UCD CENTRE FOR ECONOMIC RESEARCH

WORKING PAPER SERIES

2025

SRAITH PÁIPÉAR OIBRE AN IONAID

UM THAIGHDE EACNAMAÍOCHTA COBÁC

2025

Multinational Network, Innovation and the Growth of Employment

Ronald B. Davies
University College Dublin School of Economics, Geary Institute for Public Policy

Gianluca Santoni
CEPII

Farid Toubal
Universit. Paris-Dauphine – PSL, CEPII, CESifo & CEPR

Giulio Vannelli
Universit. Paris-Dauphine – PSL

WP25/14

June 2025

UCD SCHOOL OF ECONOMICS

UNIVERSITY COLLEGE DUBLIN

SCOIL NA HEACNAMAÍOCHTA COBÁC

COLÁISTE NA HOLLSCOILE BAILE ÁTHA CLIATH

BELFIELD
DUBLIN 4

Multinational Network, Innovation and the Growth of Employment*

Ronald B. Davies † Gianluca Santoni‡ Farid Toubal§
Giulio Vannelli¶

June 12, 2025

Abstract

There is a long-standing recognition that innovating firms often have higher employment growth. More recently, there is increasing understanding that innovation is concentrated among a small number of generally large firms. We contribute to this debate by showing that the innovation-employment link for a firm is dependent on its multinational status. While we find that more innovative firms are also faster growing ones – even after accounting for size – there is an even greater effect from innovation for multinationals. While we do find evidence suggesting that such firms benefit from innovation done by other affiliates of the same parent, we nonetheless find that they benefit more from their own innovation as well. Thus, this points to important features of multinationals such as integrated global supply chains that are key to understanding the relationship between innovation and employment.

Keywords: Knowledge Spillovers, Employment, Innovation, Technological Diversification.

JEL codes: J21; J24; O31; O33.

*This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No. 101061123.

†Department of Economics, University College Dublin, ronald.davies@ucd.ie.

‡CEPII, gianluca.santoni@cepii.fr.

§Université Paris-Dauphine – PSL, CEPII, CESifo & CEPR, farid.toubal@dauphine.psl.eu.

¶Université Paris-Dauphine – PSL, giulio.vannelli@dauphine.psl.eu.

1 Introduction

The role of technological change in economic development can hardly be overstated. Regardless of whether one considers individual players – be they workers or firms – or aggregate patterns at the regional, national, or global level, innovation is central to understanding economic evolution. By and large, the analysis points to a positive, causal relationship between innovation, often measured by patents, and growth, typically measured as income or employment.[1] This then suggests that there may well be scope for government support for R&D, a common feature in fiscal policies. At the same time, however, there is increasing recognition that innovation is a concentrated activity that is mostly carried out by small number of large firms. This then dovetails with the literature on globalization that points out that trade is largely driven by a small number of large and multinational firms (MNEs). Thus, to understand the impact of innovation on employment growth, it is important to understand the nexus between innovative activity, multinational investment, and employment. This papers seeks to do precisely this by using European firm-level data from 2019 to 2021.

In doing so, our novel dataset highlights a number of key stylized facts, most importantly that the bulk of innovative activity is undertaken by MNEs. This is true when considering the number of patents, total forward citations, citations per patent, and/or the number of technological fields covered. In particular, these large firms are sufficiently crucial that their activities drive regional innovation patterns. Although the dominance of a small number of leading innovators has been recognized elsewhere, including Autor et al. (2023), Kogan et al. (2017) and Grullon et al. (2019), the fact that these leaders are multinationals has yet to be recognized.

Finally, our analysis of firm-level employment growth shows that not only is innovation a key driver of employment growth within the firm, but that this effect is especially large for MNEs. This may be due to their ability to reallocate their relatively deep resources in response to innovation, something that Acemoglu et al. (2018) find is an important aspect of the link between innovation and growth. Additionally, we find that increased innovation by other affiliates within the MNE structure increases employment growth in a given affiliate. Thus, not only are MNEs generally larger and have the resources to undertake more R&D activity, but they seem to grow even more in response to innovation via intra-group spillovers and reallocation agility. This latter lies at the heart of the Markusen (1984) model of foreign investment where the development of a “joint" input, that is, one that can be used across affiliates, motivates the creation of the border-crossing MNE.[2]

[1]The voluminous literature on innovation and growth was recently surveyed by the contributions in Akcigit and van Reenen (2023). See also the reviews of Calvino and Virgillito (2018) and Ulku (2004).

[2]Keller and Yeaple (2013) also shows that transmission of knowledge matters in shaping sales perfor-

While the role of the innovation leaders in labour markets has been pointed out by, for example, Autor et al. (2023), the fact that these are MNEs is far more than a curious fact for two key policy reasons. First, it highlights that R&D policy is de facto multinational policy since the firms most responding to R&D subsidies are MNEs. This then provides support for the claim that recent policy changes such as the introduction of patent boxes (a tax policy that reduces the corporate income tax on income earned from patents) is just another form of tax competition (see Gaessler et al. (2021) for discussion). Second, it implies that domestic innovation policies are likely to have international employment spillovers. This matters when considering the global efficiency of heretofore presumed domestic tax policies. Finally, while these patterns may represent a virtuous circle for the MNE, it must be recognized that it can potentially further consolidate market power and innovation in the hands of the already large – and sometimes foreign – MNEs. As such, it indicates the potential need for caution when promoting R&D with broad policy strokes.

Our work sits at the intersection of two broad literatures: innovation and growth on the one hand and the performance of MNEs on the other.

In terms of innovation and employment, our paper sits alongside those specifically looking at within-firm changes.[3] A priori, it is unclear what the impact of firm innovation should be on its labour demand since the term innovation is imprecise and includes both product and process innovations. When a firm innovates and introduces new product lines, this can generate demand which then leads it to hire more workers. Alternatively, the firm can engage in process-oriented R&D. This type of technological advancement is typically intended to increase productivity, allowing the firm to produce the same level of output but in a less-costly fashion. When total factor productivity increases, this enables the firm to reduce demand for all inputs, including labour, while holding output constant. However, the impact of innovation is far more articulated as there also exist indirect effects related to changes in a firm final demand. For instance, a productivity increase due to process-innovation may spur demand through lower prices thus counterbalancing its direct negative effect on labour. Similarly, product innovation also affects firm productivity: if the new product denote higher productivity than older ones, a firm reshuffle of its production basket may induce an average increase in productivity which in turn offsets the direct effect due to the introduction of new product lines.

Despite these concerns, the data generally finds a positive effect of innovation on employment growth. This literature dates as far back as Van Reenen (1997), with Calvino and Virgillito (2018) providing a more recent overview. Harrison et al. (2014) provide a key contribution to study the impact of innovation on employment growth by disentangling the different mechanisms in a sample of firms from France, Germany, Spain and the UK for 1998–2000. They show that the increase

mances of the affiliates of US multinationals.

[3]There is a concurrent literature considering the link between regional innovation and employment. See Davies et al. (2023) for a recent overview.

in productivity resulting from process innovations significantly lowers the need for employment for a given output, but output expansion, due to price reductions, overcomes the first order effect and raises employment. However, all in all the main impact of innovation on employment growth is due to the introduction of the new products. Related to our paper is also Dachs and Peters (2014), which shows a differential impact of product vs process innovation on employment growth for foreign firms with respect to domestic enterprises. Being larger and able to benefit for the resources shared in the multinational group, the former denote different employment dynamics due to productivity increases and demand changes arising from innovation.

