

Contributions of Product Innovation, Process Innovation, and R&D to Firm Growth

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ABSTRACT

Despite its firms' regional leadership, South Africa faces extreme unemployment and inequality. This study examines the innovation divide between 'established' and 'emerging' firms, analyzing a national dataset across industries to assess disparities in R&D, product innovation, and process innovation. Findings reveal that innovation activities, critical for growth, are dominated by older, larger, and market-concentrated firms, limiting access for smaller, younger firms. This skewed innovation landscape exacerbates inequality, as emerging firms struggle to leverage innovation for employment creation and inclusive growth. The study identifies systemic barriers that constrain innovation's developmental impact and proposes mechanisms to democratize its benefits. By mapping key structural challenges, we highlight policy interventions to bridge this divide, ensuring broader participation in innovation-driven economic transformation. These insights contribute to a deeper understanding of innovation dynamics in developing economies and offer actionable strategies for equitable, sustainable growth.

Keywords: Innovation; industries; R&D; product/process innovation; productivity growth, employment growth, sales growth

1. Introduction

Paradoxically, despite its firms' regional leadership, South Africa has among the world's highest levels of unemployment and inequality, which are largely unchanged despite the advent of democracy in 1994 (Adeleye et al., 2020; Francis & Webster, 2019; Plagerson, 2023; Sulla & Zikhali, 2018). Accordingly, it is unclear to what extent these high levels of unemployment and inequality prevail due to an environment dominated by oligopolistic or monopolistic firms with high market concentration.

South Africa's firms' high market concentration persists due to a history of monopolistic, oligopolistic, and anti-competitive practices (Buthelezi et al., 2019; Fedderke & Szalontai, 2009; Heijden & Vink, 2013; Kaplinsky & Manning, 1998; Kruger et al., 2021; Okeahalam, 2002; Wesson, 2021; Wouters et al., 2019). At least 70.45% of the country's firm sectors have defined markets with dominant firms, reflected in a relatively high market concentration Herfindahl-Hirschman Index of 2986 (Buthelezi et al., 2019). Similarly, the country scores lowest in the world's Global Entrepreneurship Monitor category of lower-income countries in entrepreneurial intentions and lowest on average in entrepreneurial environmental conditions or Entrepreneurial Framework Conditions (GEM, 2023).¹ Accordingly, due to relatively high market concentration and low levels of entrepreneurship, and, therefore, innovativeness, the country's firms' contributions to reducing unemployment and inequality may be sub-optimal.

How might these contributions be improved? In highly market-concentrated contexts, innovation can disrupt monopolistic or oligopolistic markets, increasing inclusiveness and thereby contributing to societally beneficial outcomes (Christensen et al., 2006; Christensen et al., 2018;

¹ Sampling based on the question: 'Are you expecting to start a business in the next three years? (% of adults responding yes)' Page 46 of Global Entrepreneurship Monitor 2022/2023 Global Report. The 13 Entrepreneurial Framework Conditions include entrepreneurial finance and access to it, government policy support and relevance, government policy regarding taxes and bureaucracy, government entrepreneurial programs, school and post-school entrepreneurial education, R&D transfers, commercial and professional infrastructure, ease of entry regarding market dynamics and burdens and regulation, physical infrastructure, and social and cultural norms.

Christensen et al., 2013). Schumpeterian ‘creative destruction’ can disrupt monopolistic or oligopolistic processes and markets, thereby increasing competitiveness and productivity, and generating net firm and economic growth (Griliches, 1979; Pakes & Griliches, 1984; J. A. Schumpeter, 1942). Individuals or smaller firms have been described as more disruptive or innovative (Schumpeter, 1934), a perspective described as ‘Schumpeter Mark I’, yet innovative behaviour has also been described as driven primarily by the more routinised behaviours of larger firms (J. A. Schumpeter, 1942), or ‘Schumpeter Mark II’, and these theoretical debates persist (Henrekson et al., 2024).

Accordingly, despite a high market concentration that seemingly constrains the contributions of firms to employment and equality, and despite the potential of innovation to improve these contributions, without appropriate theoretical guidance, it is unclear from the literature to what extent more ‘*established*’ firms, that are *more market-concentrated*, and that might usually also be expected to be *larger*, and *older*, dominate ‘*emerging*’ firms, defined here as typically *less market-concentrated, younger, and smaller*, or *vice versa* in terms of *growth- in employment, sales, and productivity*. It is also unclear whether established or emerging firms dominate in the effectiveness of their use of the chain of innovative activities driving growth, to which both may be vulnerable to disruption, namely *investment in research and development (R&D), spending on R&D, product innovation, and process innovation*.

Hence, in line with previous studies in other contexts that use the same empirical approach (Castellacci, 2011; Crepon et al., 1998; Griffith et al., 2006; Lööf et al., 2017; Mairesse et al., 2005; Notten et al., 2017), contributions are decomposed and tested along this chain of firm innovation activities to render ‘visible’ a holistic perspective of these relationships. This advances theory through tests of theoretical predictions. In taking this approach, the work contributes to literature in several ways, as discussed in the following section.

Having outlined the paper's objective, it proceeds as follows. Section 2 considers contributions to literature. Section 3 discusses the country's historical context of high market concentration and incumbent advantage and derives hypotheses. Section 4 introduces methods. Findings are reported in Section 5 and discussed in Section 6. Section 7 discusses limitations and avenues for further research. Section 8 concludes.

2. Contributions

The study contributes to the literature in the following main ways. First, we advance theory regarding the chain of innovative activities contributing to growth by identifying theoretical boundary conditions that differ according to context. Accordingly, we contribute to debates regarding how firm innovation is influenced by geographical (Amin & Cohendet, 2005; Arauzo-Carod, 2021; Bignami et al., 2020; Lorenzen, 2005), regional (Andersson & Karlsson, 2007; Baumgartinger-Seiringer et al., 2021; Broekel & Binder, 2007; Cruz-Castro et al., 2018; M. Fritsch, 2003; Onsongo, 2019; Rypestøl et al., 2022) , or other contextual influences (Roper & Love, 2018). More specifically, we advance specific theoretical understandings of how firm innovation activity is influenced by firm characteristics (Montresor & Vezzani, 2016), including firm size (Perez-Alaniz et al., 2023), firm age (Garnsey et al., 2006; Kishna et al., 2017), and market concentration (De Vries et al., 2017). In so doing, we comparatively identify differences in influences on the chain of innovative activities contributing to growth, and the relative dominance of this chain by established versus emerging firms.

Second, we contribute to theoretical understandings of innovation by testing specific predictions of disruptive innovation theory (Christensen et al., 2006; Christensen et al., 2018; Christensen et al., 2013) in a relatively unique context that seemingly reflects a status quo associated with the dominance of incumbent firms and the influence of historical contextual factors. Accordingly, we ask whether the context is sufficiently innovative, or *inclusive in how it rewards smaller and newer firms, thereby contributing to societal equality between firms*. In doing so, the work contributes comparative

insights to the closest recent studies, including those that have used the Crepon-Duguet-Mairesse (CDM) methodology, or adapted it for use in South Africa (Baiyegunhi et al.; Gaglio et al., 2022; Kamutando & Tregenna, 2023) and other contexts such as for example, China (Gong & Wang, 2022), Columbia (Albis Salas et al., 2023), Chile (Montégu et al., 2022), Nigeria (Edeh & Acedo, 2021), Pakistan (Ullah et al., 2023), Poland (Yaghi & Tomaszewski, 2023), Russia (Mariev et al., 2023), and Tunisia (Ben Khalifa, 2023), amongst others.

In testing predictions of disruptive innovation theory, the study here extends the closest of these previous studies in South Africa to consider *why this context of firms is so market concentrated*, and therefore *why firms are not contributing as effectively as they could to reducing unemployment and inequality*. These findings offer important insights into innovation's contributions to development.

In the absence of other country-specific data, this study uses a sample of the country's firms from the 2019/2020 World Bank Enterprise Survey (WBES)², in the period preceding its Covid-19 pandemic lockdowns and disruptions. This work therefore extends similar recent studies in different contexts using a similar approach based on the WBES methodology (Broome et al., 2018; Mohan et al., 2018; Urbano et al., 2024), more specifically, studies including those of Kamutando and Tregenna (2023) and Gaglio et al. (2022) using survey data for manufacturing firms in Johannesburg, to test characteristics of the country's population of firms. Using a more nationally representative sample, we are able to investigate specific theoretical channels and relationships between innovation activities and firm growth as potential levers to challenge the status quo and improve firm inclusiveness and diversity, thereby contributing to development. By deriving a typology, or a 'map' of how chains of innovation activities act together on growth, we extend other previous similar studies using well-established methods and techniques (Castellacci, 2011; Crepon

² We thank the Enterprise Analysis Unit of the Development Economics Global Indicators Department of the World Bank Group for making the data available.

et al., 1998; Griffith et al., 2006; Lööf et al., 2017; Mairesse et al., 2005; Notten et al., 2017). Theory and literature is now introduced to contextualise the study.

3. Theory and literature

3.1. High market concentration and incumbent advantage

Despite South Africa's democratic transition of 1994, and the implementation of its Competition Act of 1998 to increase economic inclusion and address monopolistic and anticompetitive practices, its historical legacy of social and economic inequality persists in a highly concentrated Herfindahl-Hirschman Index (Buthelezi et al., 2019). Contextually, the country's relatively low levels of entrepreneurial activity (GEM, 2023) 'fits' poorly with the innovative behaviours of firms with high entrepreneurial orientation (Lumpkin & Dess, 1996).

Disruptive innovation theory suggests specific channels or mechanisms smaller and younger firms with less initial market concentration might use to disrupt incumbent markets, or *vice versa* (Christensen et al., 2006; Christensen et al., 2018; Christensen et al., 2013). Innovations will however typically be undertaken along a chain of innovative activities, such as R&D, product innovation, and process innovation (Castellacci, 2011; Crepon et al., 1998; Griffith et al., 2006; Lööf et al., 2017; Mairesse et al., 2005; Notten et al., 2017), thereby contributing to firm growth primarily in employment, sales, or productivity.

Under certain conditions, disruption of highly oligarchic and monopolistic markets and practices can create a more inclusive and competitive context. Schumpeterian creative destruction can be research-driven, by firms' innovative activities, and although some value is destroyed, on balance, more value should typically be created than lost (Aghion et al., 2015; Aghion & Howitt, 1992). Accordingly, disruption leads to better productivity 'recipes' and the net value contributed by R&D and process or product innovations result in more varieties (Romer, 1990) or improvements in the quality of goods and services (Grossman & Helpman, 1991).

Research, in the form of ideas of how to improve productivity, therefore generates net growth even when disrupting established processes or markets (C. I. Jones, 2019; Romer, 1990). Knowledge of how to improve productivity is non-rivalrous- its use by one does not diminish its usefulness to another, and it can be shared, at little or no cost (Romer, 1990). Hence, as these disruptive ideas are shared, productivity gains spread out, driving growth at scale. Consequently, because these shared ideas lead to improved and more efficient combinations of resources (such as labour and capital), more goods and services should over time be produced with the same or fewer resources, potentially giving rise to exponential growth. Knowing how disruption might increase inclusiveness and diversity amongst the country's firms may be key to unlocking their potential contributions not only to their own growth, but also to societal employment growth and equality.

3.2. Context and fit with the chain of innovation activities

A country's institutions- the formal and informal rules that organize social, economic, and political relations between people- are shaped by the contextual environment within which its firms operate (Acemoglu et al., 2001; Acemoglu & Robinson, 2012; North, 1990). Therefore, political uncertainty, corruption, or crime can affect the quality of a country's socioeconomic context if firms divert productive resources or activities to non-productive activities, including those political, rent-seeking, or even security-related (C. Jones & Vollrath, 2013).

Firms can be vulnerable to poor institutional climates (Acemoglu & Robinson, 2012; Cuervo-Cazurra, 2016; Daniel et al., 2018; North, 1990; Salahuddin et al., 2020). It is therefore unclear how institutional forces in this context shape decisions about R&D investment and process or product innovation, or what the consequences of these institutional forces are for innovation and firm growth. It is also unclear if larger and more established firms are less or more vulnerable to institutional forces, and what is the fit between innovative activities themselves in this context. Given countervailing influences, tests of theoretical predictions regarding the chain of firm innovative activities here are expected to reveal patterns, or net overarching influences.

R&D can be positively associated with firm growth in sales (Chang & Su, 2010; Chung et al., 2019; García-Manjón & Romero-Merino, 2012; Spescha, 2019), employment (Evangelista & Savona, 2002; Vivarelli, 2013; Vivarelli, 2014; Vivarelli et al., 1996), and productivity (Chudnovsky et al., 2006; Kanacs & Siliverstovs, 2016; Wakelin, 2001). Investments in R&D can in turn spur product and process innovations to boost a firm's productivity (Crepon et al., 1998; Mairesse et al., 2005; Mairesse & Robin, 2017; Notten et al., 2017).

Whereas product innovations can increase productivity, sales, and employment, process innovations can increase productivity but decrease employment (Vivarelli, 2014). Labour-replacing process improvements can therefore increase unemployment. More innovative firms are expected to use R&D to disrupt incumbent markets, but it is unclear whether this comes at the expense of employment.

Crepon et al.'s (1998) CDM model can inform these types of understandings of how research and innovation contribute to firm growth. It suggests firms invest in R&D to develop product and process innovations, which in turn contribute to productivity and other firm outcomes (Crepon et al., 1998). The CDM approach not only captures the theoretical structure of relationships between innovation and firm growth and differentiates inputs from outputs but can also be used to mitigate some biases in estimations. Separate structural equations are used to mitigate bias arising when a relatively small proportion of a sample of firms invests in R&D, an effect that can bias ordinary least squares (OLS) estimations (Crepon et al., 1998). Selection bias can occur if a minority of firms "self-select" into the sample used to predict R&D spending. Simultaneity bias can also occur when OLS results cannot discern whether innovation causes productivity or whether productivity is causing innovation (reverse causality) (Crepon et al., 1998), and the CDM model offers an approach to mitigate biases in these estimations.

As discussed, CDM theory predicts positive impacts of innovative activities in a firm along a clear causal chain: starting with R&D choices, followed by the extent of R&D investment, leading to

product innovation, process innovation, and ultimately higher firm growth. Accordingly, we hypothesize the existence of these linkages in empirical testing. Regarding characteristics of incumbent firms such as market share, firm age, and firm size, it is however unclear in this context *under what conditions these innovation-growth linkages are stronger or weaker according to each of these three dimensions that differentiate emerging from established firms*. It is also unclear what the implications are of differences in these contributions, but patterns in these linkages are expected to offer theoretical understandings of the mechanisms involved in this chain of activities.

3.3. Hypotheses

This context has historically favoured market concentration (Buthelezi et al., 2019; Fedderke & Szalontai, 2009; Heijden & Vink, 2013; Kaplinsky & Manning, 1998; Kruger et al., 2021; Okeahalam, 2002; Wesson, 2021; Wouters et al., 2019), and it is unclear to what extent emerging or established firms have a better innovative, or entrepreneurial ‘fit’ with this context, to use Lumpkin and Dess’s (1996) terminology. Testing the contributions of market share, firm age, and firm size to growth (in productivity, employment, and sales) along the chain of innovation activities (of R&D investment choice, the extent of R&D investment, product innovation, and process innovation) are therefore expected to provide a test of this ‘fit’, and any advantage of established or emerging firms.

Similarly, as discussed, under certain conditions disruptive innovation can reduce societal inequality (Christensen et al., 2006), but although hypothesised here, it cannot be assumed, *a priori*, that societally beneficial growth, including in employment, in this context is primarily driven by younger and smaller firms that are yet to establish market dominance. A nuanced understanding of these relationships is needed to inform stakeholder and policy concerns.

Whereas firm growth in sales, and productivity contributes directly to country-level growth, growth in firm employment is expected to reduce inequality. Interestingly, recent work suggests societal inequality might also be associated with differences between rather than within firms

(OECD, 2015; Song et al., 2019). The analysis here focuses on differences between firms. It is unclear if emerging firms grow their employment or their sales and productivity faster than established firms, *or vice versa*. If the growth of emerging firms can reduce the market concentration and monopolistic, oligopolistic, or anti-competitive characteristics associated with this context (Buthelezi et al., 2019; Fedderke & Szalontai, 2009; Heijden & Vink, 2013; Kaplinsky & Manning, 1998; Kruger et al., 2021; Okeahalam, 2002; Wesson, 2021; Wouters et al., 2019) then their growth might be societally beneficial.

