	No
Esteve-Perez and Manez-Castillejo (2008)	Spanish manufacturing firms	R&D and advertising	Continuous-time Cox proportional hazard model	Positive	Yes
Fontana and Nesta (2009)	121 local area network (LAN) switch equipment producers	R&D and product innovation	Discrete time hazard and competing risk models	Both R&D and product innovation reduce the risk of exit	No
Helmers and Rogers (2010)	UK firms established in 2001	Patents (EPO and UK) and trademarks	Discrete-time probit	Positive, but some sectoral heterogeneity	No
Jensen et al. (2008)	Australian firms	Patents and trademarks, applications and stocks	Piece-wise constant exponential hazard model	Positive if trademarks, insignificant or negative if patents	No
Klepper and Simmons (2005)	US manufacturers of autos, tyres, televisions, and penicillin	Counts of product and process innovations	Parametric ad semi-parametric hazard models	Lower exit hazard among earlier entrants is due to innovation	No
Mahmood (2000)	US firms	Industry R&D intensity	Log logistic hazard model	Mixed findings	No
Ortega-Argilés and Moreno (2007)	Spanish firms	R&D intensity, process and product innovation	Continuous-time Cox proportional hazard, log-logistic and log-normal models	R&D and process innovation positive; product innovation mixed	Yes
Segarra and Callejón (2002)	Spanish firms	Industry R&D intensity	Continuous-time Cox proportional hazard model	Negative	No
Wagner and Cockburn (2010)	356 Internet-related firms that made an IPO in 1990s	Patents, patent citations	Continuous-time Cox proportional hazard model	Positive	No
Wilbon (2002)	High technology IPOs	R&D intensity, Intellectual property rights instruments	Survival probability	R&D intensity negative; IPR instruments positive	No

Table A2: Studies on innovation and firm survival published after 2010

Study	Sample	Innovation measure	Estimator	Effect on survival[#]	Control for frailty
Børing (2015)	Norwegian firms	Process or product innovation dummies	Continuous-time competing risk model	Insignificant for exit, positive for mergers and acquisitions	No
Boyer and Blazy (2014)	Micro French firms	Innovation dummy	Continuous-time Cox proportional hazard model	Negative	No
Cefis and Marsili (2012)	CIS: Dutch firms	Innovator/non-innovator dummy; Process or product innovation dummies	Discrete-time multinomial logit; complementary log-logistic	Positive	Yes
Colombelli et al. (2013)	French manufacturing firms	Co-occurrence of technological classes in patent applications	Continuous-time parametric duration model	Positive	No
Colombelli et al. (2016)	CIS and INSEE: French firms	Dummies for process and product innovations, separately and jointly	Continuous-time parametric duration model	Positive when process, insignificant when product and positive when both	No
Fernandes and Paunov (2015)	Chilean plant level data	Single-product and diversified innovators	Discrete-time probit, logit, complementary log-log, continuous-time Weibull	Positive if diversified, negative if single-product innovation	Yes
Giovanetti et al. (2011)	Italian firms	Innovation and R&D dummies	Continuous-time Cox proportional hazard model	Positive if R&D, insignificant if innovation dummy	No
Helmers and Rogers (2011)	High- and medium-tech start-ups in the UK in 2000	Patents (EPO and UK) and trademarks	Discrete-time probit	Positive	No
Hyytinen et al. (2015)	Finnish start-ups	Single dummy for process and product innovation and innovation-active firm	Discrete-time probit	Negative. The negative effect is exacerbated by higher risk appetite	No
Kim and Lee (2016)	Korean firms	R&D intensity and stock	Parametric hazard model	Positive	Yes
Ortiz-Villajos and Sotoca (2018)	200 selected UK firms	Significant innovations (SI), patented (SI-P) and unpatented (SI-UP) significant innovations	Continuous-time parametric duration models	Positive and consistently significant effect if SI; Positive but partly significant effect if SI-UP.	No
Tsvetkova et al (2015)	1803 US start-ups in 1991; computer and electronic product manufacturing.	Log of patent applications at the metropolitan area level	Continuous-time parametric duration models	Negative for full sample, insignificant for firms established with 4+ employees	Yes
Ugur et al. (2016a)	UK firms	R&D intensity	Continuous-time parametric duration models	Inverted-U; complementarity with industry concentration	Yes
Wojan et al (2018)	US firms	Far-ranging / incremental innovation	Discrete-time complementary log-logistic model	Both positive, larger for far-ranging innovation	No
Zhang and Mohnen (2013)	Chinese firms	R&D intensity, product innovation	Complementary log logistic	Inverted-U for both R&D intensity and product innovation	Yes