A related strand of papers has investigate to what extent innovation and technology adoption might be factor biased and/or affect workers according to their occupation and tasks. Concerns over the possibility that human labour may be replaced by technology is not new (Mokyr et al. (2015)). During the first Industrial Revolution, the adoption of power looms and mechanical knitting frames gave rise to the Luddite movement protesting against this technology by destroying textile machinery out of fear of job losses and skill obsolescence. Nevertheless, this fear has grown increasingly loud also in the recent decades due to innovation in digital communication, automation and artificial intelligence.[4] In one of the seminal paper in this literature, Autor et al. (2003) show that computerization increased the demand of non-routine analytic and interactive tasks while it had a negative impact on routine tasks over the period 1960-1998. As concerns automating technologies such as industrial robots and artificial intelligence, Acemoglu & Restrepo acemoglu2018race and acemoglu2022tasks provide theoretical foundations describing the different mechanisms through which adoption of these technologies may lead to labour replacement or foster the introduction of new tasks.[5]

The availability of bibliographic data included in patent databases have provided an additional tool to study the content and the impact of innovation on labour outcomes. Kogan et al. (2022) measure workers' exposure to technological innovation and examine its relation with individual worker outcomes. The identification of workers' technology exposure is based on the similarity between the textual description of the tasks performed by an occupation and that of major technological breakthroughs (Kelly et al., 2021). They find that in response to a standard deviation increase in technology related to her occupation, the average worker experiences approximately a 0.02 log point decline in her wage earnings over the next five years. Building on Kogan et al. (2022), Autor et al. (2022) study the emergence of new

[4]See Duch-Brown et al. (2022) for more discussion.

[5]Empirical studies on the relationship between robot adoption and employment have been mainly conducted at the national or sub-national level. Among the others, Acemoglu and Restrepo (2020) document a negative impact of robots adoption on the employment-to-population ratio for US commuting zones in the period 1990-2007. Evidence in Graetz and Michaels (2018) over the period 1993-2007 and 238 country-industries points toward a positive effect of robot adoption on workers' wage, though a negative impact on the labor share of less-skilled relative to middle- and high-skilled is documented.

work and measure exposure to labour augmenting vs automating technology. Augmentation and automation innovations have distinct and asymmetric relationships to the creation of new work. In addition, innovation that is relatively augmenting also positively affects wages and employment in exposed occupations.

Recently, Autor et al. (2023) build on this by considering the fact that innovation activity is being primarily carried out by a small number of leading innovators, that they call "superstars" firms. While this fact is recognized elsewhere (see e.g. Kogan et al. (2017) and Grullon et al. (2019)), Autor et al. (2023) show that there appears to be a distinct difference in the technologies developed by these firms and their smaller counterparts. In particular, they find that the employment-augmenting effects of innovation for the "superstars" firms is greater than that of other firms. We contribute further to their finding by illustrating that it is not simply the size of such firms that matters but their multinational nature.

This then relates our finding to the literature on the relative performance of multinational firms.[6] Since Helpman et al. (2004), it has been understood that MNEs are far from the average firm. In comparison to exporters and purely domestic firms, MNEs are more productive, sell more, have larger workforces, and are more resilient.[7] This has been documented repeatedly across countries, industries, and time. Furthermore, the exceptional performance of MNEs is a significant driver of regional patterns (Mayer and Ottaviano, 2008). Although there is still some debate over causality (that is, whether productive firms select into MNE status or they learn and improve by doing), the relatively strong performance of cross-border firms is no longer in question.[8]

We add to this literature by pointing out that MNEs also stand out in terms of their innovation and that they seem to have a particularly strong link between innovation and employment. This may be a part of their overall superior performance if their international ownership linkages aid them in overcoming the strong negative effect of distance on knowledge transmission (see Keller (2002) for an early analysis of distance and R&D spillovers). In particular, we show the importance of within-firm knowledge transfers for employment growth. This mirrors the parent to subsidiary productivity effect found by Guadalupe et al. (2012) and their finding that this benefit is driven by the ability to access other markets via the foreign parent. Similarly, Bilar and Morales (2016) find that parental innovation contributes meaningfully to subsidiary value added.

The rest of this section proceeds as follows. In Section 2 we describe our empirical specification, the data we use as well as provide a set of stylized facts on employment and innovation. Section 4 expands on the stylized facts presenting the results of our

[6]Our work is also less directly related to that on globalization of firms and innovation; see Bloom et al. (2016) and Coelli et al. (2022) for examples.

[7]Examples include (Bernard and Jensen, 1999) and Alfaro and Chen (2018) among many others.

[8]Examples finding selection (Girma et al. (2005)), learning (Alvarez and Lopez (2005)), or both (Hejazi et al. (2023)) abound.

regression analysis. Finally, Section 5 concludes by offering a discussion of policy implications.

2 Empirical Strategy, Data, and Facts

In this section, we do two things. First, we introduce our regression specification to establish a framework for discussing our data. Following the description of our variables, we identify three key facts regarding the innovation-MNE connection.

2.1 Estimating equation.

Our primary goal is to explore the link between innovation, foreign investment, and employment within a firm. To this end, we employ a cross-section in first differences approach:

$$\Delta Emp_{i_{(c,s)}} = \beta_1 \Delta Innov_i + \mathbf{X_i'}\alpha + \gamma_{cs} + u_i, \tag{1}$$

i.e. we estimate the impact of changes in firm i's innovation ($\Delta Innov_i$) on changes in its employment ($\Delta Emp_{i_{(c,s)}}$). Below, we detail the various ways in which we measure innovation. In addition to innovation, we control for a vector of firm-specific changes in control variables ($\mathbf{X_i'}$), namely sales and investment to control for firm-specific shocks that may be related to the type, i.e. product vs process, of innovation performed. We also include a dummy variable equal to one if the firm is a multinational and zero otherwise. Note that by first-differencing, we are implicitly removing the influence of firm-specific, time-invariant characteristics. Since our dependent variable is the growth rate of employment, as is standard we also control for the initial level of employment. We additionally include 4 digit NACE industry-country (sc) fixed effects to control for industry-wide shifts and/or country-specific changes. Finally, u_i is the robust error term. As all variables are either measured in logs or, when there are zeros, the inverse hyperbolic sine, the coefficients are interpreted as elasticities.

In principle, this regression specification can be derived from a production function where sales is a function of labour, capital, and innovation. If innovation changes only drive TFP changes (i.e. they are factor-neutral process changes), then controlling for sales, there should be no link between innovation and employment. This is because any given level of output can be produced using less labour. If, however, there is still a positive effect, then this suggest skill-biased technological change in favour of labour. All in all, by controlling for both changes in sales and capital, our estimate of β provides the effect of innovation that is net of all direct and indirect impacts due to product and process innovations that channel through changes in productivity and in demand.

To further explore the link between changes in innovation and employment growth between MNEs and other firms, we likewise estimate the extended specification given by:

$$\Delta Emp_{i_{(c,s)}} = \delta_1 \Delta Innov_i + \delta_2 \left(\Delta Innov_i \times MNE_i\right) + \delta_3 MNE_i + \mathbf{X_i'}\alpha + \gamma_{cs} + \epsilon_i \quad (2)$$

which permits differences in the relationship between MNEs and domestic firms. If we find a stronger link between innovation and employment growth in MNEs, this would suggest that the labour-enhancing aspects of new technology are greater in firms with a global scope, perhaps because of the advantages their more integrated global supply chains create. Finally, we extend this specification one final time to include innovation produced by other affiliates within the same MNE. Thus, this final specification considers the “global supply chain of knowledge" within the firm.

Taken as a whole, this empirical approach allows us to examine the correlation between firm-level innovation and its MNE status which are separate from its size, common trends within its industry, and national macroeconomic shocks.

2.2 Data

Before delving into the specifics of our data, it is useful to give an overview of it. We combine data from two main sources. First, we use the information from three Orbis datasets available from Bureau Van Dijk's that cover firm-level economic data (employment, sales, investment, and industry), ownership information (allowing us to construct multinational groups), and patents (Orbis-IP, which form the basis for our innovation measures).[9] Note that ownership information is available as a snapshot at the time of our data access. As this must then be presumed to hold constant over years, we limit ourselves to analysis of the data from 2019-2021 to minimize misclassification. Note that this period covers the COVID-19 pandemic, which we cover with the industry-year fixed effects to control for the differential impact this had on different sectors and the varying degrees of lockdown across countries. Second, the patent data from Orbis-IP is then linked to the Spring 2022 version of the PATSTAT database which, for each patent, provides information on the number of forward citations, the technological fields it covers, and its patent family (discussed further below).