Disruptive innovation theory predicts that simpler, cheaper, and more innovative, or niche products, can disrupt incumbent markets (Christensen et al., 2006; Christensen et al., 2018; Christensen et al., 2013). Although most smaller and younger firms will not become fast-growing ‘gazelles’ (Eklund & van Crieking, 2022), they need to apply innovative activity to survive and grow within an emerging economy ecosystem (Yildirim et al., 2022).

Excessive bureaucracy and strategic inflexibility of incumbents can be exploited by smaller and more innovative firms using strategies such as lean start-up methodologies (Mansoori et al., 2019), minimum viable product approaches (Tripathi et al., 2019), better customer responsiveness, and customer-led innovations (von Hippel & Euchner, 2013). Activities along the chain of R&D, product innovation, and process innovation should contribute to these efforts, resulting in employment, sales, and productivity growth through improved product development and better organisational efficiencies.

Contextual uncertainties in developing contexts require strategic agility (Ahammad et al., 2021; Tarba et al., 2023), and firms can leverage alliances and networks to take advantage of ecosystem networks (Su et al., 2018; Tsujimoto et al., 2018; Yildirim et al., 2022), advantaging more agile firms. New firms can benefit from a focus by incumbents on sustaining innovation (Audretsch, 2004) to maintain market shares, in that incumbents may be less inclined to undertake disruptive innovations that disrupt their own market dominance.

Productivity, sales, and employment growth is expected to be more sensitive to innovation in firms with greater absorptive capacity (Cohen & Levinthal, 1990). Notwithstanding advantages associated with absorptive capacity and learning by doing (Haus-Reve et al., 2023), older and larger firms may struggle to enhance the appropriability of their investments in innovation for other reasons. For example, managers are often incentivized to generate growth for its own sake, by maximizing the firm's size subject to profitability (Baumol, 1959; Marris, 1963; Williamson, 1964). Similarly, agency theory (Jensen & Meckling, 1976) predicts owner and shareholder interests can be subordinated to growth over time if compensation and bonuses are linked to firm size.

Cutting-edge technological advances in digital transformation and artificial intelligence (AI) (Taherizadeh & Beaudry, 2023) and digital platforms can offer smaller and younger firms opportunities to level the competitive playing field (Akpan et al., 2021; Akpan et al., 2022). Technological innovations can bypass traditional intermediaries and challenge incumbents, tipping the scales in favour of firms using disruptive innovation (Christensen et al., 2006; Christensen et al., 2018; Christensen et al., 2013). New and smaller firms might also be better able to take advantage of shifting environmental forces and become first movers in pursuing new opportunities. As discussed, if they demonstrate higher competitive aggressiveness, proactiveness, risk taking, autonomy, and innovativeness (Lumpkin & Dess, 1996), then their EO might be a better match, or fit, with an environment of changing technological conditions and new opportunities.

Of course, given the multiple and countervailing theoretical mechanisms that explain incumbent advantages over new entrants, and *vice versa* (van Mossel et al., 2018), both challengers and incumbents could be expected to harness them and be as ambidextrous as possible, to ensure innovativeness without compromising implementation, or other aspects of their operations (O'Reilly & Tushman, 2013). Not only invention, but imitation is therefore also important, both to ensure access to information and maintain competitive rivalry (Wang et al., 2022), and a firm's

innovative capabilities will help it to both generate new ideas and to benchmark or imitate those of competitors. Based on the discussions above, the following hypotheses are derived, which, on balance, posit a theoretical advantage for emerging firms.

Hypothesis A. *Market share is significantly and negatively associated with firm innovation and growth.* Market share, or the extent to which a firm dominates its primary market, is expected to differentiate larger and older established firms from smaller and younger emerging firms in this context. As discussed, firm innovation refers to R&D investment choice, the extent of R&D investment, product innovation, and process innovation, which represent a sequential chain of innovation activities, as theorised and tested in previous work (Castellacci, 2011; Crepon et al., 1998; Griffith et al., 2006; Lööf et al., 2017; Mairesse et al., 2005; Notten et al., 2017). Firm growth refers to growth in employment, sales, and productivity. Subordinate Hypotheses A₁-A₇ relate to R&D investment choice, extent of R&D investment, product innovation, process innovation, growth in productivity, growth in employment, and growth in sales as outcomes, respectively. Subordinate hypotheses are stated in full in Table 3 and are not repeated here.

Also, according to the above discussions, Hypothesis B is derived, that *Firm age is significantly and negatively associated with firm innovation and growth.* The same approach is applied, with subordinate Hypotheses B₁-B₇ relating firm age to the same outcomes as Hypothesis A (also see Table 3).

Similarly, Hypothesis C is offered, that *Firm size is significantly and negatively associated with firm innovation and growth.* Again, subordinate Hypotheses C₁-C₇ relate to the same outcomes as Hypotheses A and B.

As discussed, these hypotheses are concerned with the extent to which incumbent characteristics differentiate firm contributions of R&D, as well as of process and product innovation, to productivity, employment, and sales growth. In this context, tests of firm growth are expected to pick up associations of firms with declining growth. A firm's growth therefore also represents its potential for resilience and survival (Coad, 2009). Even if some prefer not to grow, they typically

strive to avoid negative growth, and measures will pick up negative growth, thereby providing information about firm resilience. Interestingly, previous research suggests that firm startups in this context have been primarily opportunity-driven, incentivized by profits as opposed to a survivalist motivation (Naudé et al., 2008) unlike in the more survivalist informal sector (Callaghan, 2014a, 2014b). Methods are now introduced and discussed.

4. Methods

This section introduces the data and the empirical approach of the study.

4.1. Data

The study uses a sample of firms from the 2019/2020 South African World Bank Enterprise Group Survey, which sought to derive a sample of firms that was as representative of the population as possible (WBES, 2020). The unit of analysis is the firm, which to qualify for inclusion needed to have its own management, control over its workforce, and its own location. Stratified random sampling was undertaken of firms in the non-agricultural economy. Financial intermediation, real estate, renting, and public and utility sectors were excluded. Detailed information on sampling protocols and questionnaire items are available from WBES (2021). The universe of the study, and its total number of establishments by stratified regions, sectors, and sizes was tabulated using South African Treasury, Revenue Services, and United Nations Industrial Development Organization data, which the WBES team found to suggest an estimated population size of 150 000 firms with five or more employees. According to the World Bank Enterprise definition, firms are classified as small if they have between 5 and 19, medium with 20-99, and large with 100 or more employees. Given that the WBES is the only source of high-quality national firm-level data for South Africa as well as many other developing countries, this definition was maintained for comparative reasons. Firms differ by size in the extent to which their operations are formalized, and the World Bank differentiation was preferred in that many countries and

regions classify firm size differently. Analysis here includes about 900 firms that have full data for all tested variables. Table 1 includes a list of tested variables together with variable definitions.

A dummy variable is included for each firm that ended their financial year before or after May 2020. This is not a time series variable and is included only to control to some extent for any effects of lockdowns associated with the pandemic. A large majority (88.87%) of the 1042 firms in our total sample ended their financial years before this and although retained in all tests, this measure is not fully significant in any tested model. As a robustness check, an estimate was also included of the extent to which a firm provided access to documents to verify survey responses, or simply reported responses to survey staff, termed *precision*. This controls to some extent for sampling error variance arising from respondent reporting. In all tests, standard errors are clustered at the firm level to address heteroskedasticity.

Industry dummies are included. This is equivalent to industry fixed effects estimations, controlling for time-invariant industry characteristics. The growth variables are calculated as the percentage change from the second last financial year. This allows a test of within-firm variance in the outcome variables, which are essentially differenced, providing information about within-firm changes. It also reduces the likelihood of spurious correlations associated with the use of non-differenced dependent variable measures.

As discussed, there is currently no other known recent source of nationally representative high-quality data on South Africa's firms. The work here therefore mitigates publication bias (Adams et al., 2017; Franco et al., 2014) based on findings from studies using less representative samples and using single industry or convenience samples. In so doing, the work reduces under-representation of knowledge of South Africa's firm context. Cross-sectional data is not a problem for this work because it tests hypotheses relating to differences between firms, which are tested as predictions, not as causal estimations. In fact, the cross-sectional research design is the basis for the use of the

CDM model and its traditional use with cross-sectional data is to focus on differences between firms.

The use of the CDM model, and its Heckman process, therefore, allows more valid inferential tests of hypothesized differences between firms in cross-sectional data. Unlike a structural equation model, using different regressions to test CDM model linkages in the ‘standard’ way allows the inclusion of a larger set of control variables in the specification, reducing confounding omitted variable bias.³ The research design is therefore appropriately matched to the aim of the work, and to the only data currently available that allows a test of the appropriate hypotheses.

Over time, as longitudinal data on South African firms becomes available, different questions can be asked of the data, to build on findings here. Similarly, although the WBES study design maximizes representativeness as much as possible, future studies might undertake census sampling to improve this. The empirical approach is now discussed, and each of the tested structural equations are introduced.

4.2. Empirical approach

Our empirical approach is derived from CDM literature (Castellacci, 2011; Czarnitzki & Delanote, 2017; Griffith et al., 2006; Lööf et al., 2017; Mairesse et al., 2005; Mairesse & Robin, 2017; Notten et al., 2017) that extends Crepon et al.’s (1998) original work. In their seminal study, Crepon et al. (1998) derive their theoretical framework from Pakes and Griliches’s (1984) model.

The CDM model typically comprises four equations, two relating to R&D, one to innovation and one to productivity (Crepon et al., 1998). Adaptions of the CDM equations for this study are now described.

4.2.1. The Heckman model

³ The WBES survey is designed to be nationally representative and includes an extensive array of questions. This allows a uniquely large set of appropriate covariate variables to be tested here. Therefore, the WBES research design and scale of data collection reduces omitted variable bias.

The first equation assumes a latent dependent variable rnd_i for a firm i as follows:

$$rnd_i = \beta_0 + \beta_1 v_i + u_{0i} \quad (0)$$

where v_i represents a vector of predictors of undertaking R&D, β_0 is a constant term, β_1 a summary term representing coefficients associated with predictors and u_{0i} is the error term. The dependent variable is binary, rnd_i taking the value of 1 if a firm reports undertaking R&D and 0 otherwise. This estimation provides the first stage of the Heckman estimation eq(1). The inverse Mill's ratio term- the lambda, is included as a correction variable (Heckman, 1979) and is reported in Table A.1. in the Appendix. Accordingly, the lambda correction term is used in subsequent tests of the full sample as a control variable, in that it captures variance associated with variables that to some extent explain the choice of a firm to undertake R&D. Although this process cannot expunge endogeneity as it is not possible to obtain separate exclusion criteria variables outside of the same survey measures- a limitation of survey studies of this type- the use of the Heckman process does allow us to use a control variable that to some extent reduces omitted variable bias associated with self-selection.

Estimations of CDM models also typically need to take into account sectoral heterogeneity, or differences between industries (Baum et al., 2017; Hall & Sena, 2017). To control this the WBES industry dummies are included for the construction, hospitality, manufacturing, services, retail, and wholesale industries. Predictor variables included to test eq(0) in the first stage of the Heckman analysis include the following (see Table 1 for definitions of variables and information about how they are measured):

<i>marketshare</i>	=	Natural log of market share in leading market
<i>firmage</i>	=	Age of firm
<i>firmsize</i>	=	Size of firm
<i>foreigncomp</i>	=	0/1 Foreign competition
<i>political</i>	=	Political instability as obstacle to firm operations
<i>precision</i>	=	Extent of disclosure of records in sampling
<i>industry</i>	=	0/1 Industry dummies

Results of tests of eq(0)-eq(3) are reported in Table A.1. for the full sample, and Tables A.2.-A.4. for samples of small, mid-sized, and large firms, respectively. Table 2 summarizes these results and Table 3 provides an overview of results of hypothesis tests.

The dependent variable of the next equation eq(1) is also considered as a latent variable representing the intensity of research, or expenditure investments in R&D:

$$rndspend_i = \beta_0 + \beta_1 w_i + u_{1i} \quad (1)$$

In this specification, $rndspend_i$ is the natural log of the extent of investment in R&D by a firm that has met the minimum threshold required to decide to invest in R&D, as estimated in eq(0). In that eq(1) is estimated using Heckman's (1979) two-step estimation, included predictor variables differ. In eq(0), included explanatory variables are taken to predict the likelihood that a firm will chose to invest in R&D, and those in eq(1) include variables that predict the amount a firm will invest in R&D spending. In this model, β_0 is again the constant, β_i represents equation-specific coefficients associated with each predictor, w_i represents an equation-specific vector of predictors, and u_{1i} is the equation-specific error term. The two-step process uses the first stage estimated value of rnd_i as a predictor of $rndspend_i$. The following variables are included in the second step of the Heckman analysis, to estimate eq(1).

<i>marketshare</i>	=	Natural log of market share in leading market ⁴
<i>firmage</i>	=	Age of firm
<i>firmsize</i>	=	Size of firm
<i>foreigncomp</i>	=	0/1 Foreign competition
<i>political</i>	=	Political instability as obstacle to firm operations
<i>precision</i>	=	Extent of disclosure of records in sampling
<i>industry</i>	=	0/1 Industry dummies
<i>covid</i>	=	0/1 Financial year after Covid onset of lockdowns
<i>inverseMills</i>	=	Heckman Inverse Mills ratio term

4.2.2. Product/Process innovation

⁴ When using log transformations, 1 is added in order to avoid taking the log of zero values

To estimate associations of predictors with the likelihood of undertaking product or process innovations, the following specification is tested.

$$Product/process\ innovation_i = \beta_0 + \beta_1 x_i + u_{2i} \quad (2)$$

In this model, β_0 is a constant, β_1 represents equation-specific coefficients associated with each predictor, x_i represents an equation-specific vector of predictors, and u_{2i} is the equation-specific error term. The equation is however estimated using two separate logit models to predict the likelihood of a firm to report undertaking product or process innovation. The predicted value of the R&D spending outcome variable in the Heckman estimation, eq (1), $rndspend_i$ is included as a predictor in eq(2), termed *R&Dinvest* in the list of predictors below.

<i>marketshare</i>	=	Natural log of market share in leading market
<i>firmage</i>	=	Age of firm
<i>firmsize</i>	=	Size of firm
<i>foreigncomp</i>	=	0/1 Foreign competition
<i>political</i>	=	Political instability as obstacle to firm operations
<i>precision</i>	=	Extend of disclosure of records in sampling
<i>industry</i>	=	0/1 Industry dummies
<i>covid</i>	=	0/1 Financial year after Covid onset of lockdowns
<i>R&Dinvest</i>	=	Predicted value of R&D spending from eq(1)

Estimations of firm growth as the next test in the CDM sequence are now considered.

4.2.3. Firm growth

The following specification is used to test associations of predictors of firm growth.

$$Productivity/employment/sales\ growth_i = \beta_0 + \beta_1 z_i + u_{3i} \quad (3)$$

Again, in this model, β_0 is a constant, β_1 represents equation-specific coefficients associated with each predictor, but z_i represents an equation-specific vector of predictors, and u_{3i} is the equation-specific error term. The equation is estimated using three separate regression models to predict the contributions of predictors of productivity, employment, and sales growth. As discussed, growth is measured as the percentage difference in values over the two-year period preceding the study.

These tests complete a chain of tests of the CDM innovation model, modelling the contributions along the chain of predictors of R&D (eq1), from R&D intensity to each of product or process innovation (eq2), and from process and product innovation to each of productivity, employment, and sales growth (eq3)). The following variables are included to estimate these final specifications.