Table A3: Innovation and productivity studies based on Griliches-type knowledge capital model (post-2013)

	Sample	Innovation measure	Estimator	Effect on productivity	Comments
Altomonte et al. (2016)	French, German, Italian and Spanish manufacturing firms	R&D dummy	Simultaneous equations without instruments	Positive without instruments, reverse causality between productivity and R&D	TFP regressions.
Andrew (2019)	Compustat firm data	R&D expenditures	Skedastic regressions	R&D effects both level and volatility of TFP over life cycle. Insignificant effect over two periods.	Production function with stochastic knowledge accumulation.
Belderbos et al. (2015)	Dutch firms	Domestic (own) R&D and foreign (outsourced) R&D	System GMM estimator	Inverted-U for both; both are complementary only among firms close to technology frontier.	Production function augmented with lagged dependent variable, and own and outsourced R&D.
Bond and Guceri (2017)	Large UK firms	R&D capital R&D dummy	OLS and system GMM	Positive effect on productivity	The effect is larger if the firm is affiliated and group members are R&D-active in the same sector
Castellani et al. (2019)	Firms in EU Industrial R&D Scoreboard	R&D capital and physical capital per employee	Pooled OLS and fixed effects	Positive effects of both, but effects of R&D capital is higher among US firms.	Labour productivity as dependent variable
Kancs and Siliverstovs (2016)	Firms in EU Industrial R&D Scoreboard	Share of R&D investment in total capital expenditures	Generalised propensity score estimations of treatment effects	Positive but not monotonic; larger effects in high-tech sectors; Insignificant or negative effects at very low levels of R&D intensity	The effect follows a prolonged inverted-U shape; firms in high tech sectors invest more in R&D and secure higher productivity gains.
Máñez et al. (2015)	Spanish manufacturing firms	R&D investor and exporter dummies	Simultaneous equation modeling for the production function; OLS and system GMM for productivity estimates	Both R&D and export have positive productivity effects; R&D investment and exporting are complements	Productivity effects of R&D and exporting are slightly smaller when market power is controlled for.
Ortega-Argilés et al. (2015)	US and European firms	R&D capital stock	Pooled OLS, FE	Positive effect, the effect is larger in high-tech industries	Estimates from pooled OLS are systematically larger. Consistent with earlier findings where within estimators yield smaller estimates.

Table A4: Innovation and productivity studies based CDM model (2010 or before)

Study	Sample	Method	Output measure	Innov measure	Estimated impact of innovation
Benavente (2006)	Manf. firms, Chile	CDM model: ALS	Log VA per emp	Log innovative product sales per employee (IPSE)	0.18*
Crépon, Duguet, & Mairesse (1998)	Innovative firms, France	CDM model: ALS	Log VA per emp	Log IPSE	0.065***
Griffith, Huergo, Harrison, & Mairesse (2006)	CIS3: Manf. firms in France (FR), Germany (DE), Spain (ES), UK	CDM model: sequential with IV	Log sales per emp	Product and Process innov. dummies	FR: 0.07** process; 0.06*** product DE: 0.02 process; -0.05 product ES: -0.04 process; 0.18*** product UK: 0.03process; 0.06*** product
Janz, Loof, & Peters (2003)	CIS3: R&D-intensive manf. firms: Germany Sweden	CDM model: sequential with IV	Log sales per emp	Log IPSE, Process innov. dummy	DE: 0.27*** product; -0.14** process SE: 0.29*** product; -0.03 process
Jefferson, Bai, et al (2006)	R&D-active large firms, SMEs, China	CDM model: sequential with IV	Log sales per emp	Log IPSE	0.035***
Loof & Heshmati (2006)	CIS3:Manf, service, utility firms: Sweden	CDM variation: FIML on selection submodel; 3SLS; sensitivity analysis	Log VA per emp	Log IPSE, Process innov. dummy	Product: 0.12*** manf.; 0.09** service Process: -0.07*** manf.; -0.07 service
Loof, Heshmati, Asplund, & Naas (2001)	CIS2: Manf. Firms in Finland, Norway, Sweden	CDM variation: sequential with 3SLS	Log sales per emp	Log IPSE, Process innov. dummy	FI: 0.090 product; -0.029 process NO: 0.257*** product; 0.008 process SE: 0.148*** product; -0.148*** proc
Mairesse & Robin (2010)	CIS3 and CIS4: Manf. and serv. firms in France	CDM model: FIML for selection eqs; bivariate probit; IV	Log VA per emp	Product and process innov. dummies	Manf. 1998-2000: 0.41*** process; 0.05 product Manf. 2002-2004: 0.45*** process; -0.08 product Service: 0.27 process; 0.27 product
Mairesse, Mohnen, & Kremp (2005)	CIS3: Manf. firms in France	CDM & variations	Log VA per emp	Logit transform of IPSE, process dummy, other dummies	High-tech: 0.23* 0.07*** radical; 0.06*** process Low-tech: 0.05 *** -0.08* radical; 0.10 *** process