It is important to acknowledge that our sample is for those firms covered by the Orbis database. As is well-known, this dataset is constructed from firm reports and as such, tends to feature primarily large firms. While this means we are not able to examine the relation between innovation and employment in small- and medium-sized firms (see Zimmerman (2008)), the Orbis data are able to provide global information on MNE structures. Furthermore, it must be remembered that

[9]For more detailed information on the database see `https://www.bvdinfo.com/en-gb/`.

innovation is a concentrated activity. Within Europe, Davies et al. (2020) show that 5 percent of innovating firms comprise nearly 75 percent of patents, with over half of patenting firms that submit only one patent during their 40 years of data. Thus, even though our sample is comprised of large firms, it covers the bulk of patenting activity. We make two final restrictions. First, we limit our attention to firms in Europe (the EU27 and the UK). Given both the well-recognized differences in patenting behaviour across borders (e.g. American firms tend to patent far more frequently than European ones) and the geographic concentration of the firms found in Orbis, restricting ourselves to European firms generates a sample that is relatively homogeneous in terms of the norms for patenting behaviour. Second, we only include firms with at least one patent observed in Orbis to again create a cleaner comparison when comparing MNEs to other firms.[10]

With the general structure of our data in mind, we now turn to the specifics of innovation, ownership, and firm characteristics.

Innovation outcomes. At this point, it is important to clarify our use of the word "patent". Patent data in PATSTAT are organized in a three-level hierarchical structure: application, publication and family. The primary component of this structure is the "application", which represents a formal request for patent protection for a particular invention submitted to a patent office. Upon successful examination of an application, a "publication" is issued. Several publications may be issued during the life of a patent. Applications and resulting publications relating to the same (or closely related) inventions are grouped into "families".

Families are a natural basis for analyzing innovation at the firm level because it avoids double counting which can arise when the same innovation generates multiple patents (across time or patent offices). Likewise, when counting citations, we consider citations running from one family to another. As a last point, note that we use all patent families which are matched to Orbis, not just those which contain a granted patent. As discussed by Davies et al. (2020), just over half of patent applications to the European Patent Office are granted. Further, they demonstrate that the average time for a successful review is over five years. Given our time frame of 2019-2021, were we to use only granted patents for our analysis, we would be omitting valuable information on innovative activities. Furthermore, even non-granted patents can represent important technological changes in the firm. As concerns the timing of an invention, we use the publication date of the earliest application within the family to date an innovation and thus create the change through time.[11] Thus,

[10]Note that although all firms in our sample have at least one patent according to Orbis, some of them have no patents after 2000, which is the year in which we start building our innovation stock. Therefore, the stock of patents for these firms is zero in our analysis. More detail on the construction of the innovation stock are given in the next paragraph.

[11]Using publication date rather than filing date arguably brings our timeline closer to the initial public accessibility of the technology contained within the patent, i.e. to the point where it begins to generate spillovers.

although we use the word “patent" for brevity, we are in fact referring to patent families which may or may not include a granted patent.

From PATSTAT, for each patent we observe the number of its forward citations.[12] This can then be merged with the Orbis-IP data using the common family identifier thereby providing details for each patent owned by each firm. As is common in the literature (Berkes et al., 2022), we use fractional allocation when a patent is owned by multiple firms, that is, when n firms are listed as owning the same patent, a share $\frac{1}{n}$ of the patent count and citations are allocated to each owner.[13] This is particularly relevant in the context of MNEs where ownership can be shared across affiliates in different countries.

With this information, we then construct the stock of patents a firm owns in year t which is the sum of new applications since 2000. Note that as our period of focus is 2019-2021, this provides nearly two decades of accumulation to arrive at the stock. Likewise, for each firm, we measure its total forward citations stock in year t as the number of forward citations received by the patent stock in t. The citation stock provides therefore a measure of the total value of a firm patent stock. We use the difference for these two innovation outcomes from 2021 to 2019 in our estimation.[14]

We then calculate an additional innovation outcome that measures the quality of a firm patent stock as the number of citations per patent in t. This latter measure is used in our stylized facts.[15]

Finally, for the firm's stock of patents in year t, we can calculate the number of technology fields this encompasses. For each patent, PATSTAT attributes a share of it across 35 IPC technological fields based on the innovations within the patent (where the shares sum to one). We therefore allocate each of the firm's (fractional) patents across the 35 technological fields and construct two variables. The first is the number of fields in which its patent stock is active. Second, we calculate the Herfindahl index:

$$HHI_i = \sum_{j=1}^{35} \left(\frac{P_{ij}}{P_i} \right)^2 \tag{3}$$

where P_{ij} is the number of patents of firm i in technological field j and P_i is the total number of patents of firm i. Based on Davies et al. (2023), which found that diversification promoted regional employment growth, we anticipate that technological diversification within the firm may be indicative of agility in the face of changing

[12] Note that for citation counts, we use all citations in PATSTAT, not only those that also appear in Orbis IP.

[13] Note that as our unit of observation is the firm, we allocate patents by owners (assignees) rather than inventors.

[14] Note that we use the inverse hyperbolic sine transformation for innovation outcomes as some firms have zero patents as of 2019, as they innovated only before 2000. In our estimation sample the share of these firms equals the 19% (11,517 firms).

[15] As shown by Hall et al. (2005), there is a significant premium in market value that is associated with citation intensity. Firms with two to three times the median number of citations per patent show a value premium of 35 percent; this can rise to as much as 54 percent for firms with 20 or more citations.

market and/or technological conditions.

In summary, for each firm we have a measure of innovation quantity (number of patents), two measures of quality (total forward citations and citations per patent) and two measures of knowledge diversification (number of active technological fields and the Herfindahl index). We use this information in presenting empirical evidence on innovation *premia* for MNEs.

Firm data. From Orbis, for all of the firms in our sample, we extract employment, total assets, and sales.[16] In order to examine the relationship between innovation and employment, it is important to control for firm size otherwise it is impossible to separate out TFP changes from factor-biased technological change. Likewise, controlling for investment (the change in total assets), aids us in considering overall growth of the firm that may not have yet manifested in higher sales (particularly during the pandemic).

Beyond these measures, we use Orbis to access data concerning firms' ownership connections. We first determine the global ultimate owner (GUO) for all firms engaged in innovation. For each GUO, we then connect it with all the innovating affiliates that it directly owns a controlling interest in (i.e. it owns at least 50 percent of the equity).[17] This helps us assess innovation taking place in other subsidiaries within a GUO – information that plays a role in our econometric analysis to explore how innovation spreads within these groups.

Secondly, for each innovating firm we retrieve the list of its direct parents and affiliates (also in this case the 50 percent threshold is applied). With this set of information at hand we define a firm as MNE if it has at least one foreign parent or a foreign affiliate, or if its GUO is in a different country than the firm.

One limitation of these ownership data is that they reflect the ownership at the time of their extraction (September 2023) but does not indicate when ownership was established. This can then mis-identify a firm as a MNE in 2019 if, for example, the first foreign affiliate was not established until 2020. Likewise, firms that were part of MNE in 2019 could have been sold off and exit MNE status by 2021. To minimize these possibilities, we restrict our sample to 2019-2021. Additionally, this can confound the distinction between acquisition and innovation as might be the case if the impact of innovation hinges on whether it represents acquired knowledge (that existed prior to the acquisition) or what was generated subsequently. Therefore these potential caveats must be kept in mind during our analysis.

[16] Firms with zero or missing information in 2019 or 2021 are omitted.

[17] Although many countries define foreign investment by a less than majority ownership, in practice most MNE affiliates far exceed 50 percent ownership. See Davies et al. (2018) for discussion.

2.3 Facts

Before moving to the econometric analysis, we show three empirical facts that provide key insights into the relationship between MNEs and innovation.

Fact 1: MNEs have innovation premia. Our first fact shows that, just as there are MNE premia with respect to size and productivity, the same holds for the various innovation measures.[18] In Table 1, we use the 2021 levels cross-sectional data on our various innovation outcomes (number of patents, citations, etc.) and regress those on a dummy for whether the firm is a MNE (along with sector-country and size bin (sales deciles) fixed effects).

As the reported coefficients indicate, MNEs tend to have more patents and more citations, as one might expect given that they are generally larger than non-MNEs. That said, their patents also receive more citations on average, perhaps indicating that MNE patents generally contain a higher level of technological breakthrough. Turning to the technological variables, MNEs' patents also span more technological fields and are less concentrated technologically. This may support the notion that MNEs – because of their greater scope – may be better able to respond to market shocks and have greater absorptive capacity for new technologies. Furthermore, with the exception of the concentration of technologies, these patterns hold for both firms in manufacturing and services.[19] This sole difference may be the result that, by nature of what service firms do, the tangible nature of many of the technological fields may not be especially relevant to their activities.