<i>prodinnov</i>	=	0/1 Firm undertakes product innovation
<i>procinnov</i>	=	0/1 Firm undertakes process innovation
<i>marketshare</i>	=	Natural log of market share in leading market
<i>firmage</i>	=	Age of firm
<i>firmsize</i>	=	Size of firm
<i>foreigncomp</i>	=	0/1 Foreign competition
<i>govtwage</i>	=	0/1 Firm receives wage, investment or other direct government subsidies
<i>ISO</i>	=	Firm applies quality accreditation processes
<i>ownerman</i>	=	Largest owner is also the manager
<i>prodtargets</i>	=	Firm uses targets to manage production
<i>audited</i>	=	0/1 Financial statements are certified by an external auditor
<i>labourreg</i>	=	Extent to which labour regulations are an obstacle to firm operations
<i>powercut</i>	=	0/1 The firm experienced electricity cuts to its operations
<i>investment</i>	=	0/1 Firm capital investments in financial year
<i>bonuses</i>	=	0/1 Firm uses management bonuses
<i>political</i>	=	Political instability as obstacle to firm operations
<i>precision</i>	=	Extend of disclosure of records in sampling
<i>industry</i>	=	Industry dummies
<i>covid</i>	=	Financial year after Covid onset of lockdowns

The benefits firms obtain from innovation depends on its appropriability (Hall & Sena, 2017) and these tests of predictors of growth capture variance associated with the extent to which innovations are appropriable in this context, allowing a test of the extent to which innovation is beneficial to different firm outcomes.

Predictors of innovation decisions included here are consistent with previous work (U. Fritsch & Görg, 2015; Goedhuys, 2007) and additional context-specific, ‘control’ variables are included from the extensive WBES survey. This reduces the potential influence of omitted variables. These control variables include a measure of whether a firm receives subsidies to control for some differences in resource decisions amongst firms (Branstetter et al., 2023), as well as measures that capture a firm’s management practices, such as whether it applies internationally certified ISO quality control processes (Arocena et al., 2021), is owner-managed (Cucculelli & Peruzzi, 2020),

uses production targets (Arnold & Artz, 2015), is audited (a measure of a firm's formalization) (Maroun, 2017), and whether it pays executive bonuses (Bachmann et al., 2020). Firm estimates are also included of the extent to which certain obstacles exist to the operations of the firm, such as labour regulations and political uncertainty (Krammer & Kafouros, 2022). Finally, a measure of whether the firm has made capital investments in the financial year (Coad, 2009) is also included.

Measurement error in the form of attenuation bias can affect CDM estimations (Mairesse & Robin, 2017). Such bias can 'dilute' the strength of a regression, reducing the significance of tests and causing them to be overly conservative. To compensate for this, a full chain of CDM tests are performed, comprising about 37 tested models, to provide comparative insights into patterns of tested relationships. Variance inflation factor (VIF) statistics tests suggest multicollinearity is unlikely to threaten the interpretation of results. Augmented component-plus-residual, or partial residual plots (Mallows, 1986) were performed to check for linearity between variables. The standard deviations of the growth variables are high, as expected of growth indicators which are typically more volatile than levels. In order to address potential outliers and influential points, the growth values are winsorised (Tukey, 1962), modifying 10% of observations in each tail. Having discussed the methods used to test hypotheses, results are now reported and discussed.

5. Results

This section reports the results of hypothesis testing, which are then discussed in Section 6.

5.1. Market concentration

As discussed, a defining feature of the South African economy is that it is highly concentrated (Buthelezi et al., 2019; Fedderke & Szalontai, 2009; Heijden & Vink, 2013; Kaplinsky & Manning, 1998; Kruger et al., 2021; Okeahalam, 2002; Wesson, 2021; Wouters et al., 2019), favoring incumbent firms and contributing to a status quo of inequality between firms. A firms' market concentration, or share of its primary market, is therefore a key focus of the work here.

5.1.1. Market concentration and R&D

Of all firms entering the Heckman model ($n=927$) in the full sample, about 25% report undertaking R&D. Across the full sample as well as small, mid-sized, and large firm subsamples, those with less market share in their leading market are significantly more likely to report undertaking R&D. *Hypothesis A_1 is supported across all samples.* If market share in a firm's leading market is an inverse proxy for market diversity, this finding aligns with Crepon et al.'s (1998), that more diversified French firms are more likely to report undertaking R&D. Interestingly, Baum et al. (2017) found the opposite, with market share predicting a firm's propensity to undertake innovation, using a sample Swedish manufacturing and services firms.

According to further ad hoc analysis, firms reporting to undertake R&D include about 17% of services, 19% of construction, 20% of manufacturing, 25% of retail, and 38% of hospitality firms. Further tests of samples split by industry suggest that those with smaller market shares are more likely to undertake R&D. This is true for all separately tested industries with sufficient sample size to allow further analysis, including construction, hospitality, manufacturing, and retail. Service industry tests, however, return very high standard errors and are not interpretable. These further robustness checks suggest tests of Hypothesis A_1 are not unduly skewed by heterogeneity at the industry level nor do they seem dominated by particular industries.

In the second stage, smaller market share predicts the extent of R&D investment for the full sample as well as the samples of smaller and large firms, but not mid-sized firms; *Hypothesis A_2 is also supported for these samples.* Descriptive statistics split by industry reveal that market shares are on average about 22% in manufacturing, 15% in construction, 11.5% in hospitality, and 10% in services and retail. Given the support for Hypotheses A_1 and A_2 , less market-concentrated firms seem more innovative along the R&D channel.

5.1.2. Market share and product/process innovation

Results summarized in Table 2 suggest product innovation is not significantly associated with market concentration. Hypothesis A₃ is not supported. There is no evidence of any advantage of R&D investment nor market concentration for product innovation. However, Hypothesis A₄- that market concentration is negatively associated with process innovation- is supported for the full sample. Firms with less concentrated markets may more actively pursue process innovation. Similarly, across the full sample, firms with lower levels of investment in R&D report a significantly higher likelihood of investment in process innovation.

Interestingly, mid-sized firms with greater market share report the opposite- higher levels of process innovation. In these firms, higher R&D spending also predicts a greater likelihood of process innovation. An interesting possibility is that process innovations reduce the size of a firm when measured by employees (Vivarelli, 2014). These firms are perhaps utilizing innovative processes more effectively than other samples, with a clustering of more efficient firms that employ more frugally in the middle of the size distribution. It is unclear why these firms with more concentrated market shares are more likely to report undertaking process, and not product innovation. Perhaps they avoid disrupting their markets, being secure enough in their market share to concentrate on increasing profitability and competitiveness through operational efficiencies instead.

5.1.3. Market concentration and growth

Market concentration is not significantly associated with productivity, employment, nor sales growth in any tested samples. Hypotheses A₅, A₆, and A₇ are therefore not supported. It is weakly and negatively significant in its association with sales growth in large firms, however, suggesting a subsample of less concentrated firms may be growing more quickly. Further analysis of subsamples using different methods, including qualitative techniques, may shed light on these dynamics.

These non-significant findings do not seem due to low statistical explanatory power. R squared values of tests predicting growth reported in Table A.5. range from about 14% to 25%, explaining

more than the less than 10% found by many studies in the historical growth estimation literature (Coad, 2009), perhaps reflecting the comprehensiveness of the set of covariates in the WBES survey (WBES, 2023). On average, market concentration is unrelated to firm growth across the entire sample of firms. Therefore, there is no evidence of a growth advantage for less concentrated firms to challenge the status quo regarding market concentration.

5.2. Firm age

5.2.1. Firm age and innovativeness

Firm age is not fully significant in predicting R&D choice, R&D investment, nor product innovation in any of the tested samples. Hypotheses B₁ to A₃, respectively, are not supported. Weakly significant effects- or those with significance at less than 10% rather than the typical cut off of 5%- suggest subsets of younger firms may be more likely to report undertaking R&D in the full sample, and to undertake product innovation in the full and small firm samples. Further research using qualitative, or case study methods should be used to investigate subsamples in which younger firms may have an advantage in their use of these innovative activities.

Further tests identify some heterogeneity of industry subsamples that might be weakening statistical associations of younger firms. Manufacturing firms have the greatest longevity in the sample, on average being about 31 years old, followed by retail- 28 years, construction and services- 24 years, and hospitality- 21 years. The country's democratic transition in 1994 preceded data collection here by about 26 years. Clearly, many subsamples on average were founded before this, including large firms, which average 31 years. The average mid-sized firm was founded 26 years ago, at the time of transition, and small firms 24 years ago, after the transition. These statistics are in line with literature highlighting incumbent dominance as indicated by high levels of concentration in firms across the country (Buthelezi et al., 2019; Fedderke & Szalontai, 2009; Heijden & Vink, 2013; Kaplinsky & Manning, 1998; Kruger et al., 2021; Okeahalam, 2002; Wesson, 2021; Wouters et al., 2019). These statistics suggest incumbents may have had some control over the innovation

channels through which they are typically vulnerable to disruption. Findings here suggest the extent to which this may still be so, and how newer and younger firms might use these channels to challenge the status quo of incumbent dominance.

In contrast to product innovation, younger firms are significantly more likely to report undertaking process innovation across all samples except for small firms, in which the same association is weakly significant. Accordingly, Hypothesis B₄ is supported in these samples. Younger firms may have an advantage in process innovation.

5.2.2. Firm age and growth

Firm age is not significantly associated with productivity growth in the full sample nor in any of the samples split by size, and not with both employment and sales growth in the full, mid-sized, and large firm samples. Hypotheses B₅, B₆, and B₇ are not supported. In the small firm sample, however, younger firms report significantly higher employment and sales growth. Smaller and younger firms might have a growth advantage in sales and might accordingly employ more staff to support sales growth. Stakeholder and policymaker efforts to create a more inclusive environment to facilitate their entry may reduce unemployment.

Interestingly, significantly higher process innovation of younger firms (process innovation is fully significant across all samples except small firms, in which the effect is weakly significant) does not manifest in tested associations between process innovation and any of the growth measures. This also seems to suggest process innovation is not slowing employment growth either, a consequence of process innovation identified in previous work (Vivarelli, 2014).

Product innovation is not significantly associated with productivity or sales growth but is significantly associated with employment growth across all samples except for large firms. This seemingly attests to the potential role of disruptive innovation associated with new product competition to drive employment growth in this context.

In that the only significant associations of firm age are negative in the small firm sample, with younger firms reporting significantly higher employment and sales growth, incumbents may be vulnerable to disruptive activities, and to product innovation in particular. If so, then policy support might be warranted.

5.3. Firm size

5.3.1. Firm size and innovativeness

Overall, across the full sample, larger firms are on average significantly more likely to report undertaking R&D, and to spend more on R&D. Hypotheses C₁ and C₂, respectively, are not supported. Larger firms might defend the status quo by investing to control the innovation channels through which smaller firms might seek to disrupt them. This finding is in line with previous findings in other contexts. For example, in French, German, Spanish, and United Kingdom firms, Griffith et al. (2006) found firm size to be positively associated with R&D choice. Similarly, Baum et al. (2017) and Hall and Sena (2017) find logged numbers of employees to be significant in the selection equation predicting R&D investment choice.

Using data on Swedish firms, in the first stage of the selection model, Löf and Heshmati (2006) find firm size to be fully significant in its association with likelihood of innovation investments in services and manufacturing firms (with stronger significance in services firms). In the second leg of the equation, however, with innovation investment per employee as the outcome variable they find firm size to be negatively associated, in both services and manufacturing firms (Löf & Heshmati, 2006).

Further ad hoc tests on samples split by industry suggest that in none of the tested industries (construction, hospitality, and manufacturing) except for retail is the size variable significant in predicting R&D spending. In retail firms, larger firms are significantly more likely to report undertaking R&D and higher levels of R&D spending. It is unlikely that those in the retail industry

alone drive tested effects across the entire sample, and the lack of significance of further industry-level tests might also be due to their smaller sample sizes.

R&D as a share of South Africa's GDP was 0.62% in 2019 (WB, 2020), at about the time of the study. According to descriptive statistics in Table 1., whereas in the full sample about 24% of firms on average report undertaking R&D, larger firms report a slightly higher proportion- about 28%. Similarly, whereas in the full sample a firm's dominance of its primary market is on average 14%, it is slightly less in smaller and mid-sized firms, both at about 13%, and highest in large firms with 18%. Larger firms may be using their R&D efforts to protect their advantage in market concentration, thereby protecting the status quo.

Although firm size is not significantly related to product innovation, and although R&D investment is only positively related to process innovation in mid-sized firms, larger firms (rather than smaller firms) are significantly more likely to report undertaking process innovation. Accordingly, Hypotheses C₃ and C₄, which posit an advantage for smaller firms in product and process innovation, respectively, are not supported. Larger firms may prefer process innovation to improve operational efficiencies and lower operational costs (rather than product innovation which can disrupt their own markets), thereby protecting the status quo by enhancing barriers to competition.

5.3.2. Firm size and growth

Firm size is fully negatively significant in its association with employment growth- smaller firms seem to have higher employment growth. Size is not fully significant in its associations with productivity nor sales growth. Hypotheses C₆ is supported but C₅ and C₇ are not, Size is however positively but weakly associated with productivity growth in the full sample, suggesting the possible presence of subsamples of larger firms with higher productivity growth. Further tests of samples split by industry suggest that subsamples are not the source of this effect in that these tests are not significant.

5.4. The chain of innovative activities contributing to growth

Results reported in Table 2 document significant associations along the CDM theoretically-predicted ‘chain’ of innovation activities, and their associations to growth. Figure 2 reports these findings diagrammatically. Notably, in the sample of large firms, none of the linkages is significant. The non-significance of many channels across the CDM ‘map’ of linkages suggests this context may be characterized by low innovativeness, in that there are seemingly relatively few significant channels. The hypothesized significance of a channel, or link, is taken to reflect the sensitivity of the channel to disruptive innovation.

Only in mid-sized firms is the chain almost complete, with R&D spending associated with process innovation, and product innovation with employment growth. In small firms, although R&D is not significantly associated with product or process innovation, product innovation is associated with employment growth, and process innovation is weakly associated with sales growth. These firms might benefit by focusing competitive efforts along these channels.

Across the entire sample, firms reporting more investment in R&D report being significantly less likely to invest in process innovation, and it seems to be through the product innovation channel that innovation contributes to growth, from product innovation to employment growth, and weakly to sales growth. Mid-sized firms seem to differ from the rest of the sample. The channel from R&D to process innovation might reflect some focus on process innovation to improve operational efficiencies (and more efficient use of labour) that may have led to a clustering of these firms in the mid-sized category, even as their product innovation activities increased employment growth. These associations are taken to generalize across the entire sample of firms, and Figure 2 seemingly also suggests a map of unexploited opportunities. Further research and policy work should seek to understand how to build on the strengths of these linkages, and address those that are absent.

6. Discussion

Country contextual trends shown in Figure 1 (Feenstra et al., 2015; WB, 2020) help to locate firms in relation to these trends at the time of the study, which to some extent reflect firm activities aggregated to the country level. Although per capita gross domestic product (GDP) seems stable, notwithstanding a minor cyclical downturn (Figure 1.c.), declines are evident in the country-level R&D share of GDP (Figure 1.a.), total factor productivity (how productively capital and labour are combined in their contributions to economic growth) (Figure 1.b.), employment share of the population (Figure 1.d.), patent applications (Figure 1.e.), and the regulatory quality of the country's institutions (Figure 1.f.). In that findings here suggest a status quo regarding market concentration, yet also suggest younger and newer firms' potential to drive employment growth, further research should link firm-level findings here to the aggregate country level, to explore firms' potential to mitigate these trends. Further work should also seek to understand how findings here are relevant to ongoing negative structural change that can occur if jobs and firms are moving out of high-wage sectors like manufacturing and into the low-productivity and increasingly informal services sector (McMillan et al., 2014).

Figure 1 shows a possible trend of negative structural change, evidenced in declining value-added share of GDP of manufacturing (Figure 1.g.) and agriculture (Figure 1.h.), alongside a countervailing increase in services (Figure 1.g.). Deindustrialisation literature suggests this trend is particularly problematic for developing countries like South Africa (Callaghan, 2020; Mondliwa & Roberts, 2021; Tregenna, 2014; Tregenna et al., 2021). Accordingly, it is important to know if and how incumbent firms dominate the innovation chain linkages used by challengers to disrupt them. Anti-competitive and monopolistic behaviour might stall the inclusive development of new formal firms needed to arrest a shift to informal services. A growing informal services sector might reflect a lack of inclusive opportunities in formal sector firms sampled here.