Table A4: Innovation and productivity studies based on CDM model (2010 or before) - continued

Study	Sample	Method	Output measure	Innov measure	Estimated impact of innovation
Masso & Vahter (2008)	CIS3 and CIS4: Manf. firms in Estonia	CDM variation: sequential with bivariate probit for innov	Log VA per emp	Product and process dummies	Product: 1998-2000: 0.21*** 2002-2004: 0.00 Process: 1998-2000: -0.06 2002-2004: 0.15***
Masso & Vahter (2008)	CIS3 and CIS4: Manf. firms in Estonia	CDM variation: sequential with bivariate probit for innov	Log sales per emp	Product and process dummies	Product: 1998-2000: 0.17** 2002-2004: 0.03 Process: 1998-2000: -0.03 2002-2004: 0.18***
Polder *et al*. (2009)	CIS 3.5 – 4.5: Manf. and serv. firms in Netherlands	Augmented CDM	Log VA per emp	3 innovation dummies (process product organizational) in isolation and combined	Product and process innovation insignificant - in isolation or jointly. Organizational innovation on its own has large postive effect: 1.65 *** in manufacturing Organizational and process innovation combined has the largest effect in services: 17.11***
Raffo, Lhuillery & Miotti (2008)	CIS3 manf. firms in Argentina (AR), Brazil (BR, Mexico (MX), France (FR), Spain (ES), Switzerland (CH)	CDM model: sequential with IV	Log sales per emp	Product and organizational innov. dummies	Product innovation: AR: -0.22; BR: 0.22***; MX: 0.31***; FR: 0.08**; ES: 0.16***; CH: 0.10* Organizational innovation: Insignificant, except BR:0.054***
Siedschlag, Zhang, and Cahill (2010)	CIS3, CIS4: Irish firms	CDM variation: sequential with IV	Log sales per emp	Product, process, and organizational dummies, IPSE - all separately	IPSE: 0.11*** ; Product: 0.45*** ; Process: 0.33*** Organizational: 0.61***
van Leeuwen & Klomp (2006)	CIS2: Innovative firm in Nether- lands	CDM variation: 3SLS	Log sales per emp	Process dummy; innov sales share	Product innovation: 0.13*** Process innovation: -1.3***

Adapted from Hall (2011: Appendix). Notes: CDM = Crépon, Duguet, Mairesse model described in text. IPSE = innovative product sales per employee. ALS = asymptotic least squares on multi-equation model. 3SLS = three stage least squares. GMM = Generalised method of moment; FIML = full information maximum likelihood on multivariate normal model. OLS = ordinary least squares. IV = instrumental variable estimation. *, **, *** indicate significance at 10%, 5% and 1%.

Table A5: Innovation and productivity studies based on CDM model (post-2010)