Finally, as we control for sector-country fixed effects, these patterns are not driven by a concentration of MNE activity in certain sectors or particular countries (perhaps because of the tax treatment of innovation, see Bösenberg and Egger (2017)). Further, because we include size bins, this difference is not merely due to the larger size of MNEs, rather, their international network has a positive relation to their innovation outcomes beyond their larger sizes.

Fact 2: MNE drive the innovation process. As our first fact demonstrates, even after controlling for size, industry, and nationality, MNEs innovate more in terms of quantity, quality, and breadth. One important implication of this is that they have an outsized role in the innovation process.

To illustrate this, we provide Figure 1. In Panel (a) we sort firms on the x-axis by the number of total patents in 2021 (from the left to the right) and on the y-axis by their rank in terms of this innovation measure (firms in the bottom of the axis have a higher rank). Panel (b) does likewise, but rather than using the stock of patents on the horizontal axis, it uses the number of citations. In both panels, only

[18]See (Bernard and Jensen, 1999) for discussion of other premia for MNEs.

[19]Manufacturing includes industries in NACE C section. Services exclude financial services, real estate, and governmental sectors.

Table 1: Innovation premia for MNE

Outcome:	Sample All	Manuf	Services
# Patents	0.971***	1.045***	0.821***
	(0.130)	(0.156)	(0.260)
Quality of innovation:			
- # Citations	1.356***	1.337***	1.358***
	(0.184)	(0.196)	(0.354)
- # Citations per Patent	0.308***	0.261***	0.340***
	(0.030)	(0.031)	(0.052)
Knowledge Diversification:			
- # of tech. fields	0.246***	0.245***	0.204***
	(0.012)	(0.015)	(0.021)
- HHI	-0.013**	-0.015**	-0.008
	(0.006)	(0.007)	(0.009)

The table reports the coefficient for the MNE dummy in a cross section regression for 2021. PPML estimates with robust standard errors in parentheses. All regressions include Country x Sector and bins of turnover fixed effects. A firm is categorized as a multinational enterprise if it has a foreign parent or a foreign affiliates, or if its GUO is located in a different country with respect to the firm. Services exclude financial services, real estate, and governmental sectors. ***, **, and * significantly different from 0 at the 1%, 5%, and 10% confidence levels, respectively.

firms with a positive patent stock/citation count in 2021 are used (approximately 90,000 firms in the panel (a) and 53,000 in the panel (b)). Further, in both panels, we indicate the position of the 50th, 75th and 99th percentiles for the innovation measure. Finally, we mark the position of a MNE with a blue triangle and for a non-MNE with a red diamond.

From this, two things are quickly observed. First and consistent with the first fact, regardless of the innovation measure used, MNEs dominate the top of the distribution. Second, and something not as immediately observable in Table 1, is the extent of this difference. MNEs are not just above average, they dominate the top 1 percent of innovating firms. For example, in Panel (a), the top 1 percent of innovating firms have 150 patents or more, with around 1,000 firms (out of approximately 90,000) found in this range. Of those, nearly all are MNEs (with the most innovative firm begin a MNE with 74,786 patents).[20] While the existence of superstar innovators has been noted elsewhere (see e.g. Davies et al. (2020)), what our results add to this is that the superstars are essentially all MNEs.

To make this point even more starkly, Figure 2 zooms in on the top 1 percent of innovating firms.[21] Even within this rarified group, we see that MNEs dominate innovation. Further, this makes it clear that it is a small number of MNEs tht in particular drive the overall numbers.

[20] For clarity, note that this is 90,000 firms with a positive patent stock in 2021, not the number of firms in our regression analysis.

[21] Note that the lables for the percentages are with reference to just the top 1 percent.

(a) Distribution of patents **(b)** Distribution of citations

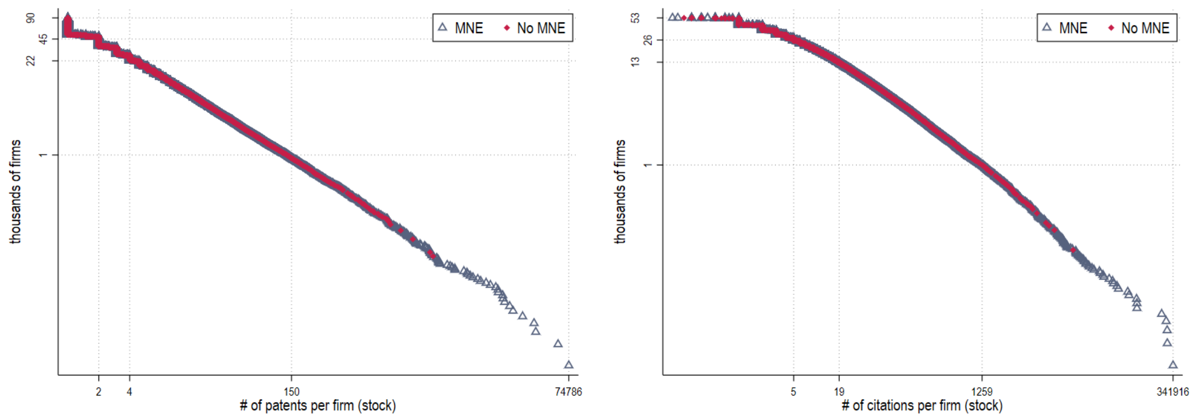

Figure 1: Distribution of innovation outcomes across firms

Notes: In each graph is reported the distribution of innovation outcomes across firms in 2021. Each marker corresponds to a firm. Blue triangles identify MNE; red diamonds identify non MNE. On the x-axis, firms are sorted by the value of the innovation outcome considered (patents or citation), i.e., firm on the left have less innovation than firms on the right. The axis labels report the values of the innovation outcome considered (patents or citation) for the firm at the 50th, 75th, 99th percentile of the distribution and the maximum of the innovation outcome. On the y-axis, firms are sorted by their rank in terms of innovation, i.e., firm on the bottom rank higher than firm on the top. The axis labels report (in ascending order) the number of firms (in thousands) that rank in the 1st, 25th, 50th percentile of the rank distribution and the total number of available firms. For instance, there are 1 thousand firms which have more than 150 patents (Panel (a)) and more than 1259 citations (Panel (b)). Firms with less than 1 patent are dropped from graph in Panel (a). Firms with less than 1 patent and with 0 citations are dropped from graph in Panel (b).

(a) Distribution of patents **(b)** Distribution of citations

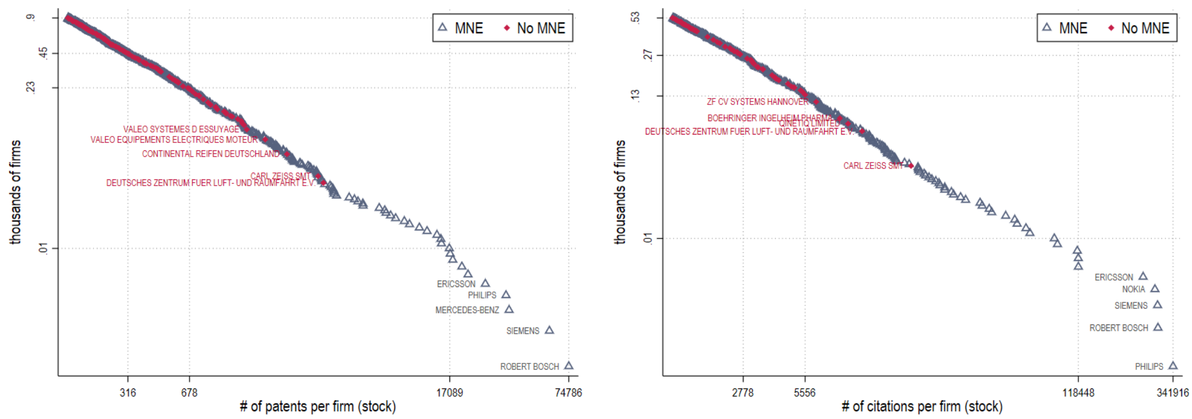

Figure 2: Distribution of innovation outcomes – Top 1% of innovators

Notes: In each graph is reported the distribution of innovation outcomes across firms in 2021 considering only firms in the top percentile of the distribution. Each marker corresponds to a firm. Blue triangles identify MNE; red diamonds identify non MNE. On the x-axis, firms are sorted by the value of the innovation outcome considered (patents or citation), i.e., firm on the left have less innovation than firms on the right. The axis labels report the values of the innovation outcome considered (patents or citation) for the firm at the 50th, 75th, 99th percentile of the distribution and the maximum of the innovation outcome. On the y-axis, firms are sorted by their rank in terms of innovation, i.e., firm on the bottom rank higher than firm on the top. The axis labels report (in ascending order) the number of firms (in thousands) that rank in the 1st, 25th, 50th percentile of the rank distribution and the total number of available firms. For instance, there are 10 firms which have more than 17089 patents (Panel (a)) and more than 118448 citations (Panel (b)). The graph only consider the distribution of innovating firms in the top percentiles of the distribution. As concerns the indication of the firms reported in the graphs and their MNE status, recall that we define a firm as MNE if it has at least one foreign parent or a foreign affiliate, or if its GUO is in a different country than the firm.

