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Multinationals and intra-regional innovation concentration ☆

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ABSTRACT

This article examines the extent to which the presence of multinational enterprises (MNEs) influences the concentration of innovation among patenting firms within US states from 1976 to 2010. Merging patent and regional socioeconomic data, this study explores the effects within 50 US states over more than three decades using Ordinary-Least-Square and Instrumental Variable estimations. It shows that MNEs significantly contribute to the concentration of patenting activity, an effect predominantly driven by domestic-owned MNEs. The impact differs across space: states with a higher share of MNEs experience a sharper increase in patenting concentration. Crucially, it is the non-MNE firms that feel the squeeze the most, with those in the middle of the patenting hierarchy producing fewer patents when domestic MNEs ramp up their activity. This suggests that economic globalisation, while enhancing innovation opportunities for some, reinforces competitive pressures and barriers for others. These findings offer a new perspective on the forces shaping regional innovation dynamics, highlighting the role of MNEs in both amplifying innovation gains and exacerbating disparities in knowledge production.

1. Introduction

For more than three decades, the US has seen patenting concentration increase in different technology classes, measured by the Gini coefficient (Forman and Goldfarb, 2020). However, less is known about the role of Multinational Enterprises (MNEs) regarding these developments. Accounting for around one-third of global Gross Domestic Product (GDP) and half of global exports in 2014, MNEs are considered the main actors in the global economy (OECD, 2018). Also, their innovative activities have seen an impressive surge, with the amount of international investment in Research and Development (R&D) and invested capital approximately doubling between 2003 and 2017 (Crescenzi et al., 2020). The presence of MNEs, their foreign operations and their overall patenting activity strongly impact the patenting activity within regions, as they do not only produce knowledge, but also affect existing firm dynamics, attract further MNEs and transfer knowledge by producing spillovers. However, while knowledge diffusion does not happen automatically (Blomström and Kokko, 1999), there seems to be increasing evidence of market concentration and knowledge concentration across firms (Feldman et al., 2021; Forman and Goldfarb, 2020). With this research, I aim to explore to what extent the presence of MNEs affects innovation concentration between firms within US states from 1976 to 2010.

There are multiple reasons why we should analyse innovation concentration between firms within a region. First, the level of patent concentration or competition matters for the innovative output. Similar to the product market, a monopolist might have a lower incentive to be innovative than a firm in a competitive market, which is also called the "Arrow replacement effect" (Arrow, 1962). From this view, competition spurs innovation. Second, as pointed out by Schumpeter (1942), competition is central for creative destruction and therefore a key driver for long-run economic growth. Most importantly, these dynamics could strongly affect regional development and prosperity. Fostering innovation is seen as a key priority as it fosters regional growth and higher wages (Lee and Rodríguez-Pose, 2013), which is why this relationship should be explored. Thirdly, economic globalisation could play a role by raising the potential gains from innovation due to a market size effect while at the same time heightening losses due to a competition effect (Aghion et al., 2021). However, relatively little is known about the role of MNEs in contributing to these regional

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innovation dynamics, specifically how they contribute to the increasing patenting concentration within the US over the long run.

This study analyses the effect of the presence of MNEs on patenting concentration within US states from 1976 to 2010. Using patent data from the United States Patent and Trademark Office (USPTO), I construct the Gini coefficient as a measure of patenting concentration between firms within states and calculate the share of patents by MNEs. The Gini coefficient is calculated for two distinct groups. First, to evaluate the overall concentration of innovation, it is calculated using patents from all firms. Second, to measure the impact on firms that are not MNEs (non-MNEs), patents attributed to MNEs are excluded. The findings reveal that MNEs significantly contribute to the overall concentration of patenting activity, an effect predominantly driven by domestic-owned MNEs. Foreign-owned MNEs, in contrast, are not significantly related to higher patenting concentration. The impact differs across space: states with a higher share of domestic MNEs experience a sharper increase in patenting concentration. Moreover, the effect on patenting concentration for non-MNEs is more pronounced than for all patenting firms. A one standard deviation increase in the domestic-owned MNE patent share is estimated to raise the Gini coefficient by 0.14 points. This effect is mostly driven by an adverse effect on patenting of non-MNEs, with those in the middle of the non-MNE patenting distribution feeling the squeeze the most. To verify the robustness, multiple sensitivity checks are conducted, confirming the reliability of the observed relationship.