Study	Sample/country	Method	Output measure	Innovation measure	Productivity effects of innovation (elasticity/semi-elasticity)
Aboal and Garda (2016)	Manf. and services firms in Uruguay. Two waves of services and manf. surveys	CDM with Heckman selection in stage 1; bivariate probit second stage; sequential	Log sales per employee	Product and process (technological) innovation dummy; Organisational and marketing (non-technological) innovation dummy	Predicted innovation expenditures Positive and large effect in full sample (0.489) and among small firms (0.756) Predicted technological and non-technological innovation Productivity differentials larger than 1. Productivity differentials are larger with non-technological innovation
Aboal and Tascir (2018)	Manf. and services firms in Uruguay. Two waves of services and manf. surveys	CDM with Heckman selection in stage 1; bivariate probit second stage; sequential	Log sales per employee	ICT investor dummy; Organisational and marketing innovator dummy	Predicted ICT probability Positive effect in services only (0.159) Predicted technological and non-technological innovation Productivity differentials large (> 1) with predicted non-tech innovation in services. Productivity differentials are negative (< - 1) with predicted non-tech innovation in manufacturing
Aboal et al. (2019)	Farm survey data in Uruguay, one wave	CDM variation: Sequential estimation of two models, OLS	Log of sales per hectare	Ratio of farm's innovation activities to total number of activities in the survey	Predicted innovation activity ratio Positive and larger effect (> 2); Effect similarity in Oilseed & grain and beef & cattle farms
Acosta et al. (2015)	Food and beverages firms in Spain	CDM variation: sequential with trivariate probit for innovation	Log sales per emp	Product, process and org. innovation dummies	Product innovation: positive Process innovation: insignificant Organizational innovation: positive and larger Combined: positive and larger
Alvarez et al. (2015)	Manf. and services firms in Chile, two waves of Chilean innovation survey	CDM with Tobit in stage 1; IV probit second stage; sequential	Log sales per emp	Product or process innovation dummy	Product innovation: negative effect in manufacturing, positive effect in services Process innovation: Positive effect in manufacturing, negative effect in services
Bartelsman et al. (2017)	Micro moments database (MMD) aggregated data	CDM variation: sequential with tivariate probit for innovation	Log VA per emp	Dummies of ICT use for: Resource Planning (ERP); Customer Resource Management (CRM); and Supply Chain Management (SCM)	Positive productivity effects The effect is larger as more ICT uses are combined.

Table A5: Innovation and productivity studies based on CDM model (post-2010) – continued

Study	Sample/country	Method	Output measure	Innovation measure	Productivity effects of innovation (elasticity/semi-elasticity)
Baum et al. (2017)	CIS Panel of Swedish manufacturing firms 2008-2012	CDM variation: Generalized Structural Equation Model (GSEM) estimation of tivariate probit for innovation with FIML.	Log VA per emp	Logit of innovative product sales per employee (Log IPSE)	Productivity effects are positive but differ by level of technology and knowledge intensity. Lager effects 0.10 to 0.13 in high-tech manufacturing and knowledge intensive services Smaller effects (0.02 to 0.05) in the rest.
Castellaci (2011)	CIS3, CIS4, CIS5 panel of Norwegian firms	CDM augmented with competition; sequential estimation; bivariate probit for innov; IV in stage 3	Log sales per emp	Log IPSE	Positive effect ranging from 0.242 to 0.552 Smaller effects among firms in more concentrated industries
Crespi and Zuniga (2912)	Innovation surveys in 6 Latin American countries, four waves	CDM variation: sequential estimation; bivariate Tobit for innovation; IV in stage 3	Log sales per emp	Process or product innovation dummy Log IPSE	Predicted innovation dummy and IPSE Positive effect Effect is larger when innovation dummy is used Effects are larger in Colombia and Panama compared to Argentina, Chile and Uruguay
Damijan et al. (2011)	CIS and accounting data for a panel of Slovenian firms from 1996-2002	CDM variation: ALS estimation Plus propensity score matching	Log VA per emp.	Innovation dummy (any of process or product innovation)	Positive and large (0.93) effect on labour productivity in ALS estimation Insignificant effect on TFP in growth accounting and matching estimations.
Demmel et al. (2017)	World Bank Enterprise survey data for Argentina, Mexico, Colombia and Peru; two waves	CDM: sequential Multivariate probit; Joint estimation of innovation and output equations	Log sales per emp	Process or product innovation dummy; or both	Product innovation Positive in Argentina and Mexico; insignificant in Colombia and Peru Process innovation Insignificant in all samples
Hall & Sena (2017)	ONS and CIS firm-level data 1998-2006	CDM augmented with intellectual property protection measures; trivariate probit; simultaneous estimation	Log sales	Dummies for process and product innovation interacted with formal and informal IP measures	Process innovation: Full sample Process innovation itself: insignificant Interaction with formal IP: insignificant Interaction with informal IP: insignificant Interaction with both: Positive significant Product innovation: Full sample Product innovation itself: insignificant Interaction with formal IP: Positive significant Interaction with informal IP: insignificant Interaction with both: Positive significant All above are either insignificant or negative in manufacturing.