As discussed, despite regulatory attempts such as the Competition Act of 1998 to diversify and reduce anti-competitive and monopolistic practices, and to reduce the country's high market concentration of firms, this status quo continues to be reflected in a highly concentrated Herfindahl-Hirschman Index (Buthelezi et al., 2019).

Disruptive innovation is expected to be beneficial to society by enabling newer and younger firms and those with less market dominance to disrupt incumbent markets (Christensen et al., 2006), but, as discussed, it has to date been unclear to what extent incumbent or challenger firms have the advantage across the chain of innovative activities that drives disruption, driving productivity, employment, and sales growth.

Tests of hypotheses were used to investigate the extent that *three characteristics of 'less entrepreneurial' incumbent firms explained whether incumbent firms maintain the status quo by dominating the chain of activities along which innovation drives firm growth, thereby dominating these dimensions of growth*. The importance of knowing if incumbents dominate this chain is underscored by high market concentration associated with historical monopolistic, oligopolistic, and anti-competitive practices (Buthelezi et al., 2019; Fedderke & Szalontai, 2009; Heijden & Vink, 2013; Kaplinsky & Manning, 1998; Kruger et al., 2021; Okeahalam, 2002; Wesson, 2021; Wouters et al., 2019) in a context with some of the world's highest levels of inequality and unemployment (Adeleye et al., 2020; Francis & Webster, 2019; Plagerson, 2023; Sulla & Zikhali, 2018). The average firm seems to have been founded before the first democratic elections in 1994, and only on average the small firm sample after this date.

Neither product nor process innovation is fully significant in predicting growth in sales in any tested sample.

Disruptive innovation (Christensen et al., 2006; Christensen et al., 2018; Christensen et al., 2013) as it relates to sales growth may not be occurring through these channels.

In contrast, other predictions of disruptive innovation theory are supported. *Product innovation, however, relates positively to employment growth* in all tested samples except for large firms, supporting the argument that the disruption of established markets by new products can have a *net beneficial*

Schumpeterian effect of ‘creative destruction’ (J. A. Schumpeter, 1942), thereby increasing net employment growth across the entire sample. Large firms may not be creating employment through the same mechanism. When firm size is itself tested as a variable, it is negatively related to employment growth; smaller firms seemingly have higher employment growth. This supports predictions of the benefits of entrepreneurship if smaller and mid-sized firms tend to be more entrepreneurial than they may be contributing disproportionately to reducing societal poverty and inequality through this channel. If so, then small business should receive more attention from policy makers and other societal stakeholders.

Interestingly, *process innovation is unrelated to any of the growth measures*. There is no evidence of a productivity channel associated with process innovation, nor of reduced employment growth, which often results from improved operational processes that reduce the use of labour (Vivarelli, 2014). Process innovation is weakly associated with sales growth in small firms, suggesting subsamples of small firms may benefit from this effect. More agile and innovative operational approaches and methodologies (Mansoori et al., 2019; Tripathi et al., 2019; von Hippel & Euchner, 2013) can favour more entrepreneurial or smaller firms using digital platforms (Thurik et al., 2024) to level the playing field. Indeed, *younger firms report significantly higher sales growth*. Further research should investigate characteristics of these potential subsamples of firms in which process innovation may be driving sales growth, so that they can receive targeted policy support.

Firm size is however weakly related to productivity growth. One or more underlying subsamples of larger firms may have an advantage in productivity. As discussed, heterogeneity in within-industry effects do not seem to underlie this effect, as further tests of samples split by industry suggest size is not significantly related to productivity growth. Large firms would be expected to have an advantage predicted by the resource-based view, in that they may have had more resources to marshal to develop inimitable capabilities and resources (Barney, 2001; Barney et al., 2021), dynamic capabilities (Teece, 2018), and economies of scale and scope (Kaplinsky & Kraemer-Mbula, 2022).

The finding that older firms report significantly higher process innovation should be considered in light of the weak positive association between firm size and productivity growth. Forces related to the process innovation- productivity growth linkage may contribute to the status quo if large firms are better able to restrict competition by increasing capital requirements (Oduor et al., 2017) and developing economies of scale and bargaining power to lower supplier and distribution channel costs (Dyerson & Pilkington, 2005; Petit & Teece, 2021). Larger firms may thereby counter the advantages of smaller, younger, and more entrepreneurial firms. Further research using qualitative and case study methods should seek to identify if the status quo is being maintained by a subset of larger firms that still dominate in their productivity growth.

Market concentration is not found to be significantly related to productivity, employment, nor sales growth. This suggests firms with less market concentration are not growing faster than incumbents that dominate their markets. Environmental fitness (Lumpkin & Dess, 1996) therefore does not seem to favor either incumbents or challengers. The status quo seemingly prevails regarding market share.

The advantage of less concentrated firms in R&D choice, R&D expenditure, and process innovation seem to be failing to translate into firm growth. As discussed, and as shown in Figure 1, there seems a break between process innovation and the growth measures, with no evidence of a transmission of process innovation to growth. In contrast, as discussed, R&D spending does not link with product innovation, but *product innovation does link with employment growth* in the full, small, and mid-sized samples, but not for large firms. Similarly, as discussed, younger firms report significantly higher sales growth. They may be growing sales, but there is no advantage for less market concentrated firms.

There is no evidence here of entrepreneurial disruption of incumbent firm market dominance in this context. If the status quo persists, this is problematic, perhaps reinforcing a longstanding historical lack of competitiveness and market concentration of the country's firms (Buthelezi et al., 2019; Fedderke

& Szalontai, 2009; Heijden & Vink, 2013; Kaplinsky & Manning, 1998; Kruger et al., 2021; Okeahalam, 2002; Wesson, 2021; Wouters et al., 2019). If this changes in future it might be due to the faster sales growth of younger firms. However, if younger firms (as findings here suggest) are less likely to undertake process innovation this could be remedied to boost their productivity growth. These weaknesses may be ‘low hanging fruit’. Product innovation seems to hold promise for employment creation, contributing to societal ends through this channel. As discussed, South Africa scores lowest of sampled countries in the world on average for its environment of 13 Entrepreneurial Framework Conditions. These should be the focus of policy and stakeholder interventions, which may increase the sensitivity of growth in this context to innovative activity. These conditions include a focus on entrepreneurial finance and access to it, government policy support and relevance, government policy regarding taxes and bureaucracy, government entrepreneurial programmes, school and post-school entrepreneurial education, R&D transfers, commercial and professional infrastructure, ease of entry regarding market dynamics and burdens and regulation, physical infrastructure, and social and cultural norms (GEM, 2023). Findings here therefore highlight issues with the entrepreneurial ‘fit’ of this context with the innovation activities and how they contribute to the growth of its firms. Policy and stakeholder interventions to improve these enabling conditions for entrepreneurship, that are guided by findings here, should reduce societal unemployment and inequality. Overall, findings here shed light on the ‘black box’ of workings of innovation activities and identifies patterns in how incumbents and new entrants use them to drive their growth, and how they might contribute to reducing societal unemployment and inequality.

7. Limitations and Future Research

Here, the methodological focus of the study was delimited to studying differences between firms to understand why the country has such as high market concentration (Buthelezi et al., 2019; Fedderke & Szalontai, 2009; Heijden & Vink, 2013; Kaplinsky & Manning, 1998; Kruger et al.,

2021; Okeahalam, 2002; Wesson, 2021; Wouters et al., 2019), low levels of entrepreneurship (GEM, 2023), and high unemployment and income inequality (Adeleye et al., 2020; Francis & Webster, 2019; Plagerson, 2023; Sulla & Zikhali, 2018). As such, the work focuses on differences between firms, to better understand why incumbents seemingly continue to dominate and maintain a status quo of high market concentration.

Accordingly, the study shares well documented limitations with a large body of similar work (Castellacci, 2011; Crepon et al., 1998; Griffith et al., 2006; Lööf et al., 2017; Mairesse et al., 2005; Notten et al., 2017). These limitations offer opportunities for further research.

Findings derive from data that is as representative as possible, given the rigor of the WBES survey design and its representative design. Weak significance of some associations may indicate subsample effects, and the presence of underlying heterogeneity. Further ad hoc testing of industry-level subsamples suggests opportunities remain for further research to investigate differences between subsamples of firms due to sample size limitations in analysis of ever-smaller subsamples. Analysis here included post hoc tests at industry level, but further qualitative and case study methodologies should extend this work to better understand heterogeneous subsamples with unique characteristics. Findings here may nevertheless be useful in that they identify relationships that are strong enough to manifest across this sample of the country's firms.

The study's objectives relate to differences between incumbent and challenger firms and are appropriate for cross-sectional data. As discussed, although statistical analysis cannot produce causal results, tests here follow the well-established and well-theorized CDM methodology designed to mitigate bias using separate steps in the estimation process. Heckman tests also reduce selection bias, in that it is not usually possible to estimate how much a firm spends on R&D if only a fraction of firms undertake R&D, and it is necessary to first estimate the propensity to do so, and then include a term to correct for this bias in the following estimation. As discussed, the study

shares specific and well-research limitations with other CDM studies, offering specific opportunities for further research.

For example, CDM models usually tested on cross sectional data do not allow for analysis of feedback effects and dynamics between recursive stages of estimation (Baum et al., 2017; Mairesse & Robin, 2017). Although these dynamics are not the focus of the study design here, as adequate data becomes available in time, further research may ask different research questions to consider these dynamics and extend findings here. Increasing the time dimension will also allow identification of selectivity, endogeneity, errors in variables, and use of firm fixed effects (Mairesse & Robin, 2017). The importance of firms' contributions to societal outcomes such as employment and equality in this context might warrant large-scale investments in data collection to build on findings here.

These investments might make use of strategies to combine data sets. For example, Hall and Sena (2017) test a modified CDM model on UK data combined from different sources, including the UK Community Innovation Survey, the Annual Respondents Database, and the Business Strategy Database. Developing appropriately rich data could extend this work to link it more explicitly with that on societal unemployment and inequality. Findings here suggest destructive forces of Schumpeterian and disruptive innovation have the potential to create net benefits for firm growth, even though they entail destruction of established markets, processes, and even firms. Linkages between innovation and growth, especially employment growth, are assumed here to reduce unemployment and inequality, but further research should explicitly investigate these assumptions. This would extend the CDM logic of a 'chain' of relationships to establish their societal relevance. Future research using qualitative methods, such as causal mapping and case studies might yield these types of insights, since they might be difficult to establish empirically.

Another important avenue for further research is therefore extending tests of the CDM model to aggregated data to investigate how relationships differ between micro and macro levels

(Bartelsman et al., 2017), in that societal unemployment and inequality are macro-level phenomena, and their linkages should be considered to extend studies like this one with the firm as unit of analysis.

Work here therefore applies a 'standard' or conventional CDM approach, at the expense of methodological innovation, but future studies might extend its finding by using more innovative approaches. Baum et al. (2017) use generalized structural equation modelling with full-information maximum likelihood test the CDM model. They include a latent variable to address omitted variables bias and a mixed process model to incorporate both censored and continuous data. They also use FIML estimates to address simultaneity. In contrast, this study uses the only available source of data appropriate to its objectives to apply a standard sequence of CDM regression tests, accommodating a comprehensive set of WBES covariate controls that may be too numerous to be accommodated by a SEM design.

Overall, this work highlights linkages in the innovation-growth chain of relationships in the country's firms but it was beyond the scope of the study to specifically investigate the way the country's context shapes these relationships. Further research should investigate how to improve the entrepreneurial context in which firms find themselves. Improved support for newer and younger firms and those that have yet to establish themselves in their markets might go a long way to reducing unemployment and inequality in this context.

8. Conclusion

This study examines how incumbent firms maintain dominance of the status quo in South African innovation chains. Findings suggest patterns explaining why the status quo persists. Findings indicate that the connection between the development of new products and the increase in employment offers a promising opportunity for young and innovative companies to challenge established market leaders by leveraging the potential of entrepreneurial 'creative destruction' or Schumpeterian dynamics. Product innovation, smaller firms, and younger firms in the small firm

sample seem to drive employment growth. Despite the status quo in current market concentration, this study highlights ways in which firms in the country can positively impact societal outcomes. By targeting these specific areas through policy and other stakeholder efforts, it may be possible to reduce high unemployment rates, inequality, market concentration, and low levels of entrepreneurial entry. However, whereas findings here explain some of the puzzle of how the country's population of firms might become less market-concentrated and dominated by incumbents, future research should investigate how to improve the country's entrepreneurial environment, which may also go a long way to addressing these challenges.

REFERENCES

- Acemoglu, D., Johnson, S., & Robinson, J. A. (2001). The colonial origins of comparative development: An empirical investigation. *American Economic Review*, 91(5), 1369-1401.
- Acemoglu, D., & Robinson, J. A. (2012). *Why nations fail: The origins of power, prosperity, and poverty*. Crown Books.
- Adams, R. J., Smart, P., & Huff, A. S. (2017). Shades of Grey: Guidelines for Working with the Grey Literature in Systematic Reviews for Management and Organizational Studies. *International Journal of Management Reviews*, 19(4), 432-454.
<https://search.ebscohost.com/login.aspx?direct=true&db=eoah&AN=43457916&site=pdf-live>
- Adeleye, B. N., Gershon, O., Ogunidipe, A., Owolabi, O., Ogunrinola, I., & Adediran, O. (2020). Comparative investigation of the growth-poverty-inequality trilemma in Sub-Saharan Africa and Latin American and Caribbean Countries. *Heliyon*, 6(12).
- Aghion, P., Akcigit, U., & Howitt, P. (2015). Lessons from Schumpeterian growth theory. *American Economic Review*, 105(5), 94-99.
- Aghion, P., & Howitt, P. (1992). A Model of Growth Through Creative Destruction. *Econometrica*, 60(2), 323-351. <https://doi.org/10.2307/2951599>
- Ahammad, M. F., Basu, S., Munjal, S., Clegg, J., & Shoham, O. B. (2021). Strategic agility, environmental uncertainties and international performance: The perspective of Indian firms. *Journal of World Business*, 56(4), 101218.
<https://doi.org/https://doi.org/10.1016/j.jwb.2021.101218>
- Akpan, I. J., Soopramanien, D., & Kwak, D.-H. (2021). Cutting-edge technologies for small business and innovation in the era of COVID-19 global health pandemic. *Journal of Small Business & Entrepreneurship*, 33(6), 607-617.
- Akpan, I. J., Udoh, E. A. P., & Adebisi, B. (2022). Small business awareness and adoption of state-of-the-art technologies in emerging and developing markets, and lessons from the COVID-19 pandemic. *Journal of Small Business & Entrepreneurship*, 34(2), 123-140.
- Albis Salas, N., Mora Holguin, H., Lucio-Arias, D., Sánchez, E. C., & Villarreal, N. (2023). Innovation and productivity in small and medium-sized enterprises: evidence from the Colombian manufacturing sector. *Journal of Small Business and Enterprise Development*, 30(5), 1011-1034. <https://doi.org/10.1108/JSBED-12-2022-0502>