Fact 3: MNEs drive aggregate regional patterns. One of the main advantages in using ORBIS-IP data for studying innovation is that it allows to have comprehensive information about innovating firms, such as their detailed location.[22] For our third fact, we exploit this information at the NUTS 2-digits administrative level to show the correlation between the presence of MNEs within a European region and the region's innovation output.

Figure 3 indicates the relative number of MNEs (Panel (a)) and 2021 stock of patents (Panel (b)) for the different regions. This reveals a strong correlation between the two, i.e. a strong innovation performance is highly related to the ability to host MNEs. In particular, Île de France (NUTS2 FR10), Oberbayern (DE21), Stuttgart (DE11) and Lombardy (IT) stands out as European leaders for both MNE and innovation. On the contrary, peripheral regions in Eastern and Southern Europe denote poor innovation outcomes along with low presence of MNE. This indicates that although it is possible for domestic firms to generate enough patents to overcome a lack of MNE presence, this is very uncommon. Conversely, it suggests that to understand the innovation performance of a region, it is necessary to consider the innovation of the MNEs it hosts. Thus, our study of the MNE, innovation, employment nexus contributes meaningfully to the regional innovation and employment literature.

(a) # of MNE **(b)** # of patents

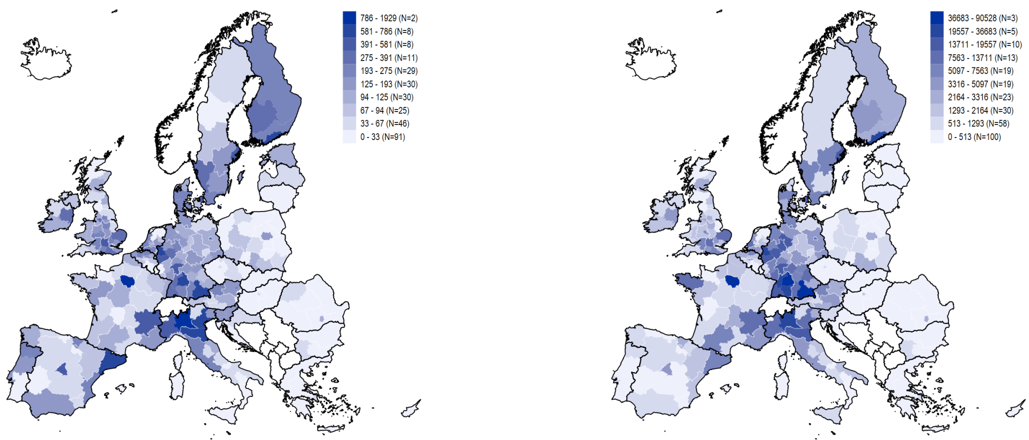

Figure 3: MNEs and innovation in European regions

Notes: The maps report the number of MNEs (Panel (a)) and the number of patents across European economic regions (NUTS2 administrative units).

[22] See Davies et al. (2023) for a recent review of the literature studying regional innovation and employment.

3 Empirical strategy

4 Estimation Results

We now turn to our empirical estimation to tease out the relationships between changes in innovation – measured by the number of patents and the number of citations – and employment growth within the firm.

4.1 Innovation and employment growth

We begin by using the growth rate of the patent stock (Δ Innovation) as the measure of innovation change in Table 2. In column (1), we use only the growth of the patent stock; column (2) additionally interacts this with the firm's MNE status. Columns (3) and (4) use the subsample of manufacturing and service firms respectively. Across all four specifications, we (unsurprisingly) see a positive correlation between employment growth and the growth in output and/or capital. In addition, MNEs tend to grow faster than domestic firms.

Turning to our innovation variable, column (1) indicates that firms with higher growth rates for their patent stocks have higher employment growth, with the elasticity suggesting that a 10% increase in patent growth would increase employment growth by approximately 0.5%. Note that this controls for sales growth. If innovation increased TFP, holding sales constant, we would expect a slowdown in employment growth. Likewise, if innovation introduced new products and therefore sales with no other factor-biases, the sales coefficient alone should drive employment changes. As such, the positive coefficient we find suggests that apart from TFP and new product changes, innovation may be labour-productivity enhancing and thus employment generating.

In column (2), we interact the innovation growth with MNE status and find a significantly positive coefficient. Compared to column (1), for non-MNEs we find a somewhat smaller coefficient on the innovation variable, suggestive of an elasticity of 0.036. For MNEs, on the other hand, the point estimate is over twice as large at 0.8. This suggests two things. First, an increase in innovation is associated with a much higher increase in employment for MNEs. As we control for sales growth, investment, and sector-country fixed effects, this is not due to a size effect. Rather, it suggests that MNEs may be more able to exploit their technological advantages, suggesting greater absorptive capacity and higher agility. Second, by comparing the innovation coefficients in columns (1) and (2), it is clear that MNEs exert a strong effect on the overall average effect. This is to be expected given their outsized role in innovation as discussed above. Finally, as shown in columns (3) and (4), these patterns hold for both manufacturing and services firms.

Table 3 repeats this approach but does so using the growth rate in total citations

Table 2: Innovation and employment growth

	Dep. Variable: Δ Employment			
Sample	Whole		Manuf.	Services
	(1)	(2)	(3)	(4)
Δ Innovation	0.054***	0.036***	0.030***	0.044***
	(0.006)	(0.008)	(0.009)	(0.015)
Δ Innovation × MNE		0.047***	0.036***	0.061***
		(0.012)	(0.013)	(0.023)
MNE status	0.028***	0.023***	0.028***	0.012*
	(0.004)	(0.004)	(0.004)	(0.007)
Δ Output	0.175***	0.175***	0.204***	0.158***
	(0.008)	(0.008)	(0.015)	(0.010)
Δ Capital	0.167***	0.167***	0.165***	0.166***
	(0.010)	(0.010)	(0.017)	(0.011)
Employment$_{(2019)}$	-0.023***	-0.023***	-0.021***	-0.024***
	(0.001)	(0.001)	(0.002)	(0.002)
Country × Sector	Yes	Yes	Yes	Yes
Obs.	60,816	60,816	36,525	24,291
Adj. R^2	0.254	0.254	0.270	0.243

Sample years: 2021. The dependent variable is employment growth between 2019 and 2021. Services exclude financial services, real estate, and governmental sectors. OLS estimates with robust standard errors. ***, **, and * significantly different from 0 at the 1%, 5%, and 10% confidence levels, respectively.

(Δ Citations) rather than the number of patents. While the results for the additional controls remain the same, we see a marked difference in the innovation measure. Here, the estimates suggest that an increase in the number of citations increases employment growth but that this effect is only found among the multinationals. The last two columns confirm that these results hold in both manufacturing and services.