Table A5: Innovation and productivity studies based on CDM model (post-2010) – continued

Study	Sample/country	Method	Output measure	Innovation measure	Productivity effects of innovation (elasticity/semi-elasticity)
Hall et al. (2013)	Unicredit survey of Italian firms, waves 7 to 10	CDM variation: sequential estimation with quadrivariate probit for innovation, IV	Log sales per emp.	Product, process and org. innovation dummies; R&D and ICT intensity per employee	Predicted process or product innovation Insignificant. R&D and ICT intensity Positive; but ICT effect < R&D effect. R&D and ICT: Neither complements nor substitutes.
Halpern & Muraközy (2012)	CIS of Hungarian firms; two waves; matched with alance sheet data	CDM variation: Heckman selection in stage 1 and 2; predicted innovation	Log sales per emp.	Innovation (any of process or product) dummy; Innovation engagement dummy	Predicted process or product innovation dummy Insignificant effect with one innovation dummy Positive effect (0.1 – 0.5) with both dummies Effect is smaller in high-tech industries.
Hashi & Stojčić (2013)	CIS4 data for 16 European countries	CDM variation: Joint estimation of Tobit for innovation with ML; 3SLS estimation of output model	Log sales per emp.	Log IPSE	Positive effect in both Western European and CEEC samples. Effect is larger in WE sample.
Moris (2018)	Panel of World Bank Enterprise Survey data, firms from 43 countries	CDM model: sequential with IV	Log sales per emp.	Innovation dummy	Positive effect in both cross-section and panel estimations The effect in cross-section is larger
Peters et al. (2017a)	Manheim Innovation Panel data high-tech manufacturing firms in Germany	CDM variation: dynamic model with stochastic productivity	Log sales per emp.	Process and product innovation dummies; the latter combined	Process or product innovation: Positive (0.039 and 0.037), but smaller than most estimates in the field. Process*product innovation: Insignificant
Peters et al. (2017b)	Manheim Innovation Panel data high- and low-tech manufacturing firms in Germany	CDM variation: dynamic model with stochastic productivity	Log sales per emp.	Process and product innovation dummies; the latter combined	High-tech: Positive (0.029 for product and 0.036 for process innovation). Low-tech: Process innovation significant (0.035); product innovation insignificant.

Table A5: Innovation and productivity studies based on CDM model (post-2010) – continued

Study	Sample/country	Method	Output measure	Innovation measure	Productivity effects of innovation (elasticity/semi-elasticity)
Peters et al. (2018)	CIS of services firms in Germany, Ireland and UK, one wave	CDM augmented with non-technological innovation, Probit est. of innovation output, stochastic productivity	Log sales per emp.	Technological (process and product) innovation Non-technological (organizational and marketing) innovation	Technological innovation: Product and process innovation: positive and significant in Germany and UK, only process is significant in Ireland). Non-technological innovation: Same patterns as above; but effects are larger
Ramírez et al. (2019)	Colombian surveys of manufacturing firms	CDM augmented with human capital; sequential; OLS followed with bivariate probit, IV	Log sales per emp.	Predicted prob. of process or product innovation; Predicted R&D investment	Predicted process or product innov: Positive. Predicted R&D investment: Positive but smaller. Effect of predicted innov. is larger in large firms. Effect of predicted R&D is smaller in large firms
Raymond et al. (2015)	CIS data for Dutch and French firms, three waves	CDM variation: Joint estimation of innovation with FIML	Log sales per emp.	Product innovation dummy Log IPSE	Predicted innovation measures: positive effect, statistically not different in both countries Observed innovation measures: Product innov effect is larger in Netherlands IPSE effect is larger in France
Moris (2018)	Panel of World Bank Enterprise Survey data, firms from 43 countries	CDM model: sequential with IV	Log sales per emp.	Innovation dummy	Positive effect in both cross-section and panel estimations The effect in cross-section is larger
Tello (2015)	Small sample of manufacturing firms in Peru	CDM model: sequential Probit or Heckman selection for innovation; Predicted innovation in productivity equation	Log sales per emp.	Technological, non-technological innovation dummies; Log IPSE	Only log IPSE is significant. The effect is positive or negative, depending on Heckman selection specification Techn. and non-tech. innovation insignificant

Notes: CDM = Crepon, Duguet, Mairesse model described in text; CIS = Community Innovation Survey; ICT = Information and communication technologies; IPSE = innovative product sales per employee; TFP = total factor productivity. Estimators: ALS = asymptotic least squares on multi-equation model; FIML = full information maximum likelihood estimation of multivariate normal models; OLS = ordinary least squares; IV = instrumental variable estimation; 2/3SLS = two/three stage least squares.