- Amin, A., & Cohendet, P. (2005). Geographies of Knowledge Formation in Firms. *Industry and Innovation*, 12(4), 465-486. <https://doi.org/10.1080/13662710500381658>
- Andersson, M., & Karlsson, C. (2007). Knowledge in Regional Economic Growth-The Role of Knowledge Accessibility. *Industry and Innovation*, 14(2), 129-149. <https://doi.org/10.1080/13662710701252450>
- Arauzo-Carod, J.-M. (2021). Location determinants of high-tech firms: an intra-urban approach. *Industry and Innovation*, 28(10), 1225-1248. <https://doi.org/10.1080/13662716.2021.1929868>
- Arnold, M. C., & Artz, M. (2015). Target difficulty, target flexibility, and firm performance: Evidence from business units' targets. *Accounting, Organizations and Society*, 40, 61-77.
- Arocena, P., Orcos, R., & Zouaghi, F. (2021). The impact of ISO 14001 on firm environmental and economic performance: The moderating role of size and environmental awareness. *Business Strategy and the Environment*, 30(2), 955-967.
- Audretsch, D. B. (2004). Sustaining Innovation and Growth: Public Policy Support for Entrepreneurship. *Industry and Innovation*, 11(3), 167-191. <https://doi.org/10.1080/1366271042000265366>
- Bachmann, R. L., Loyeung, A., Matolcsy, Z. P., & Spiropoulos, H. (2020). Powerful CEOs, cash bonus contracts and firm performance. *Journal of Business Finance & Accounting*, 47(1-2), 100-131.
- Baiyegunhi, L., Zondo, B., & Chasomeris, M. The Impact of Human Capital and Innovation on Sugarcane Farm Productivity in the Kwazulu-Natal North Coast, South Africa. *Heliyon*. file:///C:/Users/27722/Downloads/SSRN-id4416234.pdf
- Barney, J. B. (2001). Is the resource-based "view" a useful perspective for strategic management research? Yes. *Academy of Management Review*, 26(1), 41-56.
- Barney, J. B., Ketchen Jr, D. J., & Wright, M. (2021). Bold voices and new opportunities: an expanded research agenda for the resource-based view. *Journal of Management*, 47(7), 1677-1683.
- Bartelsman, E., van Leeuwen, G., & Polder, M. (2017). CDM using a cross-country micro moments database. *Economics of innovation and new technology*, 26(1-2), 168-182. <https://doi.org/10.1080/10438599.2016.1202517>
- Baum, C. F., Löff, H., Nabavi, P., & Stephan, A. (2017). A new approach to estimation of the R&D–innovation–productivity relationship. *Economics of innovation and new technology*, 26(1-2), 121-133. <https://doi.org/10.1080/10438599.2016.1202515>
- Baumgartinger-Seiringer, S., Miörner, J., & Tripl, M. (2021). Towards a stage model of regional industrial path transformation. *Industry and Innovation*, 28(2), 160-181. <https://doi.org/10.1080/13662716.2020.1789452>
- Baumol, W. J. (1959). *Business behavior, value and growth*. Macmillan.
- Ben Khalifa, A. (2023). Impact of research and development (R&D) and information, and communication technology (ICT) on innovation and productivity evidence from Tunisian manufacturing firms. *Economics of Transition and Institutional Change*, 31(2), 341-361.
- Bignami, F., Mattsson, P., & Hoekman, J. (2020). The importance of geographical distance to different types of R&D collaboration in the pharmaceutical industry. *Industry and Innovation*, 27(5), 513-537. <https://doi.org/10.1080/13662716.2018.1561361>
- Branstetter, L. G., Li, G., & Ren, M. (2023). Picking winners? Government subsidies and firm productivity in China. *Journal of Comparative Economics*.
- Broekel, T., & Binder, M. (2007). The Regional Dimension of Knowledge Transfers-A Behavioral Approach. *Industry and Innovation*, 14(2), 151-175. <https://doi.org/10.1080/13662710701252500>
- Broome, T., Moore, W., & Alleyne, P. (2018). Financing constraints and the R&D decision in the Caribbean [Article]. *Entrepreneurship & Regional Development*, 30(9/10), 964-986. <https://doi.org/10.1080/08985626.2018.1515820>
- Buthelezi, T., Mtani, T., & Mncube, L. (2019). The extent of market concentration in South Africa's product markets. *Journal of Antitrust Enforcement*, 7(3), 352-364.

- Callaghan, C. W. (2014a). Changes in the structure of earnings of informal street traders. *Acta Commercii*, 14(1), 1-13.
- Callaghan, C. W. (2014b). Development and Gender: Longitudinal Entrepreneurial Gender Effects of the Inner-City Johannesburg Street-Trading Context. *Development Southern Africa*, 31(3), 412-426. <https://doi.org/http://www.tandfonline.com/loi/cdsa20>
- Callaghan, C. W. (2020). *Essays on industrialisation and deindustrialisation*. University of Johannesburg (South Africa).
- Castellacci, F. (2011). How does competition affect the relationship between innovation and productivity? Estimation of a CDM model for Norway. *Economics of innovation and new technology*, 20(7), 637-658.
- Chang, H.-L., & Su, C.-W. (2010). Is R&D always beneficial? *Review of Pacific Basin Financial Markets and Policies*, 13(01), 157-174.
- Christensen, C. M., Baumann, H., Ruggles, R., & Sadtler, T. M. (2006). Disruptive innovation for social change. *Harvard Business Review*, 84(12), 94.
- Christensen, C. M., McDonald, R., Altman, E. J., & Palmer, J. E. (2018). Disruptive innovation: An intellectual history and directions for future research. *Journal of Management Studies*, 55(7), 1043-1078.
- Christensen, C. M., Raynor, M. E., & McDonald, R. (2013). *Disruptive innovation*. Harvard Business Review Brighton, MA, USA.
- Chudnovsky, D., López, A., & Pupato, G. (2006). Innovation and productivity in developing countries: A study of Argentine manufacturing firms' behavior (1992–2001). *Research Policy*, 35(2), 266-288. <https://doi.org/https://doi.org/10.1016/j.respol.2005.10.002>
- Chung, H., Eum, S., & Lee, C. (2019). Firm growth and R&D in the Korean pharmaceutical industry. *Sustainability*, 11(10), 2865.
- Coad, A. (2009). *The growth of firms: A survey of theories and empirical evidence*. Edward Elgar Publishing.
- Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative science quarterly*, 128-152.
- Crepon, B., Duguet, E., & Mairesse, J. (1998). Research, Innovation And Productivity: An Econometric Analysis At The Firm Level. *Economics of innovation and new technology*, 7(2), 115-158. <https://doi.org/10.1080/10438599800000031>
- Cruz-Castro, L., Holl, A., Rama, R., & Sanz-Menéndez, L. (2018). Economic crisis and company R&D in Spain: do regional and policy factors matter? *Industry and Innovation*, 25(8), 729-751. <https://doi.org/10.1080/13662716.2017.1355231>
- Cucculelli, M., & Peruzzi, V. (2020). Innovation over the industry life-cycle. Does ownership matter? *Research Policy*, 49(1), 103878.
- Cuervo-Cazurra, A. (2016). Corruption in international business. *Journal of World Business*, 51(1), 35-49. <https://doi.org/https://doi.org/10.1016/j.jwb.2015.08.015>
- Czarnitzki, D., & Delanote, J. (2017). Incorporating innovation subsidies in the CDM framework: empirical evidence from Belgium. *Economics of innovation and new technology*, 26(1-2), 78-92. <https://doi.org/10.1080/10438599.2016.1202514>
- Daniel, G. O., Fu, K., & Dolfsma, W. (2018). Institutional Quality and Economic Development in Sub-Saharan Africa: Can Management Effort and Bribes Compensate for Low-Quality Institutions? *Journal of Economic Issues*, 52(2), 473-482. <https://doi.org/http://www.tandfonline.com/loi/mjei20>
- De Vries, G., Pennings, E., Block, J. H., & Fisch, C. (2017). Trademark or patent? The effects of market concentration, customer type and venture capital financing on start-ups' initial IP applications. *Industry and Innovation*, 24(4), 325-345. <https://doi.org/10.1080/13662716.2016.1231607>

- Dyerson, R., & Pilkington, A. (2005). Gales of creative destruction and the opportunistic incumbent: The case of electric vehicles in California. *Technology Analysis & Strategic Management*, 17(4), 391-408.
- Edeh, J. N., & Acedo, F. J. (2021). External supports, innovation efforts and productivity: Estimation of a CDM model for small firms in developing countries. *Technological Forecasting and Social Change*, 173, 121189. <https://doi.org/https://doi.org/10.1016/j.techfore.2021.121189>
- Eklund, C., & van Criekingen, K. (2022). Fast as a gazelle - young firms gaining from educational diversity. *Industry and Innovation*, 29(8), 927-947. <https://doi.org/10.1080/13662716.2022.2044764>
- Evangelista, R., & Savona, M. (2002). The impact of innovation on employment in services: Evidence from Italy. *International Review of Applied Economics*, 16(3), 309-318.
- Fedderke, J., & Szalontai, G. (2009). Industry concentration in South African manufacturing industry: Trends and consequences, 1972–96. *Economic Modelling*, 26(1), 241-250.
- Feenstra, R. C., Inklaar, R., & Timmer, M. P. (2015). The next generation of the Penn World Table. *American Economic Review*, 105(10), 3150-3182.
- Francis, D., & Webster, E. (2019). Poverty and inequality in South Africa: critical reflections. *Development Southern Africa*, 36(6), 788-802. <https://doi.org/10.1080/0376835X.2019.1666703>
- Franco, A., Malhotra, N., & Simonovits, G. (2014). Publication bias in the social sciences: Unlocking the file drawer. *Science*, 345(6203), 1502-1505.
- Fritsch, M. (2003). Does R&D-Cooperation behavior differ between regions? *Industry and Innovation*, 10(1), 25-39. <https://doi.org/10.1080/1366271032000068087>
- Fritsch, U., & Görg, H. (2015). Outsourcing, importing and innovation: Evidence from firm-level data for emerging economies. *Review of International Economics*, 23(4), 687-714.
- Gaglio, C., Kraemer-Mbula, E., & Lorenz, E. (2022). The effects of digital transformation on innovation and productivity: Firm-level evidence of South African manufacturing micro and small enterprises. *Technological Forecasting and Social Change*, 182, 121785. <https://doi.org/https://doi.org/10.1016/j.techfore.2022.121785>
- García-Manjón, J. V., & Romero-Merino, M. E. (2012). Research, development, and firm growth. Empirical evidence from European top R&D spending firms. *Research Policy*, 41(6), 1084-1092. <https://doi.org/https://doi.org/10.1016/j.respol.2012.03.017>
- Garnsey, E., Stam, E., & Heffernan, P. (2006). New Firm Growth: Exploring Processes and Paths. *Industry and Innovation*, 13(1), 1-20. <https://doi.org/10.1080/13662710500513367>
- GEM. (2023). *Global Entrepreneurship Monitor 2022/2023 Global Report* (<https://www.gemconsortium.org/reports/latest-global-report>)
- Goedhuys, M. (2007). Learning, product innovation, and firm heterogeneity in developing countries; Evidence from Tanzania. *Industrial and Corporate Change*, 16(2), 269-292.
- Gong, Z., & Wang, N. (2022). The driving process of technological innovation in construction: a firm-level CDM analysis. *Construction Innovation*, 22(2), 222-241. <https://doi.org/10.1108/CI-12-2020-0194>
- Griffith, R., Huergo, E., Mairesse, J., & Peters, B. (2006). Innovation and Productivity Across Four European Countries. *Oxford Review of Economic Policy*, 22(4), 483-498. <https://doi.org/10.1093/oxrep/grj028>
- Griliches, Z. (1979). Issues in Assessing the Contribution of Research and Development to Productivity Growth. *The Bell Journal of Economics*, 10(1), 92-116. <https://doi.org/10.2307/3003321>
- Grossman, G. M., & Helpman, E. (1991). Quality Ladders in the Theory of Growth [Article]. *Review of Economic Studies*, 58(1), 43. <https://doi.org/10.2307/2298044>
- Hall, B. H., & Sena, V. (2017). Appropriability mechanisms, innovation, and productivity: evidence from the UK. *Economics of innovation and new technology*, 26(1-2), 42-62. <https://doi.org/10.1080/10438599.2016.1202513>

- Haus-Reve, S., Fitjar, R. D., & Rodríguez-Pose, A. (2023). DUI it yourself: Innovation and activities to promote learning by doing, using, and interacting within the firm. *Industry and Innovation*, 30(8), 1008-1028. <https://doi.org/10.1080/13662716.2022.2131509>
- Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, 47(1), 153-161. <https://doi.org/10.2307/1912352>
- Heijden, T. v. d., & Vink, N. (2013). Good for whom? Supermarkets and small farmers in South Africa—a critical review of current approaches to increasing access to modern markets. *Agrekon*, 52(1), 68-86.
- Henrekson, M., Johansson, D., & Karlsson, J. (2024). To be or not to be: The entrepreneur in neo-Schumpeterian growth theory. *Entrepreneurship theory and practice*, 48(1), 104-140.
- Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics*, 3(4), 305-360.
- Jones, C., & Vollrath, D. (2013). Introduction to Economic Growth WW Norton. New York.
- Jones, C. I. (2019). Paul Romer: Ideas, nonrivalry, and endogenous growth. *The Scandinavian Journal of Economics*, 121(3), 859-883.
- Kamutando, G., & Tregenna, F. (2023). Complementarity between product and process innovation in small and micro-enterprises in Johannesburg, South Africa. *Economics of innovation and new technology*, 1-27.
- Kancs, d. A., & Siliverstovs, B. (2016). R&D and non-linear productivity growth. *Research Policy*, 45(3), 634-646. <https://doi.org/https://doi.org/10.1016/j.respol.2015.12.001>
- Kaplinsky, R., & Kraemer-Mbula, E. (2022). Innovation and uneven development: The challenge for low- and middle-income economies. *Research Policy*, 51(2), 104394. <https://doi.org/https://doi.org/10.1016/j.respol.2021.104394>
- Kaplinsky, R., & Manning, C. (1998). Concentration, competition policy and the role of small and medium-sized enterprises in South Africa's industrial development. *The Journal of Development Studies*, 35(1), 139-161.
- Kishna, M., Negro, S., Alkemade, F., & Hekkert, M. (2017). Innovation at the end of the life cycle: discontinuous innovation strategies by incumbents. *Industry and Innovation*, 24(3), 263-279. <https://doi.org/10.1080/13662716.2016.1226163>
- Krammer, S. M., & Kafourous, M. I. (2022). Facing the heat: Political instability and firm new product innovation in sub-Saharan Africa. *Journal of Product Innovation Management*, 39(5), 604-642.
- Kruger, W., Nygaard, I., & Kitzing, L. (2021). Counteracting market concentration in renewable energy auctions: lessons learned from South Africa. *Energy Policy*, 148, 111995.
- Lööf, H., & Heshmati, A. (2006). On the relationship between innovation and performance: A sensitivity analysis. *Economics of innovation and new technology*, 15(4-5), 317-344.
- Lööf, H., Mairesse, J., & Mohnen, P. (2017). CDM 20 years after. *Economics of innovation and new technology*, 26(1-2), 1-5. <https://doi.org/10.1080/10438599.2016.1202522>
- Lorenzen, M. (2005). Knowledge and Geography. *Industry and Innovation*, 12(4), 399-407. <https://www.proquest.com/scholarly-journals/knowledge-geography/docview/201498944/se-2?accountid=15083>
- Lumpkin, G. T., & Dess, G. G. (1996). Clarifying the entrepreneurial orientation construct and linking it to performance. *Academy of Management Review*, 21(1), 135-172.
- Mairesse, J., Mohnen, P., Kremp, E., & Kremp, E. (2005). The Importance of R&D and Innovation for Productivity: A Reexamination in Light of the French Innovation Survey. *Annales d'Économie et de Statistique*(79/80), 487-527. <https://doi.org/10.2307/20777586>
- Mairesse, J., & Robin, S. (2017). Assessing measurement errors in the CDM research–innovation–productivity relationships. *Economics of innovation and new technology*, 26(1-2), 93-107. <https://doi.org/10.1080/10438599.2016.1210771>
- Mallows, C. L. (1986). Augmented partial residuals. *Technometrics*, 28(4), 313-319.