This paper contributes to the literature by answering the question to what extent the presence of domestic and foreign MNEs influences the intra-regional innovation concentration, focusing on all patenting firms as well as non-MNEs. To the best of my knowledge, this question has not been answered yet. By doing so, it contributes to two main literature strands, one on internationalisation and domestic patenting dynamics and the other one on innovation concentration and its determinants. The first strand has identified a market size and competition effect but has not taken into account that it might result in increasing patenting concentration. Previous papers have found evidence for a positive market size effect, showing that (at least some) firms that internationalise become more innovative (Verhoogen, 2008; Lileeva and Trefler, 2010; Bas and Ledezma, 2010; Bernard et al., 2011). This also indirectly affects the domestic market through a competition effect that influences all firms by making the market more competitive (Shu and Steinwender, 2019). However, these papers have not looked at the effect of internationalisation on patenting concentration dynamics between firms, but rather looked at the effects of firm outcomes.

The second strand has not looked at the role of MNEs and what their contribution in the rise in patenting concentration is. Concentration of firm patenting has already been looked at in the 1940s (Edwards, 1949) but recently became increasingly the focus of academic work. Previous work has focused on the concentration of innovative activity from a regional or national perspective and put emphasis on highly innovative firms (Forman and Goldfarb, 2020; Ozcan and Greenstein, 2020; Akcigit and Ates, 2021; Bandyopadhyay and Greenstone, 2021; Chattergoon and Kerr, 2022). In contrast, this paper focuses more on the role of economic globalisation by connecting it to MNEs, showing which role they play in the increase in patenting concentration. Therefore, it contributes to innovation concentration and its determinants. While it has been argued that concentration of innovative activities ("Schumpeter Mark II") depends on the technology class (Malerba and Orsenigo, 1996), I find that concentration increases for nearly all classes. In addition to contributing to the academic literature, the question is also of high policy relevance, given that it might be linked to other trends currently observed, such as lower productivity and higher product market concentration.

This draft is organised in the following way: It first summarises relevant literature, then sketches out a conceptual framework and hypotheses tested in the empirical section. It describes the data and setting for this research, plots descriptive statistics and estimates the results. Further, it explores heterogeneity and reports robustness checks.

2. Relevant literature and state of the art

2.1. Competitive advantage: Technological competence and internationalisation

From a resource-based view (Penrose, 1959), a firm's growth and competitive advantage stems from the internal resources available to a firm. This includes many factors, such as the role of human capital but also the incentives within the firm (Kryscynski et al., 2021). The competence-based approach states that heterogeneity in firm growth is primarily rooted in differences in technological competence (Mansfield, 1962). Higher technological competence would increase the chance of the adoption of recent advances in technologies, for example recent advances in digital technologies and artificial intelligence, which could be a source of a competitive advantage (Leão and da Silva, 2021; Kemp, 2024). Therefore, higher firm growth and higher market shares are the results of internal resources of the firm, in particular technological competence, which reinforces R&D investment. Firms that internationalise tend to be more productive and innovative (Melitz, 2003), and thus have higher technological competence already before participating in international markets. Firms with higher technological competence select themselves into internationalisation allowing to increase the "extent of the market", which fosters the division of labour and reinforces the realisation of economies of scale (Smith, 1776). From a transaction cost perspective (Coase, 1991; Williamson, 1965), firms can decrease costs and achieve a higher market share by internalising R&D activities and international operations. R&D activities can create barriers to entry if they are linked to the existence of economies of scale as well as to first-mover advantages that firms gain stemming from innovating successfully (Mueller and Tilton, 1969; Klepper and Graddy, 1990). Moreover, there is an additional benefit concerning centralising R&D globally: sending intangible research findings is less cost-intensive than for tangible components (Teece, 1977; Caves, 2007). Setting up operations internationally also enables MNEs to tap into external location specific advantages, exploiting differences in factor endowment, in particular skilled labour or technology, inventor networks and access to natural resources (Hejazi and Pauly, 2003; Castellani et al., 2022). Therefore, technological competence and internationalisation are both viewed as source of a firm's competitive advantage as they can exploit increasing returns to scale and tap into location specific advantages, which will predict the innovativeness and the market share of the firm.