Table 4 includes both the change in the number of patents and in the number of citations. For reference, columns (1) and (2) repeat the first column of the prior two tables. When including both in column (3), we only find a significant coefficient for the number of patents. Column (4) introduces the two interaction terms. This specification suggests that the results of the prior tables continue to hold. Specifically, once again non-MNEs see higher employment growth when they have an increase in the number of patents but not when these new patents are more valuable (ciation grow). MNEs, on the other hand see employment growth rise concurrently when either the number of patents and/or citations grow faster. Further, the point estimate for the number of patents relationship continues to be twice as large as for non-MNEs. In addition, the estimated coefficient for citations is 50 percent larger still. This latter suggests that for MNEs citations may play an even bigger role in employment growth than the volume of patents. One possible reason for this is that other affiliates in the MNE network may be citing a given firm's patents when developing their own. Indeed, both Guadalupe et al. (2012) and Bilar and Morales (2016) find that parental innovation contributes significantly to affiliate productivity, something that then may spill over to employment. Likewise,

Table 3: Citations and employment growth

	Dep. Variable: Δ Employment			
Sample	Whole		Manuf.	Services
	(1)	(2)	(3)	(4)
Δ Citations	0.066**	-0.017	-0.038	-0.000
	(0.030)	(0.041)	(0.049)	(0.064)
Δ Citations × MNE		0.182***	0.169**	0.195**
		(0.058)	(0.067)	(0.093)
MNE status	0.028***	0.027***	0.032***	0.019***
	(0.004)	(0.004)	(0.004)	(0.007)
Δ Output	0.176***	0.176***	0.205***	0.159***
	(0.008)	(0.008)	(0.015)	(0.010)
Δ Capital	0.170***	0.170***	0.167***	0.170***
	(0.010)	(0.010)	(0.017)	(0.011)
$\text{Employment}_{(2019)}$	-0.022***	-0.022***	-0.021***	-0.024***
	(0.001)	(0.001)	(0.002)	(0.002)
Country × Sector	Yes	Yes	Yes	Yes
Obs.	60,816	60,816	36,525	24,291
Adj. R^2	0.253	0.253	0.269	0.242

Sample years: 2021. The dependent variable is employment growth between 2019 and 2021. Services exclude financial services, real estate, and governmental sectors. OLS estimates with robust standard errors. ***, **, and * significantly different from 0 at the 1%, 5%, and 10% confidence levels, respectively.

this behaviour could be indicative of important intra-firm spillovers for knowledge creation and/or the integrated global supply chains inherent to MNEs. We explore these possibilities next.

Table 4: Innovation, citations, and employment growth

	Dep. Variable: Δ Employment					
Sample	Whole				Manuf.	Services
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Innovation	0.054***		0.054***	0.038***	0.032***	0.046***
	(0.006)		(0.006)	(0.008)	(0.009)	(0.016)
Δ Citations		0.066**	0.005	-0.057	-0.069	-0.051
		(0.030)	(0.030)	(0.042)	(0.050)	(0.067)
Δ Innovation × MNE				0.041***	0.031**	0.054**
				(0.013)	(0.013)	(0.024)
Δ Citations × MNE				0.123**	0.128*	0.110
				(0.059)	(0.067)	(0.098)
MNE status	0.028***	0.028***	0.028***	0.023***	0.029***	0.013*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
Δ Output	0.175***	0.176***	0.175***	0.175***	0.204***	0.158***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.015)	(0.010)
Δ Capital	0.167***	0.170***	0.167***	0.167***	0.165***	0.166***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.017)	(0.011)
$\text{Employment}_{(2019)}$	-0.023***	-0.022***	-0.023***	-0.023***	-0.021***	-0.024***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Country × Sector	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	60,816	60,816	60,816	60,816	36,525	24,291
Adj. R^2	0.254	0.253	0.254	0.254	0.270	0.243

Sample years: 2021. The dependent variable is employment growth between 2019 and 2021. Services exclude financial services, real estate, and governmental sectors. OLS estimates with robust standard errors. ***, **, and * significantly different from 0 at the 1%, 5%, and 10% confidence levels, respectively.

4.2 Within-group innovation diffusion

These last results suggest that MNEs have an edge in translating innovation into jobs, perhaps because of the greater ability to exploit knowledge within their integrated supply chains. With this in mind, we next explore whether knowledge diffusion within the MNE relates to employment in a given affiliate. To this end, restrict ourselves to MNE affiliates and introduce a new variable, the innovation of other affiliates within the same MNE

Table 5 begins by including just the innovation growth of a given firm in column (1) and then introduces the innovation of other affiliates within the same MNE group in column (2). Comparing these, we see two things. First, the within-firm innovation is essentially unaffected by the inclusion of the innovation of other affiliates. Second, the innovation of other affiliates is also strongly correlated with that of a given firm, although the point estimate is roughly one-third smaller. This suggesting that MNE affiliates benefit significantly from innovation in other parts of the same MNE but that this effect is somewhat weaker than innovation done locally. Columns (3) and (4) re-estimate this latter specification for firms in manufacturing and services separately. As before, the estimates show that faster innovation growth is associated with faster employment growth in both sectors; this table then confirms this for both both within-firm and within-MNE innovation.

Table 5: Innovation, within-group knowledge diffusion, and employment growth

	Dep. Variable: Δ Employment			
Sample	Whole		Manuf.	Services
	(1)	(2)	(3)	(4)
Δ Innovation	0.083***	0.082***	0.064***	0.103***
	(0.010)	(0.010)	(0.010)	(0.017)
Δ Innovation (other affiliates)		0.054***	0.048***	0.063**
		(0.016)	(0.017)	(0.030)
Δ Output	0.203***	0.203***	0.229***	0.184***
	(0.015)	(0.015)	(0.023)	(0.019)
Δ Capital	0.144***	0.144***	0.129***	0.157***
	(0.019)	(0.019)	(0.030)	(0.020)
$\text{Employment}_{(2019)}$	-0.017***	-0.018***	-0.017***	-0.018***
	(0.002)	(0.002)	(0.003)	(0.003)
Country × Sector	Yes	Yes	Yes	Yes
Obs.	23,083	23,083	14,529	8,554
Adj. R^2	0.293	0.293	0.311	0.278

Sample years: 2021. The dependent variable is employment growth between 2019 and 2021. Services exclude financial services, real estate, and governmental sectors. OLS estimates with robust standard errors. ***, **, and * significantly different from 0 at the 1%, 5%, and 10% confidence levels, respectively.

In a similar fashion, Table 6 examines the relationship between a firm's employment growth and citation growth, both for itself and others in the same MNE. Here, we see that own-firm citations are positively correlated with employment growth. Recalling that the sample is now restricted to MNEs, this supports the results of Table 3. The citations received by other affiliates, however, are not significantly correlated with a given firm's employment. Again, we see a similar pattern when looking just within manufacturing or services.

Table 6: Citations, within-group knowledge diffusion, and employment growth

	Dep. Variable: Δ Employment			
Sample	Whole		Manuf.	Services
	(1)	(2)	(3)	(4)
Δ Citations	0.162***	0.162***	0.135***	0.184***
	(0.042)	(0.042)	(0.048)	(0.068)
Δ Citations (other affiliates)		0.017	-0.008	0.023
		(0.063)	(0.092)	(0.082)
Δ Output	0.205***	0.205***	0.230***	0.185***
	(0.015)	(0.015)	(0.023)	(0.019)
Δ Capital	0.147***	0.147***	0.131***	0.163***
	(0.019)	(0.019)	(0.030)	(0.021)
$\text{Employment}_{(2019)}$	-0.017***	-0.017***	-0.017***	-0.017***
	(0.002)	(0.002)	(0.003)	(0.003)
Country × Sector	Yes	Yes	Yes	Yes
Obs.	23,083	23,083	14,529	8,554
Adj. R^2	0.290	0.290	0.309	0.275

Sample years: 2021. The dependent variable is employment growth between 2019 and 2021. Services exclude financial services, real estate, and governmental sectors. OLS estimates with robust standard errors. ***, **, and * significantly different from 0 at the 1%, 5%, and 10% confidence levels, respectively.

Finally, Table 7 combines the prior two tables to include innovation and citation growth both for a given firm and others in the same MNE. As can be seen, in both the full sample results and when considering just manufacturing or services, faster innovation growth is correlated with faster employment growth. This holds both for the firm's own innovation and – with a slightly smaller estimated effect – for innovation done elsewhere in the MNE. Once again, citation growth appears unimportant. Comparing this latter with Table 4's result for MNEs, where citations were marginally significantly correlated with employment growth, suggests an interesting interpretation of the results.