- Mansoori, Y., Karlsson, T., & Lundqvist, M. (2019). The influence of the lean startup methodology on entrepreneur-coach relationships in the context of a startup accelerator. *Technovation*, 84, 37-47.
- Mariev, O., Davidson, N., Nagieva, K., & Pushkarev, A. (2023). Innovations and their complementarities: which types of innovations drive export performance? *Post-Communist Economies*, 35(7), 708-743. <https://doi.org/10.1080/14631377.2023.2215022>
- Maroun, W. (2017). Assuring the integrated report: Insights and recommendations from auditors and preparers. *The British Accounting Review*, 49(3), 329-346.
- Marris, R. (1963). A model of the "managerial" enterprise. *The quarterly journal of economics*, 77(2), 185-209.
- McMillan, M., Rodrik, D., & Verduzco-Gallo, I. (2014). Globalization, structural change, and productivity growth, with an update on Africa. *World Development*, 63(1), 11-32.
- Mohan, P., Strobl, E., & Watson, P. (2018). In-firm training, innovation and productivity: the case of Caribbean Small Island Developing States [Article]. *Entrepreneurship & Regional Development*, 30(9/10), 987-1011. <https://doi.org/10.1080/08985626.2018.1515824>
- Mondliwa, P., & Roberts, S. (2021). Corporate Structure, Industrial Development, and Structural Change in South Africa. In A. Oqubay, F. Tregenna, & I. Valodia (Eds.), *The Oxford Handbook of the South African Economy* (pp. 349-374).
- Montégu, J. P., Pertuze, J. A., & Calvo, C. (2022). The effects of importing activities on technological and non-technological innovation: evidence from Chilean firms. *International Journal of Emerging Markets*, 17(7), 1659-1678. <https://doi.org/10.1108/IJOEM-05-2020-0534>
- Montresor, S., & Vezzani, A. (2016). Intangible investments and innovation propensity: Evidence from the Innobarometer 2013. *Industry and Innovation*, 23(4), 331-352. <https://doi.org/10.1080/13662716.2016.1151770>
- Naudé, W., Gries, T., Wood, E., & Meintjies, A. (2008). Regional determinants of entrepreneurial start-ups in a developing country [Article]. *Entrepreneurship & Regional Development*, 20(2), 111-124. <https://doi.org/10.1080/08985620701631498>
- North, D. C. (1990). *Institutions, Institutional Change, and Economic Performance*. Cambridge University Press.
- Notten, A., Mairesse, J., & Verspagen, B. (2017). The CDM framework: knowledge recombination from an evolutionary viewpoint. *Economics of innovation and new technology*, 26(1-2), 21-41. <https://doi.org/10.1080/10438599.2016.1202520>
- O'Reilly, C. A., & Tushman, M. L. (2013). Organizational Ambidexterity: Past, Present, and Future. *Academy of Management Perspectives*, 27(4), 324-338. <https://doi.org/10.5465/amp.2013.0025>
- Oduor, J., Ngoka, K., & Odongo, M. (2017). Capital requirement, bank competition and stability in Africa. *Review of Development Finance*, 7(1), 45-51.
- OECD. (2015). *The future of productivity* (<https://www.oecd.org/economy/growth/OECD-2015-The-future-of-productivity-book.pdf>)
- Okeahalam, C. (2002). *Structure and conduct in the commercial banking sector of South Africa*. Trade and Industrial Policy Strategies.
- Onsongo, E. (2019). Institutional entrepreneurship and social innovation at the base of the pyramid: the case of M-Pesa in Kenya. *Industry and Innovation*, 26(4), 369-390. <https://doi.org/10.1080/13662716.2017.1409104>
- Pakes, A., & Griliches, Z. (1984). Patents and R&D at the Firm Level in French Manufacturing: A First Look. In Z. Griliches (Ed.), *Research and Development, Patents and Productivity* (pp. 55-72). Chicago University Press.
- Perez-Alaniz, M., Lenihan, H., Doran, J., & Hewitt-Dundas, N. (2023). Financial resources for research and innovation in small and larger firms: Is it a case of the more you have, the more you do? *Industry and Innovation*, 30(2), 189-232. <https://doi.org/10.1080/13662716.2022.2036597>

- Petit, N., & Teece, D. J. (2021). Innovating big tech firms and competition policy: favoring dynamic over static competition. *Industrial and Corporate Change*, 30(5), 1168-1198.
- Plagerson, S. (2023). Mainstreaming poverty, inequality and social exclusion: A systematic assessment of public policy in South Africa. *Development Southern Africa*, 40(1), 191-207.
- Romer, P. M. (1990). Endogenous technological change. *Journal of political economy*, 98(5, Part 2), S71-S102.
- Roper, S., & Love, J. H. (2018). Knowledge context, learning and innovation: an integrating framework. *Industry and Innovation*, 25(4), 339-364.
<https://doi.org/10.1080/13662716.2017.1414744>
- Rypestøl, J. O., Martin, R., & Kyllingstad, N. (2022). New regional industrial path development and innovation networks in times of economic crisis. *Industry and Innovation*, 29(7), 879-898.
<https://doi.org/10.1080/13662716.2022.2082271>
- Salahuddin, M., Vink, N., Ralph, N., & Gow, J. (2020). Globalisation, poverty and corruption: Retarding progress in South Africa. *Development Southern Africa*, 37(4), 617-643.
- Schumpeter, J. A. (1934). *The theory of economic development: An enquiry into profits, capital, credit, interest, and the business cycle*. Harvard University Press.
- Schumpeter, J. A. (1942). Creative destruction. *Capitalism, socialism and democracy*, 825, 82-85.
- Schumpeter, J. A. (1942). *Socialism, capitalism and democracy*. Harper and Brothers.
- Song, J., Price, D. J., Guvenen, F., Bloom, N., & Von Wachter, T. (2019). Firming up inequality. *The quarterly journal of economics*, 134(1), 1-50.
- Spescha, A. (2019). R&D expenditures and firm growth—is small beautiful? *Economics of innovation and new technology*, 28(2), 156-179.
- Su, Y.-S., Kajikawa, Y., Tsujimoto, M., & Chen, J. (2018). Innovation ecosystems: Theory, evidence, practice, and implications. *Technological Forecasting and Social Change*, 136, 14-17.
<https://doi.org/https://doi.org/10.1016/j.techfore.2018.08.009>
- Sulla, V., & Zikhali, P. (2018). *Overcoming poverty and inequality in South Africa: An assessment of drivers, constraints and opportunities* (
- Taherizadeh, A., & Beaudry, C. (2023). An emergent grounded theory of AI-driven digital transformation: Canadian SMEs' perspectives. *Industry and Innovation*, 30(9), 1244-1273.
<https://doi.org/10.1080/13662716.2023.2242285>
- Tarba, S. Y., Frynas, J. G., Liu, Y., Wood, G., Sarala, R. M., & Fainshmidt, S. (2023). Strategic agility in international business. *Journal of World Business*, 58(2), 101411.
<https://doi.org/https://doi.org/10.1016/j.jwb.2022.101411>
- Teece, D. J. (2018). Business models and dynamic capabilities [Article]. *Long Range Planning*, 51(1), 40-49. <https://doi.org/10.1016/j.lrp.2017.06.007>
- Thurik, R., Benzari, A., Fisch, C., Mukerjee, J., & Torrès, O. (2024). Techno-overload and well-being of French small business owners: identifying the flipside of digital technologies [Article]. *Entrepreneurship & Regional Development*, 36(1/2), 136-161.
<https://doi.org/10.1080/08985626.2023.2165713>
- Tregenna, F. (2014). A new theoretical analysis of deindustrialisation. *Cambridge Journal of Economics*, 38(6), 1373-1373.
<http://search.ebscohost.com/login.aspx?direct=true&db=eoh&AN=34098160&site=pfi-live>
- Tregenna, F., Nell, K., & Callaghan, C. W. (2021). Determinants of Industrial Development. In N. Foster-McGregor, L. Alcorta, A. Szirmai, & B. Verspagen (Eds.), *New Perspectives on Structural Change: Causes and Consequences of Structural Change in the Global Economy* (pp. 378-406). Oxford University Press.
- Tripathi, N., Oivo, M., Liukkunen, K., & Markkula, J. (2019). Startup ecosystem effect on minimum viable product development in software startups. *Information and Software Technology*, 114, 77-91.

- Tsujimoto, M., Kajikawa, Y., Tomita, J., & Matsumoto, Y. (2018). A review of the ecosystem concept — Towards coherent ecosystem design. *Technological Forecasting and Social Change*, 136, 49-58. <https://doi.org/https://doi.org/10.1016/j.techfore.2017.06.032>
- Tukey, J. W. (1962). The future of data analysis. *The annals of mathematical statistics*, 33(1), 1-67.
- Ullah, S., Ahmad, T., Mehmood, T., & Sami, A. (2023). Innovation and economic performance of firms in national science & technology park, Islamabad, Pakistan. *Foresight*, 25(5), 633-648. <https://doi.org/10.1108/FS-08-2021-0151>
- Urbano, D., Aparicio, S., Scott, S., & Martinez-Moya, D. (2024). Inside out: The interplay between institutions and digital technologies for SMEs performance [Article]. *Entrepreneurship & Regional Development*, 36(1/2), 162-181. <https://doi.org/10.1080/08985626.2023.2208555>
- van Mossel, A., van Rijnsoever, F. J., & Hekkert, M. P. (2018). Navigators through the storm: A review of organization theories and the behavior of incumbent firms during transitions. *Environmental Innovation and Societal Transitions*, 26, 44-63. <https://doi.org/https://doi.org/10.1016/j.eist.2017.07.001>
- Vivarelli, M. (2013). TECHNOLOGY, EMPLOYMENT AND SKILLS: AN INTERPRETATIVE FRAMEWORK. *Eurasian Business Review*, 3(1), 66-89. <https://search.proquest.com/docview/1399324899?accountid=15083>
- Vivarelli, M. (2014). Innovation, Employment and Skills in Advanced and Developing Countries: A Survey of Economic Literature. *Journal of Economic Issues*, 48(1), 123-154. <https://search.proquest.com/docview/1509070593?accountid=15083>
- Vivarelli, M., Evangelista, R., & Pianta, M. (1996). Innovation and employment in Italian manufacturing industry. *Research Policy*, 25(7), 1013-1026. [https://doi.org/https://doi.org/10.1016/0048-7333\(95\)00878-0](https://doi.org/https://doi.org/10.1016/0048-7333(95)00878-0)
- von Hippel, E., & Euchner, J. (2013). User innovation. *Research-Technology Management*, 56(3), 15-20.
- Wakelin, K. (2001). Productivity growth and R&D expenditure in UK manufacturing firms. *Research Policy*, 30(7), 1079-1090. [https://doi.org/https://doi.org/10.1016/S0048-7333\(00\)00136-0](https://doi.org/https://doi.org/10.1016/S0048-7333(00)00136-0)
- Wang, Y., Yao, X., & Li, K. (2022). Imitation and rapid internationalization of emerging market firms. *Journal of World Business*, 57(6), 101364. <https://doi.org/https://doi.org/10.1016/j.jwb.2022.101364>
- WB. (2020). *World Bank World Development Indicators* <https://databank.worldbank.org/source/world-development-indicators>
- WBES. (2020). *World Bank Enterprise Survey: South Africa*. <https://www.enterprisesurveys.org/en/data>
- WBES. (2023). *World Bank Enterprise Surveys- South Africa data*. <https://login.enterprisesurveys.org/content/sites/financeandprivatesector/en/library/library-detail.html/content/dam/wbgassetshare/enterprisesurveys/economy/south-africa/South%20Africa-2020-full%20data.dta>
- Wesson, N. (2021). Will mandatory audit firm rotation reduce audit market concentration in South Africa? *South African Journal of Business Management*, 52(1), 13.
- Williamson, O. E. (1964). *The economics of discretionary behavior: Managerial objectives in a theory of the firm*. Prentice-Hall.
- Wouters, O. J., Sandberg, D. M., Pillay, A., & Kanavos, P. G. (2019). The impact of pharmaceutical tendering on prices and market concentration in South Africa over a 14-year period. *Social Science & Medicine*, 220, 362-370.
- Yaghi, Z.-A., & Tomaszewski, T. (2023). The interdependence of R&D, innovations, and productivity: case of Polish manufacturing companies. *Ekonomia i Prawo*, 23(online first).
- Yildirim, A., Clarysse, B., & Wright, M. (2022). The impact of institutional voids and ecosystem logics in the spread of ecosystems in emerging economies. *Industry and Innovation*, 29(5), 649-671. <https://doi.org/10.1080/13662716.2021.2007760>

FIGURES

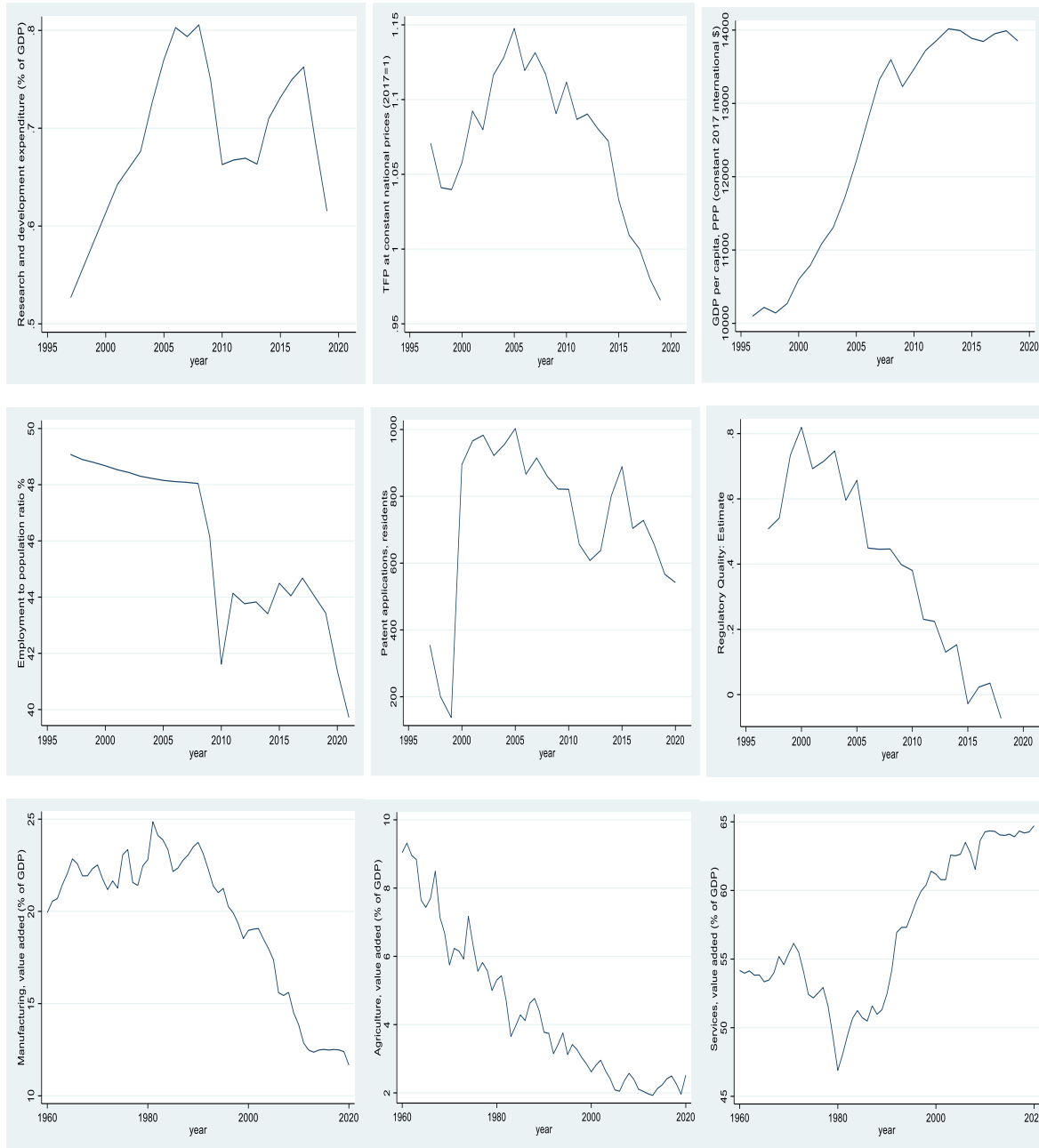


Figure 1.

South Africa's contextual trends in research and development share of gross domestic product (GDP) (1.a. Top left), total factor productivity (1.b. Top middle), real GDP (1.c. Top right), employment share of the population (1.d. Middle left), patent applications (1.e. Middle middle), regulatory quality (1.f. Middle right), manufacturing value added share of GDP (1.g. Bottom left), agriculture value added share of GDP (1.h. Bottom middle), and services value-added share of GDP (1.i. Bottom right).

Notes. All data from World Bank Development Indicators (WB, 2020), except for 1.b. from the Penn World Tables (Feenstra et al., 2015).