There is comprehensive literature on endogenous firm location, assessing the motivation why firms choose to locate in certain regions and rationales behind setting up operations in a foreign country (Iammarino and McCann, 2013). For each of their foreign operations' location choices, MNEs prefer particular spatial characteristics (Iammarino and McCann, 2013). For a firm to develop technological capabilities in a region, the initial technological infrastructure and local human capital are key variables guiding the location decision (Carlino et al., 2009; Siedschlag et al., 2013). The initial technological infrastructure can include several factors, such as the existing research capacities, the distance to centres of technological excellence and agglomeration economies that emerged due to foreign research activities (Siedschlag et al., 2013). Particularly when other firms are conducting research in the region, it signals to other firms that they can also successfully set up their research activities (Feldman, 2003). Compared to their geographically isolated counterparts, firms within these clusters tend to invest more in R&D and take bigger risks regarding its direction (Gerlach et al., 2009). Other determinants of technological capabilities are the regional and national innovation system (Yang et al., 2012), public investment in R&D (Amendolagine et al., 2019) and highly skilled workers. The internationalisation of R&D activities is highly concentrated within a small number of locations, which are often centres of excellence (Meyer-Krahmer and Reger, 1999). Thus, MNEs are likely to be drawn to locations and sectors where economic and innovative activity concentrates (Dunning, 1958; Flowers, 1976; Caves and Pugel, 1980), with the aim to tap into local spillovers as knowledge is "in the air" (Marshall, 1890) to achieve a competitive advantage. For these reasons, innovative activity tends to be more concentrated than industrial activity, with particularly software patents increasingly concentrating in tech centres (Carlino and Kerr, 2015; Chattergoon and Kerr, 2022).

2.2. The market size and competition effect

Since the mid-1970s, the world has been in an increased globalisation phase (Martin et al., 2018) that has, in combination with technological change, rearranged the geography of production and the global division of labour (Iammarino, 2018). But what happens to domestic patenting when firms internationalise? This subsection discusses how firms respond to the exposure to international markets, describing two different effects: the market size and the competition effect. The market size effect only impacts firms that internationalise, whereas all domestic firms are affected by the competition effect. A positive market size effect refers to the case when firms participating in the international market end up innovating more (Shu and Steinwender, 2019; Akcigit and Melitz, 2022). Firms select themselves into international market participation, and those who do tend to be more productive than those that operate only in the home market. Firms that operate solely in the home country are characterised by lower productivity (Helpman et al., 2004) and have already been less productive than exporting firms before them internationalising (Bernard et al., 1995; Melitz, 2003). Focusing on export markets, the majority of empirical evidence tends to emphasise a positive link between exporting and innovation/productivity at least for certain firms (Verhoogen, 2008; Lileeva and Trefler, 2010; Bas and Ledezma, 2010; Bernard et al., 2011; Iacovone, 2012; Aghion et al., 2018; Munch and Schaur, 2018; Shu and Steinwender, 2019). In line with the market size effect, those firms that are initially more productive and more innovative are experiencing the highest gains due to exporting (Lileeva and Trefler, 2010; Iacovone, 2012; Aghion et al., 2018). While these findings focus on exporting, we might also expect a positive home market effect when a domestic-owned firm sets up an R&D centre outside the US. These effects might be even stronger in comparison to exporting, given that engaging in export activities can occur without any innovation-related investments. Thus, we might expect a larger positive market size effect when MNEs selectively open research labs abroad, as they can exploit location-specific regional advantages and access highly specialised human capital. It is likely also affecting the most innovative MNEs within the US more favourably. Thus, economic globalisation tends to increase the potential gains from innovation through the market size effect, in particular for innovative firms (Aghion et al., 2021).