In particular, it suggests that the prior result for citations for MNEs may have been driven not by its own overall citations, but by intra-firm citations specifically. For example, suppose that an affiliate generates an innovation that then feeds into the creation of knowledge elsewhere in the same MNE. This would create citations for the affiliate in question while creating new innovation elsewhere in the MNE at the same time. When omitting the innovation by other affiliates in Table 4, this can create a bias lending significance to the citation variable for MNEs. When correcting this omission in Table 7, the bias disappears and we find no significant result. This is then a similar omitted variable bias that Table 4 corrected for non-MNEs but not MNEs. This then suggests that what matters for employment growth in both non-MNEs and MNEs is not the citations their patents receive but the amount of innovation, both within a given firm and, for MNEs, that which occurs elsewhere in the group.

Finally, although this hints that part of the MNE premium is that it is able to benefit from the larger scale facilitated by the cross-border activities of such firms, it does not appear to be the full story. In Table 4's column (4), the estimated elasticity for within-firm innovation for MNEs was 0.079 while in Table 7's column (2) it is a nearly identical 0.078. Thus, it is still the case that MNEs appear better equipped to translate innovation growth into employment growth even after accounting for the larger stock of knowledge they can access via their affiliate network.

Table 7: Innovation, citations, within-group knowledge diffusion and employment growth

	Dep. Variable: Δ Employment			
Sample	Whole		Manuf.	Services
	(1)	(2)	(3)	(4)
Δ Innovation	0.079***	0.078***	0.060***	0.100***
	(0.010)	(0.010)	(0.010)	(0.019)
Δ Innovation (other affiliates)		0.058***	0.052***	0.068**
		(0.017)	(0.018)	(0.032)
Δ Citations	0.063	0.062	0.064	0.045
	(0.042)	(0.042)	(0.046)	(0.073)
Δ Citations (other affiliates)		-0.066	-0.121	-0.053
		(0.060)	(0.097)	(0.081)
Δ Output	0.203***	0.204***	0.229***	0.184***
	(0.015)	(0.015)	(0.023)	(0.019)
Δ Capital	0.144***	0.144***	0.129***	0.158***
	(0.019)	(0.019)	(0.030)	(0.020)
$\text{Employment}_{(2019)}$	-0.017***	-0.018***	-0.017***	-0.018***
	(0.002)	(0.002)	(0.003)	(0.003)
Country × Sector	Yes	Yes	Yes	Yes
Obs.	23,083	23,083	14,529	8,554
Adj. R^2	0.293	0.293	0.311	0.278

Sample years: 2021. The dependent variable is employment growth between 2019 and 2021. Services exclude financial services, real estate, and governmental sectors. OLS estimates with robust standard errors. ***, **, and * significantly different from 0 at the 1%, 5%, and 10% confidence levels, respectively.

5 Conclusion and Policy Implications

There is a long-standing acknowledgement that innovation and employment are intertwined in complex ways. Innovation can represent the introduction of new products, thereby increasing labour demand, or labour-saving process changes that can reduce the need for workers. Alternatively, process changes can be factor-biased and increase or decrease demand for labour depending on which factors the new technologies favour. These effects can play out both within firms as well as across firms within regions. Further, they can play out across firms *and* regions, particularly in the context of multinationals. Furthermore, all of works in a setting where innovation is concentrated in the hands of a few major innovators.

This study seeks to bring together these strands of the literature to highlight that the innovation-employment link must also be understood within the context of the overarching dominance of MNEs. In particular, our results suggest that while employment growth is faster in more innovative firms, that this effect is most keenly observed in MNEs. One facet of this is that MNE affiliates are able to draw not only from innovative activity within themselves but from that within the international group. This, however, is not the sole difference as our estimates suggest that MNEs are able to expand employment by more post-patenting than non-MNEs can. This suggests that there is something inherent to the MNE structure (e.g. better integrated value chains) which allows them to make the most of new technologies and products.

These insights then suggest three primary policy implications. First, it suggests that there may be particular benefits from attracting FDI by innovative MNEs. This notion underpins policies such as patent boxes which are designed specifically to support innovative firms. Indeed, there is a literature suggesting that MNEs respond to patent boxes by allocating R&D to such countries (e.g. Schwab and Todtenhaupt (2021)). While some have suggested that patent boxes are simply another example of wasteful tax competition because of the limited effects they seem to have on innovation (e.g. Bösenberg and Egger (2017); Davies et al. (2020); Gaessler et al. (2021)), such studies only consider their effect on patenting, not employment. Thus, to truly appreciate the potential benefit of patent boxes or other R&D tax subsidies, it may be necessary to look at broader effects.

Second, it must be remembered that innovation is concentrated among a few firms. As such, encouraging innovation overall is likely to mean primarily supporting the activities of these firms. As such, promoting R&D may well lead to faster growth by large – and in particular multinational – firms. While this may have benefits, it also means greater concentration of employment. This can have significant implications for the functioning of labour markets potentially leading to lower wages (see the analysis of Benmelech et al. (2022) for further discussion). In addition, increased concentration of employment in foreign multinationals can generate concerns over national self-determination. Although the estimates of Setzler and Tintelnot (2019) and others point to net benefits from working for a foreign-owned firm, there is no denying that the current political and populist climate nevertheless makes this an issue.

Finally, the fact that innovation in one part of the MNE is associated with employment effects elsewhere means that “domestic" R&D and tax policies are in fact international. In particular, our estimates suggest that the employment benefits created by domestic policy are felt globally, meaning that there is an uninternalized positive employment externality to local R&D supports.[23] Therefore, similar to Bauer et al. (2014), there may be unrealized gains when innovation policies are uncoordinated across jurisdictions. Such possibilities may be important in the context of multilateral efforts to change the international tax landscape for MNEs such as the OECD’s Base Erosion and Profit Shifting initiative.[24] In particular, it

[23]For example, Bilar and Morales (2016) find that 20 percent of the value added benefits from US MNE innovation is manifested in the performance of their non-US affiliates.

[24]More details on this are at `https://www.oecd.org/tax/beps/`.

provides a new take on the role of carve-outs (exceptions to the proposed minimum tax requirements) for R&D policy.

Although there are important questions that our analysis is unable to fully answer – in particular what precisely is driving the MNE premium from own innovation – we hope that our analysis provides a useful contribution to our understanding of innovation and employment, including the need to consider it in an international context.

References

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N., and Kerr, W. (2018). Innovation, reallocation, and growth. *American Economic Review*, 108(11):3450–3491.

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. *Journal of political economy*, 128(6):2188–2244.

Akcigit, U. and van Reenen, J. (2023). *The Economics of Creative Destruction: New Research on Themes from Aghion and Howitt*. Harvard University Press.

Alfaro, L. and Chen, M. X. (2018). Selection and market reallocation: Productivity gains from multinational production. *American Economic Journal: Economic Policy*, 10(2):1–38.

Alvarez, R. and Lopez, R. A. (2005). Exporting and performance: Evidence from chilean plants. *Canadian Journal of Economics*, 38(4):1384–1400.

Autor, D., Chin, C., Salomons, A. M., and Seegmiller, B. (2022). New frontiers: The origins and content of new work, 1940–2018. Technical report, National Bureau of Economic Research.

Autor, D., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, 118(4):1279–1333.

Autor, D., Salomons, A., and Seegmiller, B. (2023). Patenting with the stars: Where are technology leaders leading the labor market?

Bauer, C., Davies, R. B., and Haufler, A. (2014). Economic integration and the optimal corporate tax structure with heterogeneous firms. *Journal of Public Economics*, 110:42–56.

Benmelech, E., Bergman, N. K., and Kim, H. (2022). Strong employers and weak employees: How does employer concentration affect wages? *Journal of Human Resources*, 57(S):200–250.

Berkes, E., Manysheva, K., and Mestieri, M. (2022). Global innovation spillovers and productivity: Evidence from 100 years of world patent data.

Bernard, A. B. and Jensen, J. B. (1999). Exceptional exporter performance: cause, effect, or both? *Journal of International Economics*, 47(1):1–25.

Bilar, K. and Morales, E. (2016). Innovation in the global firm. Technical report, NBER Working Paper No. w22160.

Bloom, N., Draca, M., and van Reenan, J. (2016). Trade induced technical change? the impact of chinese imports on innovation, it and productivity. *Review of Economic Studies*, 83(1):87–117.

Bösenberg, S. and Egger, P. H. (2017). R&d tax incentives and the emergence and trade of ideas. *Economic Policy*, 32(89):39–80.