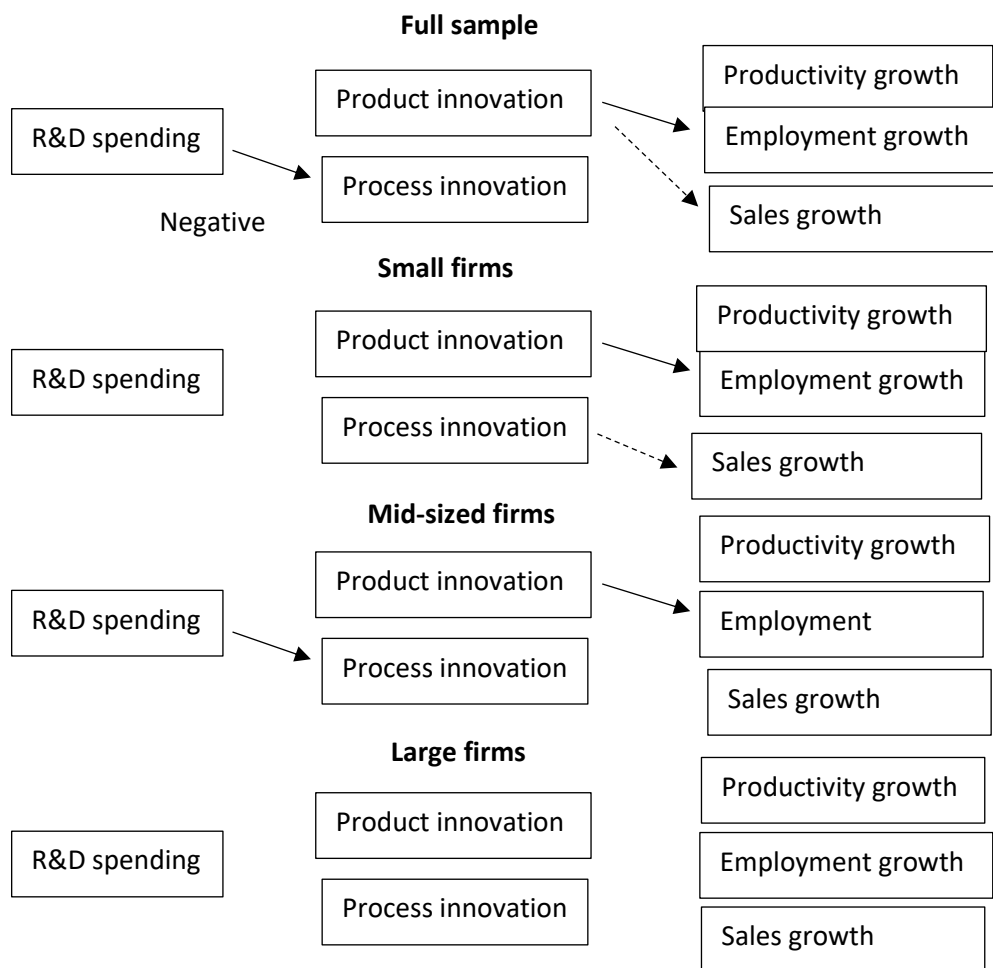


Figure 2.

Findings: Empirical linkages along the innovation chain

Notes. All solid arrows represent positive and significant associations unless indicated otherwise. Dotted arrows represent associations that are not fully significant but are significant within the ten percent significance level.

TABLES

Table 1
Descriptive Statistics
A. Full sample

Variable	Definitions	Obs	Mean	Std. Dev.
rnd	0/1 Firm invests in R&D	1040	.243	.429
spendrnd	Rand value of spending on R&D- natural log used in tests and reported as 'R&Dinvest'	245	39710.645	56740.849
firmage	Firm age in years	1035	26.866	21.663
foreigncomp	0/1 Firm's main competitor is foreign	1018	.066	.248
prodinnov	0/1 Product innovation	1042	.038	.192
procinnov	0/1 Process innovation	1041	.021	.144
gprod	Growth in productivity- sales/employees	1042	90.427	3097.229
gemploy	Growth in employment	1042	6.442	54.275
gsales	Growth in sales	1042	110.185	3715.896
govtwage	0/1 Firm receives wage, investment, or other direct subsidies	1037	.052	.222
ISO	0/1 Firm has an internationally recognised quality certification	1034	.071	.256
ownerman	0/1 Largest owner is also the manager	1040	.735	.442
prodtargets	0/1 Firm uses production targets	1040	.355	.479
audited	0/1 Annual financial statements audited	1030	.401	.49
oblabourreg	Extent to which labour regulations pose an obstacle to firm operations- Survey index 0-4	1042	.367	.595
political	Extent to which political instability poses an obstacle to firm operations- Survey index 0-4	1039	.84	1.293
powercut	0/1 Firm experienced power outages	1042	.914	.281
investment	0/1 Firm investment in fixed assets	1038	.037	.188
bonuses	0/1 Performance bonuses for managers	997	.098	.298
marketshare	Share of sales value in its main market. Natural log used in tests and reported as 'marketshare'.	943	14.439	26.407
size	Small (5-19 staff), medium (20-99 staff), large (100+ staff)	1042	1.895	.814
construct	0/1 Construction industry	1042	.117	.322
manufacturing	0/1 Manufacturing industry	1042	.315	.465
services	0/1 Services industry	1042	.08	.271
retail	0/1 Retail industry	1042	.281	.45
hospitality	0/1 Hospitality industry	1042	.194	.396
wholesale	0/1 Wholesale industry	1042	.013	.115
covid	0/1 Firm's financial year ends in or after May 2020	1042	.111	.315
precision	Comprehensiveness of data provided by the firm- Survey index 1-4	1042	3.444	.52

Notes. Variables used in each specification are listed in the text. Obs.: Observations; Std. Dev.: Standard deviation. 0/1: Indicates binary variable with values zero or one. Regression tests are performed for firms with a full set of the included variables. Each model test is reported in Tables A.1.-A.5. along with the number of included firms.

B. Small firms

Variable	Obs	Mean	Std. Dev.
rnd	403	.231	.422
spendrnd	90	33744.8	63328.55
firmage	403	24.345	22.466
foreigncomp	399	.05	.218
prodinnov	405	.032	.176
procinnov	404	.012	.111
gprod	405	-12.811	77.566
gemploy	405	10.09	73.85
gsales	405	-9.571	72.247
govtwage	404	.052	.222
ISO	404	.05	.217
ownerman	405	.775	.418
prodtargets	404	.295	.456
audited	404	.376	.485
oblabourreg	405	.343	.557
political	405	.837	1.3
powercut	405	.911	.285
investment	403	.025	.156
bonuses	396	.071	.257
marketshare	375	13.275	25.764
size	405	1	0
construct	405	.141	.348
manufacturing	405	.254	.436
services	405	.081	.274
retail	405	.23	.421
hospitality	405	.281	.45
wholesale	405	.012	.111
covid	405	.079	.27
precision	405	3.41	.512

Notes. Variable information and definitions are listed in Table 1

C. Mid-sized firms

Variable	Obs	Mean	Std. Dev.
rnd	341	.229	.421
spendrnd	76	40263.355	41375.279
firmage	339	26.342	17.807
foreigncomp	333	.063	.243
prodinnov	341	.032	.177
procinnov	341	.026	.161
gprod	341	-3.651	99.177
gemploy	341	5.035	21.588
gsales	341	-1.228	98.499
govtwage	337	.05	.219
ISO	338	.062	.242
ownerman	341	.736	.441
prodtargets	341	.381	.486
audited	336	.396	.49
oblabourreg	341	.39	.607
political	340	.785	1.238
powercut	341	.924	.266
investment	340	.044	.206
bonuses	325	.114	.318
marketshare	304	12.961	23.472
firmsize	341	2	0
construct	341	.094	.292
manufacturing	341	.343	.475
services	341	.088	.284
retail	341	.302	.46
hospitality	341	.152	.36
wholesale	341	.021	.142
covid	341	.111	.315
precision	341	3.469	.511

Notes. Variable information and definitions are listed in Table 1

D. Large firms

Variable	Obs	Mean	Std. Dev.
rnd	296	.277	.448
spendrnd	79	45975.456	61384.491
firmage	293	30.939	23.961
foreigncomp	286	.091	.288
prodinnov	296	.054	.227
procinnov	296	.027	.162
gprod	296	340.062	5808.986
gemploy	296	3.071	48.55
gsales	296	402.393	6970.466
govtwage	296	.054	.227
ISO	292	.11	.313
ownerman	294	.677	.468
prodtargets	295	.407	.492
audited	290	.441	.497
oblabourreg	296	.372	.63
political	294	.908	1.346
powercut	296	.905	.293
investment	295	.044	.206
bonuses	276	.12	.325
marketshare	264	17.795	30.054
size	296	3	0
construct	296	.111	.315
manufacturing	296	.365	.482
services	296	.068	.251
retail	296	.328	.47
hospitality	296	.122	.327
wholesale	296	.007	.082
covid	296	.155	.363
precision	296	3.463	.539

Notes. Variable information and definitions are listed in Table 1

Table 2

Summary of results

Variable	Significance in full sample (coefficient/standard error)	Significance in small firm sample (coefficient/standard error)	Significance in med-sized firm sample (coefficient/standard error)	Significance in large firm sample (coefficient/standard error)
First stage Heckman: Predictors of R&D decision				
	Table A.1. Model 2	Table A.2. Model 2	Table A.3. Model 2	Table A.4. Model 2
foreigncomp	-	-1.841***/ 0.686	-	-
firmage	-0.006*/ 0.003	-	-	-
marketshare	-0.593***/ 0.054	-0.498***/ 0.096	-0.904***/ 0.127	-0.549***/ 0.088
firmsize	0.187**/ 0.079	-	-	-
political	0.378***/ 0.051	0.366***/ 0.084	0.570***/ 0.225	0.281***/ 0.094
precision	1.146***/ 0.137	1.365***/ 0.245	0.986***/ 0.264	1.373***/ 0.260
Second stage Heckman: Predictors of R&D spending				
	Table A.1. Model 1	Table A.2. Model 1	Table A.3. Model 1	Table A.4. Model 1
marketshare	-1.320**/ 0.522	-1.868**/ 0.778	-	-1.384**/ 0.541
firmsize	0.450**/ 0.204	-	-	-
covid	-	-	-	-1.209**/ 0.581
Knowledge Production Function: Predictors of Product Innovation				
	Table A.1. Model 4	Table A.2. Model 4	Table A.3. Model 4	Table A.4. Model 4
firmage	-0.025*/ 0.014	-0.054*/ 0.032	-	-
political	0.675*/ 0.360	-	-	-
covid	-1.653*/ 0.997	-	-	-
Knowledge Production Function: Predictors of Process Innovation				
	Table A.1. Model 6	Table A.2. Model 6	Table A.3. Model 6	Table A.4. Model 6
R&Dinvest	-4.105**/ 1.626	-	24.207***/ 8.925	-
marketshare	-4.985**/ 2.15	-	17.391***/ 6.295	-
firmage	-0.045***/ 0.017	-0.172*/ 0.088	-0.251***/ 0.089	-0.067**/ 0.033
firmsize	2.227***/ 0.742	-	-	-
political	2.030***/ 0.608	1.222***/ 0.306	3.712***/ 1.244	-
covid	-	-	2.700*/ 1.520	-
Growth in productivity				
	Table A.5. Model 1	Table A.5. Model 2	Table A.5. Model 3	Table A.5. Model 4
ISO	7.831**/ 3.193	-	-	15.389***/ 4.357
prodtargets	7.626***/ 2.511	10.052**/ 4.206	-	11.644**/ 4.916
audited	4.940*/ 2.605	-	10.128**/ 4.21	-
labourreg	4.546***/ 1.696	6.165*/ 3.198	-	5.065*/ 2.751
political	-1.577*/ 0.918	-	-	-
investment	10.944**/ 4.755	-	-	16.978**/ 8.564
firmsize	1.736*/ 1.004	-	-	-
powercut	-	11.819***/ 4.546	-	-
bonuses	-	-	18.716***/ 4.699	-15.368***/ 5.069
Growth in employment				
	Table A.5. Model 5	Table A.5. Model 6	Table A.5. Model 7	Table A.5. Model 8
prodinno	7.651**/ 3.846	18.274***/ 6.593	9.973**/ 4.623	-
govtwage	-8.906***/ 2.131	-8.963**/ 4.035	-10.578**/ 4.225	-6.251**/ 3.034
ISO	-	-	6.309*/ 3.392	-
ownerman	3.798***/ 1.169	-	7.913***/ 2.282	4.188**/ 2.023
audited	3.216*/ 1.775	6.984**/ 3.543	-	-

Variable	Significance in full sample (coefficient/standard error)	Significance in small firm sample (coefficient/standard error)	Significance in med-sized firm sample (coefficient/standard error)	Significance in large firm sample (coefficient/standard error)
political	-2.514***/ 0.617	-3.534***/ 1.086	-	-2.593***/ 0.986
firmage	-	-0.131**/ 0.064	-	-
investment	-	-	-9.825**/ 4.850	-
bonuses	9.790***/ 1.982	8.189*/ 4.311	8.731**/ 3.444	8.395***/ 2.742
size	-1.463**/ 0.582	-	-	-
covid	-	-	-5.042**/ 2.151	-
Growth in sales				
	Table A.5. Model 9	Table A.5. Model 10	Table A.5. Model 11	Table A.5. Model 12
proinnov	10.179*/ 6.052	-	-	-
procinnov	-	19.286*/ 11.466	-	-
govtwage	-7.230*/ 4.074	-	-	-
ISO	8.882***/ 3.407	-	-	12.829**/ 5.05
ownerman	-	-	7.794*/ 4.241	-
prodtargets	5.744**/ 2.875	-	-	11.724**/ 5.842
audited	8.321***/ 3.173	15.137***/ 5.47	9.097*/ 4.99	-
labourreg	5.491**/ 2.128	-	8.240**/ 3.365	-
political	-4.981***/ 1.117	-6.262***/ 2.041	-4.301**/ 2.027	-3.718*/ 1.905
powercut	-	15.901***/ 5.055	-	-
firm age	-	-0.131**/ 0.064	-	-
investment	-	-	-	18.539*/ 10.033
bonuses	10.946***/ 3.814	-	26.861***/ 5.165	-
mrketshare	-	-	-	-3.104*/ 1.636

Notes. Variable information and definitions are listed in Table 1

Table 3.

Summary of hypothesis testing

Hypothesis	Full sample	Small firms	Mid-sized firms	Large firms
Hypothesis A, market share is significantly and negatively associated with:				
Hypothesis A1, R&D investment choice.	Supported	Supported	Supported	Supported
Hypothesis A2, R&D investment.	Supported	Supported	Not supported	Supported
Hypothesis A3, product innovation.	Not supported	Not supported	Not supported	Not supported
Hypothesis A4, process innovation.	Supported	Not supported	Not supported	Not supported
Hypothesis A5, growth in productivity.	Not supported	Not supported	Not supported	Not supported
Hypothesis A6, growth in employment.	Not supported	Not supported	Not supported	Not supported
Hypothesis A7, growth in sales.	Not supported	Not supported	Not supported	Not supported
Hypothesis B, Firm age is significantly and negatively associated with:				
Hypothesis B1, R&D investment choice.	Not supported	Not supported	Not supported	Not supported
Hypothesis B2, R&D investment.	Not supported	Not supported	Not supported	Not supported
Hypothesis B3, product innovation.	Not supported	Not supported	Not supported	Not supported
Hypothesis B4, process innovation.	Supported	Not supported	Supported	Supported
Hypothesis B5, growth in productivity.	Not supported	Not supported	Not supported	Not supported
Hypothesis B6, growth in employment.	Not supported	Not supported	Not supported	Not supported
Hypothesis B7, growth in sales.	Not supported	Supported	Not supported	Not supported
Hypothesis C, Firm size is significantly and negatively associated with:				
Hypothesis C1, R&D investment choice.	Not supported	-	-	-
Hypothesis C2, R&D investment.	Not supported	-	-	-
Hypothesis C3, product innovation.	Not supported	-	-	-
Hypothesis C4, process innovation.	Not supported	-	-	-
Hypothesis C5, growth in productivity.	Not supported	-	-	-
Hypothesis C6, growth in employment.	Supported	-	-	-
Hypothesis C7, growth in sales.	Not supported	-	-	-

Appendix A

Tables A.1-4 report results for predictors of R&D choice, R&D spending, product innovation, and process innovation, for the full sample and small, medium, and large firms, respectively. Table A.5 reports results for tests of predictors of firm growth.