In contrast, the direction of the competition effect tends to be ambiguous. The "Arrow replacement effect" (Arrow, 1962) describes how a monopolist might have a lower incentive for innovation than a firm in a competitive market. From this view, competition spurs innovation. This perspective is juxtaposed by the Schumpeterian view (Schumpeter, 1942), which is, that higher competition can reduce the incentive for firms due to lower rents and lower resources to invest in R&D. Aghion et al. (2005) reconciles these findings on competition and innovation by showing evidence on the relationship resembling an inverted U-shape in the UK and how they differ for leading and laggard firms. Competition tends to foster innovation in industries that are originally characterised by a lower level of competition. In this case neck-and-neck firms innovate, which is labelled as "escape-competition effect". The Schumpeterian effect prevails for laggard firms in industries with high level of competition and large technological distance. In this case, higher competitive pressure discourages innovation for those firms further away from the technological frontier. There is empirical evidence of the Schumpeterian effect from exporting (Baldwin et al., 2009; Aghion et al., 2018) and from importing (Autor et al., 2020a), where increased competition decreases innovation in less innovative firms. A negative competition effect is likely to be exacerbated if MNEs foreclose other firms in existing or new technological areas (Gallini, 1984; Hall and Rosenberg, 2010). Large firms might build a defensive patent portfolio in an attempt to block other firms and protect their rents (Shapiro, 2001; Choi and Gerlach, 2017), reinforcing a negative effect on patenting for other firms. Relative to other industries, R&D activities can in particular serve as entry barriers, as they tend to create economies of scale and might establish first-mover advantages (Mueller and Tilton, 1969; Klepper and Graddy, 1990). In this case, policy intervention, such as taxing incumbent's operations might produce sizable welfare gains (Acemoglu et al., 2018).

2.3. How the presence of MNEs can increase or decrease innovation concentration

Questions related to firm patenting concentration have been already explored since the 1940s. Scholars in earlier times have pointed out concerns about the concentration of patents within large firms (Edwards, 1949) and questioned whether new innovations contribute to higher overall welfare (Anderson and Harris, 1986; Tirole, 1988). While theory has held that new innovations would increase social welfare, patents could also decrease it through defensive patenting draining all parties' resources (Kimmel et al., 2017).

Decrease in patenting concentration due to firm entry, knowledge diffusion and a positive competition effect

There are three main mechanisms how domestic and foreign MNEs and their patenting activity can reduce concentration of innovative activity between firms. Following the concentration definition by Hirschman (1946) "concentration of the few", which means concentration stemming from a small number of firms patenting, we would expect ceteris paribus to see patenting concentration decrease with the increase of firm entry. MNEs can serve as anchor firms (Feldman, 2003) signalling other firms that technological capacities are present in a region. This, in turn, could attract additional firms, including other MNEs. Therefore, due to the anchoring effect, we would expect a decrease in concentration as more firms begin patenting locally. However, previous work found surprisingly small effects on concentration stemming from new entry, but larger effects from booms and busts (Ozcan and Greenstein, 2020). Moreover, we could also observe a decrease in patenting concentration in the case of a positive competition effect. If a US domestic-owned enterprise starts investing abroad or a foreign-owned subsidiary starts producing patents within a state, this might lead to increase competitive pressure for firms. Depending on the technological distance to the firm and the technological frontier, firms could respond competing neck-and-neck for technological leadership, which might decrease innovation concentration for innovative firms. Moreover, higher levels of competition foster riskier and novel innovation, increasing the likelihood of breakthrough outcomes (Callander et al., 2021). However, this effect might be different for less innovative firms.