Calvino, F. and Virgillito, M. E. (2018). The innovation-employment nexus: A critical survey of theory and empirics. *Journal of Economic Surveys*, 32(1):83–117.

Coelli, F., Moxnes, A., and Helene Ulltveit-Moe, K. (2022). Better, faster, stronger: Global innovation and trade liberalization. *The Review of Economics and Statistics*, 104(2):205–216.

Dachs, B. and Peters, B. (2014). Innovation, employment growth, and foreign ownership of firms: A european perspective. *Research Policy*, 43(1):214–232.

Davies, R. B., Desbordes, R., and Ray, A. (2018). Greenfield versus merger and acquisition fdi: Same wine, different bottles? *Canadian Journal of Economics/Revue canadienne d'économique*, 51(4):1151–1190.

Davies, R. B., Hynes, R., and Kogler, D. F. (2020). Patent boxes and the success rate of applications. Technical report, CESifo Working Paper No. 8375.

Davies, R. B., Santoni, G., Toubal, F., and Vannelli, G. (2023). Knowledge, jobs, and unemployment in regions. Technical report, Mimeo.

Duch-Brown, N., Gomez-Herrera, E., Mueller-Langer, F., and Tolan, S. (2022). The innovation-employment nexus: A critical survey of theory and empirics. *Research Policy*, 51(3):104446.

Gaessler, F., Hall, B. H., and Harhoff, D. (2021). Should there be lower taxes on patent income? *Research Policy*, 50:104129.

Girma, S., Kneller, R., and Pisu, M. (2005). Exports versus fdi: An empirical tes. *Review of World Economics*, 114(2):193–218.

Graetz, G. and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5):753–768.

Grullon, G., Larkin, Y., and Michaely, R. (2019). Are us industries becoming more concentrated? *Review of Finance*, 23(4):697–743.

Guadalupe, M., Kuzmina, O., and Thomas, C. (2012). Innovation and foreign ownership. *American Economic Review*, 102(7):3594–3627.

Hall, B. H., Jaffe, A., and Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of economics*, pages 16–38.

Harrison, R., Jaumandreu, J., Mairesse, J., and Peters, B. (2014). Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. *International Journal of Industrial Organization*, 35:29–43.

Hejazi, W. H., Tang, J., and Wang, W. (2023). Absorptive capacity, learning and profiting from outward fdi: Evidence from canadian firms. *Journal of World Busines*, 58(3):101427.

Helpman, E., Melitz, M. J., and Yeaple, S. R. (2004). Export versus fdi with heterogeneous firms. *American Economic Review*, 91(1):300–316.

Keller, W. (2002). Geographic localization of international technology diffusion. *American Economic Review*, 92(1):120–142.

Keller, W. and Yeaple, S. R. (2013). The gravity of knowledge. *American Economic Review*, 103(4):1414–1444.

Kelly, B., Papanikolaou, D., Seru, A., and Taddy, M. (2021). Measuring technological innovation over the long run. *American Economic Review: Insights*, 3(3):303–320.

Kogan, L., Papanikolaou, D., Schmidt, L., and Seegmiller, B. (2022). Technology, vintage-specific human capital, and labor displacement: Evidence from linking patents with occupations. Technical report, Mimeo.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics*, 132(2):655–712.

Markusen, J. R. (1984). Multinationals, multi-plant economies, and the gains from trade. *Journal of International Economics*, 16(3-4):205–226.

Mayer, T. and Ottaviano, G. I. (2008). The happy few: the internationalisation of european firms: new facts based on firm-level evidence. *Intereconomics*, 43(3):135–148.

Mokyr, J., Vickers, C., and Ziebarth, N. L. (2015). The history of technological anxiety and the future of economic growth: Is this time different? *Journal of Economic Perspectives*, 29(3):31–50.

Schwab, T. and Todtenhaupt, M. (2021). Thinking outside the box: The cross-border effect of tax cuts on r&d. *Journal of Public Economics*, 204.

Setzler, B. and Tintelnot, F. (2019). The effects of foreign multinationals on workers and firms in the united states. Technical report, NBER Working Paper No. 26149.

Ulku, H. (2004). R&d, innovation, and economic growth: An empirical analysis. Technical report, IMF Working Paper No. WP/04/185.

Van Reenen, J. (1997). Employment and technological innovation: evidence from uk manufacturing firms. *Journal of labor economics*, 15(2):255–284.

Zimmerman, V. (2008). The impact of innovation on employment in small and medium enterprises with different growth rates. Technical report, ZEW Discussion Papers 08-134.

UCD CENTRE FOR ECONOMIC RESEARCH – RECENT WORKING PAPERS
SRAITH PÁIPÉAR OIBRE AN IONAID UM THAIGHDE EACNAMAÍOCHTA COBÁC

WP24/09 Ciarán Mac Domhnaill: 'All hail? The impact of ride hailing platforms on the use of other transport modes' April 2024
WP24/10 Margaret Samahita: '"Luxury beliefs": Signaling through ideology?' June 2024
WP24/11 Alan de Bromhead,Seán Kenny: 'Irish Regional GDP since Independence' June 2024
WP24/12 Ronald B. Davies, James R. Markusen: 'Capital Ideas: Modelling and Measuring Factors in the Knowledge Capital Model' July 2024
WP24/13 Karl Whelan: 'Samuelson's Fallacy of Large Numbers With Decreasing Absolute Risk Aversion' July 2024
WP24/14 Cormac Ó Gráda: 'H1N1 and WW1: The Spanish Flu and the Great War' July 2024
WP24/15 Benjamin Elsner, Eoin T. Flaherty, Stefanie Haller: 'Brexit Had no Measurable Effect on Irish Exporters' August 2024
WP24/16 Eoin T. Flaherty: 'Are workers with multinational experience a determinant in startup success?' August 2024
WP24/17 Timothy G. Conley, Morgan Kelly: 'The Standard Errors of Persistence' October 2024
WP24/18 Zilong Li, Xi Chen, Zuzanna Studnicka: 'Have you eaten? The long-run impact of the Great Leap Famine on recent trade' November 2024
WP24/19 Karl Whelan: 'On Estimates of Insider Trading in Sports Betting' December 2024
WP25/20 Ciarán Mac Domhnaill: 'Driving over the hill: Car intensity during structural transformation' December 2024
WP25/01 Judith M. Delaney, Paul J. Devereux: 'Levelling the Playing Field? SES Differences in Graduate Degree Choices' February 2025
WP25/02 Zilong Li: 'International and Domestic Border Effects in China: Multilateral Resistances, Trade Substitution Patterns and Linguistic Differences' March 2025
WP25/03 Karl Whelan: 'The Gambler's Ruin with Asymmetric Payoffs' March 2025
WP25/04 David Madden: 'What Factors Are Associated with the Decline in Young People's Mental Health During the Early Stages of the Covid Pandemic?' March 2025
WP25/05 Zilong Li: 'Home Bias in Trade within China: The Role of Trust' March 2025
WP25/06 Bing Guo, Sarah Parlane, Lisa Ryan: 'Regulatory Compliance in the Automobile Industry' March 2025
WP25/07 Zhiyong Huang, Fabrice Kämpfen: 'Do Health Check-Ups for Seniors Improve Diagnosis and Management of Hypertension and Diabetes in China?' April 2025
WP25/08 Bernardo S. Buarque, Ronald B. Davies, Ryan M. Hynes, Gianluca Tarasconi, Dieter F. Kogler: 'The Uneven Regional Geography of Telecommunication Standard Essential Patents' April 2025
WP25/09 Ronald B. Davies: 'Deriving the Trump Tariffs' April 2025
WP25/10 Ciarán Mac Domhnaill, Lisa Ryan, Ewa Lazarczyk: 'When markets merge: evidence from Ireland's integration with the European wholesale electricity market' April 2025
WP25/11 Sara Amoroso, Ronald B. Davies: 'M&As and Innovation: A New Approach to Classifying Technology' April 2025
WP25/12 Margaret Samahita, Martina Zanella: 'Confident, but undervalued: evidence from the Irish Economic Association Conference' April 2025
WP25/13 Xidong Guo, Zilong Li, Zuzanna Studnicka, Jiming Zhu: 'Environmental Unfamiliarity and Work Performance: Evidence from Chinese Basketball during COVID-19' June 2025

UCD Centre for Economic Research
Email economics@ucd.ie