Table A.1.

Full sample predictors of R&D choice, R&D spending, product innovation, and process innovation

VARIABLES	(1) Full sector controls lnspendrnd	(2) rnd	(3) /mills	(4) Full sector controls prodinno	(5) Full sector controls procinnov
firmage	-0.005 (0.009)	-0.006* (0.003)		-0.025* (0.014)	-0.045*** (0.017)
lnmarketshare	-1.320** (0.522)	-0.593*** (0.054)		-0.410 (1.293)	-4.985** (2.150)
size	0.450** (0.204)	0.187** (0.079)		0.483 (0.497)	2.227*** (0.742)
2.industry	1.048* (0.594)	0.462** (0.233)		2.078 (1.644)	4.604** (1.894)
3.industry	1.753*** (0.641)	0.448** (0.226)		2.900 (2.159)	8.672*** (2.927)
4.industry	-0.515 (0.737)	-0.001 (0.328)		0.380 (1.516)	
5.industry	0.634 (0.549)	0.145 (0.233)		1.168 (1.418)	2.308 (1.592)
6.industry	1.088 (2.000)	0.133 (0.640)			
political	0.210 (0.232)	0.378*** (0.051)		0.675* (0.360)	2.030*** (0.608)
covid	-0.175 (0.435)			-1.653* (0.997)	-1.489 (0.952)
precision	0.603 (0.942)	1.146*** (0.137)			
foreigncomp		-0.173			

lambda		(0.253)	1.610 (1.169)		
R&Dinvest			-0.496 (0.977)	-4.105** (1.626)	
6o.industry			-	-	
o.precision			-	-	
5o.industry					
4o.industry				-	
Constant	5.786 (4.564)	-4.616*** (0.554)	-1.960 (7.320)	24.863** (12.402)	
Observations	927	927	927	913	839

Notes. Column 1 reports second stage of Heckman procedure. Column 2 reports first stage. Column 3 reports inverse Mills ratio for Heckman process. Column 4 reports logit results of predictors of product innovation, and Column 5 reports the same but with process innovation as the dependent variable. Standard errors in parentheses

o. designates a variable dropped in the regression due to collinearity

*** p<0.01, ** p<0.05, * p<0.1

Table A.2.

Predictors of R&D choice, R&D spending, product innovation, and process innovation in small firms

VARIABLES	(1) lnspendrnd	(2) rnd	(3) /mills	(4) prodinnov	(5) procinnov
foreigncomp		-1.841*** (0.686)			
firmage	-0.018 (0.032)	-0.010 (0.008)		-0.054* (0.032)	-0.172* (0.088)
lnmarketshare	-1.868** (0.778)	-0.498*** (0.096)		-0.037 (0.631)	-0.274 (0.574)
2.industry	0.718 (1.131)	0.134 (0.342)		1.196 (1.131)	-0.779 (1.288)
3.industry	2.997* (1.552)	0.778** (0.370)		1.075 (1.337)	1.715 (1.062)
4.industry	-2.140 (1.638)	0.434 (0.492)		1.207 (1.513)	
5.industry	-0.949 (1.305)	0.053 (0.395)			
6.industry		-3.584 (0.000)			
political	0.371 (0.429)	0.366*** (0.084)		0.347 (0.335)	1.222*** (0.306)
precision	2.963 (2.122)	1.365*** (0.245)			
covid	1.382 (1.381)				
lambda			3.752* (1.950)		
R&Dinvest				0.044 (0.272)	-0.379 (0.255)
5o.industry				-	-
6o.industry				-	-
o.covid				-	-
o.precision				-	-

Lnspondrnd

4o.industry

Constant	-3.692 (9.603)	-5.149*** (0.971)	-3.766* (2.117)	-2.110 (2.943)
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Observations	368	368	368	280	254
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Notes. Column 1 reports second stage of Heckman procedure. Column 2 reports first stage. Column 3 reports inverse Mills ratio for Heckman process. Column 4 reports logit results of predictors of product innovation, and Column 5 reports the same but with process innovation as the dependent variable. Standard errors in parentheses

o. designates a variable dropped in the regression due to collinearity

*** p<0.01, ** p<0.05, * p<0.1

Table A.3.

Predictors of R&D choice, R&D spending, product innovation, and process innovation in mid-sized firms

VARIABLES	(1) lnspendrnd	(2) rnd	(3) /mills	(4) prodinnov	(5) procinnov
foreigncomp		-0.473 (0.807)			
firmage	0.009 (0.012)	-0.001 (0.008)		-0.124 (0.098)	-0.251*** (0.089)
lnmarketshare	-0.680 (0.517)	-0.904*** (0.127)		8.115 (6.039)	17.391*** (6.295)
2.industry	1.106 (0.749)	0.790 (0.483)		-13.792 (8.884)	12.068*** (4.449)
3.industry	2.204*** (0.756)	0.128 (0.452)		-24.664 (18.207)	-12.412** (5.371)
4.industry	1.232 (0.933)	-0.436 (0.661)			
5.industry	1.599** (0.729)	-0.225 (0.466)		-19.759 (13.047)	
6.industry		-5.519 (0.000)			
political	-0.037 (0.225)	0.570*** (0.110)		1.938 (1.181)	3.712*** (1.244)
precision	-0.310 (0.584)	0.986*** (0.264)			
covid	-0.072 (0.594)			0.958 (1.581)	2.700* (1.520)
lambda			0.333 (0.917)		
R&Dinvest				11.335 (8.545)	24.207*** (8.925)
4o.industry				-	-
6o.industry				-	-
o.precision				-	-
Lnspendrnd					
2o.industry					

3o.industry

5o.industry

Constant	10.173*** (2.639)	-3.439*** (1.064)	-108.782 (80.258)	-270.406*** (98.154)
Observations	301	301	268	238

Notes. Column 1 reports second stage of Heckman procedure. Column 2 reports first stage. Column 3 reports inverse Mills ratio for Heckman process. Column 4 reports logit results of predictors of product innovation, and Column 5 reports the same but with process innovation as the dependent variable. Standard errors in parentheses

o. designates a variable dropped in the regression due to collinearity

*** p<0.01, ** p<0.05, * p<0.1

Table A.4.

Predictors of R&D choice, R&D spending, product innovation, and process innovation in large firms

VARIABLES	(1) lnspendrnd	(2) rnd	(3) /mills	(4) prodinnov	(5) procinnov
firmage	-0.011 (0.011)	-0.006 (0.005)		-0.023 (0.018)	-0.067** (0.033)
lnmarketshare	-1.384** (0.541)	-0.549*** (0.088)		0.354 (1.561)	-1.048 (1.971)
2.industry	0.274 (1.186)	0.573 (0.520)		0.130 (0.925)	-0.264 (1.346)
3.industry	0.740 (1.155)	0.431 (0.463)		0.873 (0.801)	0.568 (1.422)
4.industry	0.407 (1.644)	-0.265 (0.734)			
5.industry	0.416 (1.110)	0.504 (0.474)			
6.industry	2.057 (2.437)	1.610 (1.043)			
political	0.259 (0.239)	0.281*** (0.094)		0.542 (0.553)	1.149 (0.757)
covid	-1.209** (0.581)				
precision	0.855 (1.255)	1.373*** (0.260)			
foreigncomp		0.524 (0.355)			
lambda			1.650 (1.311)		
R&Dinvest				-0.013 (1.103)	-1.057 (1.418)
4o.industry				-	-
5o.industry				-	-
6o.industry				-	-
o.covid				-	-
o.precision				-	-

lnspendrnd

2o.industry

Constant	6.916 (5.469)	-4.969*** (0.937)		-3.956 (11.146)	6.570 (13.410)
Observations	258	258	258	170	136

Notes. Column 1 reports second stage of Heckman procedure. Column 2 reports first stage. Column 3 reports inverse Mills ratio for Heckman process. Column 4 reports logit results of predictors of product innovation, and Column 5 reports the same but with process innovation as the dependent variable. Standard errors in parentheses
o. designates a variable dropped in the regression due to collinearity
*** p<0.01, ** p<0.05, * p<0.1

Table A.5.

Predictors of growth in productivity, employment, and sales

VARIABLES	(1) Full sample gprod	(2) Small firms gprod	(3) Mid-sized firms gprod	(4) Large firms gprod	(5) Full sample gemploy	(6) Small firms gemploy	(7) Mid-sized firms gemploy	(8) Large firms gemploy	(9) Full sample gsales	(10) Small firms gsales	(11) Mid-sized firms gsales	(12) Large firms gsales
prodinnov	5.641 (5.174)	3.784 (11.044)	6.970 (9.928)	14.639 (8.881)	7.651** (3.846)	18.274*** (6.593)	9.973** (4.623)	-4.131 (6.304)	10.179* (6.052)	17.998 (13.130)	15.831 (10.532)	7.999 (11.855)
procinnov	0.488 (6.780)	15.171 (9.726)	-11.171 (12.620)	-3.741 (13.590)	2.506 (5.450)	2.010 (6.412)	5.273 (6.559)	-5.864 (9.794)	11.154 (8.014)	19.286* (11.466)	2.698 (11.803)	1.956 (17.255)
govtwage	1.122 (3.502)	2.769 (5.979)	8.390 (6.455)	-6.009 (4.922)	-8.906*** (2.131)	-8.963** (4.035)	-10.578** (4.225)	-6.251** (3.034)	-7.230* (4.074)	-8.738 (6.978)	-0.090 (8.135)	-9.200 (5.841)
ISO	7.831** (3.193)	8.536 (7.109)	-0.373 (5.991)	15.389*** (4.357)	-0.438 (1.757)	-2.799 (3.523)	6.309* (3.392)	-3.133 (2.385)	8.882*** (3.407)	10.015 (6.857)	6.468 (6.861)	12.829** (5.050)
ownerman	-1.482 (1.951)	-3.550 (3.110)	2.005 (3.537)	-4.662 (3.611)	3.798*** (1.169)	2.246 (1.963)	7.913*** (2.282)	4.188** (2.023)	1.692 (2.325)	-1.104 (4.050)	7.794* (4.241)	-0.451 (3.900)
prodtargets	7.626*** (2.511)	10.052** (4.207)	-0.479 (4.068)	11.644** (4.916)	-2.180 (1.499)	-3.232 (2.559)	-1.541 (2.435)	1.123 (3.070)	5.744** (2.875)	6.940 (4.952)	-1.311 (4.511)	11.724** (5.842)
audited	4.940* (2.603)	5.647 (4.388)	10.128** (4.261)	-3.130 (4.836)	3.216* (1.775)	6.984** (3.543)	-0.394 (2.588)	1.865 (3.163)	8.321*** (3.173)	15.137*** (5.470)	9.097* (4.990)	-1.831 (5.974)
oblabourreg	4.546*** (1.696)	6.165* (3.198)	4.799 (2.912)	5.065* (2.751)	1.039 (1.204)	1.600 (2.134)	2.838 (2.041)	0.433 (2.222)	5.491** (2.128)	6.459 (4.087)	8.240** (3.365)	4.800 (3.665)
political	-1.577* (0.918)	-1.731 (1.649)	-1.930 (1.671)	-1.155 (1.629)	-2.514*** (0.617)	-3.534*** (1.086)	-0.965 (1.203)	-2.593*** (0.986)	-4.981*** (1.117)	-6.262*** (2.041)	-4.301** (2.027)	-3.718* (1.905)
powercut	3.707 (3.093)	11.819*** (4.546)	-8.079 (6.339)	-0.712 (5.129)	1.815 (1.453)	3.377 (2.339)	0.202 (2.618)	-0.805 (3.009)	5.594 (3.512)	15.901*** (5.055)	-9.400 (7.508)	-0.282 (5.367)
firmage	0.018 (0.036)	-0.067 (0.061)	0.077 (0.074)	0.055 (0.057)	-0.015 (0.020)	-0.067* (0.035)	0.056 (0.046)	-0.026 (0.025)	0.008 (0.042)	-0.131** (0.064)	0.115 (0.095)	0.047 (0.063)
investment	10.944** (4.755)	0.746 (9.052)	14.046 (10.018)	16.978** (8.564)	-5.161 (3.804)	-9.276 (6.374)	-9.825** (4.850)	4.422 (8.145)	3.403 (5.637)	-6.955 (11.637)	-1.281 (10.112)	18.539* (10.033)
bonuses	3.052 (3.366)	0.511 (7.399)	18.716*** (4.699)	-15.368*** (5.069)	9.790*** (1.982)	8.189* (4.311)	8.731** (3.444)	8.395*** (2.742)	10.946*** (3.814)	3.629 (8.310)	26.861*** (5.165)	-5.941 (6.025)
lnmarketshare	-1.109 (0.778)	0.380 (1.283)	-1.700 (1.468)	-1.821 (1.477)	0.016 (0.462)	0.981 (0.866)	-1.560* (0.826)	-0.058 (0.729)	-1.529 (0.931)	0.579 (1.636)	-2.229 (1.753)	-3.104* (1.636)
size	1.736* (1.004)				-1.463** (0.582)				0.075 (1.174)			
o.political	-	-	-	-	-	-	-	-	-	-	-	-
covid	-1.351 (2.467)	-1.345 (4.503)	-2.696 (4.277)	0.046 (4.379)	-1.925 (1.267)	0.832 (2.623)	-5.042** (2.151)	-1.756 (1.926)	-3.739 (2.680)	-3.427 (5.191)	-7.391 (4.701)	-0.717 (4.651)

precision	1.728 (2.291)	-1.641 (3.638)	1.793 (3.416)	7.284 (4.933)	-2.093 (1.479)	-2.565 (2.484)	-2.727 (2.474)	-2.672 (2.968)	0.809 (2.771)	-4.081 (4.668)	1.971 (4.229)	3.906 (5.501)
2.industry	8.775*** (3.072)	11.491*** (4.098)	7.844 (6.494)	3.648 (6.478)	-0.390 (1.784)	-3.406 (2.584)	-1.378 (3.032)	4.893 (3.805)	8.644** (3.809)	8.782 (5.432)	5.119 (7.622)	10.902 (7.458)
3.industry	9.034*** (2.744)	13.254*** (3.823)	3.186 (5.933)	7.436 (5.735)	0.168 (1.543)	-1.999 (2.514)	1.904 (2.342)	2.087 (3.053)	9.212*** (3.304)	10.627** (5.047)	2.995 (6.826)	12.319** (6.193)
4.industry	9.588** (4.117)	15.021** (5.877)	3.978 (7.686)	9.969 (9.258)	-0.032 (2.048)	-2.155 (3.079)	1.352 (3.654)	-1.060 (3.974)	8.360* (4.751)	10.776 (6.948)	2.673 (9.063)	11.903 (9.906)
5.industry	6.517** (2.857)	9.801** (4.233)	2.499 (5.819)	3.433 (5.910)	-3.342** (1.547)	-6.889*** (2.535)	0.457 (2.284)	-2.814 (2.851)	2.923 (3.422)	2.951 (5.586)	0.685 (6.696)	2.582 (6.353)
6.industry	-0.559 (6.259)	0.187 (8.524)	-7.561 (12.111)	16.132** (6.565)	1.723 (4.670)	11.719 (7.126)	-8.684* (4.582)	11.910 (12.815)	-1.445 (7.301)	6.028 (7.371)	-18.629 (13.305)	29.464*** (10.419)
Constant	-38.634*** (8.607)	-37.082*** (13.488)	-21.912 (15.134)	-43.174** (16.907)	11.685** (5.245)	12.146 (8.696)	9.227 (8.939)	10.139 (9.903)	-29.741*** (10.064)	-24.484 (16.428)	-19.839 (17.707)	-32.945* (19.086)
Observations	913	368	294	251	913	368	294	251	913	368	294	251
R-squared	0.139	0.165	0.182	0.222	0.175	0.251	0.190	0.222	0.121	0.158	0.182	0.182

Notes. Standard errors in parentheses

o. designates a variable dropped in the regression due to collinearity

*** p<0.01, ** p<0.05, * p<0.1