Innovation concentration can also be decreased through knowledge diffusion, such as spillover effects and firm alliances. Many papers have explored the linkage between the geography of innovation and globalisation and how the diffusion process is fostered due to the latter (Crescenzi et al., 2020; Bournakis, 2021; Greenaway et al., 2004). The role of MNEs when entering a foreign market has been emphasised in relation to the internationalisation of knowledge as well as knowledge creation and diffusion (Cantwell and Iammarino, 2005). Proximity is viewed as one main predictor for knowledge diffusion in the form of spillover effects, as spillovers are geographically localised (Jaffe, 1989; Feldman and Kogler, 2010). R&D related FDI has been traditionally regarded as a primary mechanism to spread out knowledge across borders (Abramovitz, 1986). With foreign-owned MNEs setting up their operations in the US, they become embedded in the local ecosystem, interact with actors within the region and transfer knowledge to the local economy. By setting up R&D related FDI, MNEs can affect the US states by producing spillover effects and initiating collective learning (Athreye and Cantwell, 2007). These Marshallian externalities (Marshall, 1890) are seen as key benefits of agglomerations, combining spillover effects, pooled labour markets and specialised input (Krugman, 1991). Large and dense areas enable positive externalities supporting the exchange of knowledge, with density playing a key role for knowledge transfer (Duranton and Puga, 2001; Storper and Venables, 2004). This is in line with earlier work, pointing about a potentially concentration decreasing effect of foreign MNEs (Rosenbluth, 1970; Dunning, 1974; Caves, 2007). Foreign intervention has also contributed to the emergence of the most significant technological hubs by linking their location to other technology clusters (Saxenian, 2007). The recent study by Crescenzi et al. (2020) provides evidence that regional innovation rates in the home market are substantially enhanced due to foreign intervention by MNEs. For these reasons, foreign MNEs are viewed as key actors in the international diffusion of knowledge when entering a foreign market, which applies to foreign-owned MNEs.

Increase in patenting concentration due to knowledge concentration, selective gains from globalisation, and a negative competition effect

However, knowledge is not necessarily always "in the air" (Marshall, 1890) in clusters. Fitjar and Rodríguez-Pose (2017) show that there is "much less is the air" in the Norwegian case as typically suggested by the literature. Geographical proximity is not a necessary nor sufficient condition (Boschma, 2005) for innovation to take place. Knowledge diffusion in the form of FDI spillovers and linkages to local firms do not happen automatically (Blomström and Kokko, 1999), or as described by several scholars, there is a cost-benefit trade-off between inward and outward spillovers (Myles Shaver and Flyer, 2000; Crescenzi et al., 2020). While firms appreciate inwards spillovers as they learn from other firms, they have an incentive not to share knowledge to keep and enhance their competitive edge. Sharing knowledge with competitors can come at a high cost. Indeed, Crescenzi et al. (2020) finds evidence that technological leaders produce on average fewer spillovers and form less strategic alliances with local firms compared to other less innovative MNEs. Thus, for the case of MNEs not creating outward spillovers, but producing patents, it might be that patenting concentration within a region is rising as it becomes increasingly concentrated within large firms.

More patents can increase innovation concentration if these are increasingly produced by large firms that can better harvest the gains from internationalisation. Due to the market size effect, we expect domestic-owned MNEs that set up a foreign R&D centre to become more innovative and produce more patents than those that do not internationalise or that ceteris paribus benefit less from internationalisation. As these are likely firms that have been more productive or innovative before, we would expect an increase in patenting concentration as more innovative firms would be more able to reap the benefits from economic globalisation. For this case, we would expect an increase in patenting concentration because of a change at the top of the patenting distribution, as the most innovative MNEs are becoming more innovative. There seems to be evidence for increasingly larger firms patenting (Archibugi et al., 1995) and an increase in patenting concentration within the US (Akcigit and Ates, 2021; Forman and Goldfarb, 2020).

Moreover, due to increased pressure from internationalisation, we may observe a negative competition effect. This is more likely to be the case where technological knowledge is more dispersed between firms, as is the case for countries close to the technological frontier like the US. In this case, we could expect higher competitive pressure because of domestic-owned MNEs becoming more innovative as they set up a foreign R&D facility. Less innovative firms might struggle to keep up with their competitors, discouraging them from innovating. This effect will likely depend on the distance to the technological frontier as firms strongly differ in their capacity to absorb knowledge. One crucial predictor of the firm's absorptive capacity (Cohen and Levinthal, 1990) is cognitive proximity, which refers to the knowledge gap between new knowledge and a firm's prior knowledge base. Therefore, with increased competitive pressure it is likely to become more difficult for less innovative firms to absorb knowledge, apply and reuse it in a different setting (Cohen and Levinthal, 1990). There is empirical evidence for a negative competition effect showing how over the last three decades import competition within the US has affected the patent production of the least profitable firms the most (Autor et al., 2020a). In case of a negative competition effect, we expect an increase in patenting concentration because of a decrease in patenting from less innovative firms.

In addition, we could see an increase in concentration if incumbent firms use strategic patenting to gain a competitive edge over other firms and block firms from innovating. In this case, a higher number of patents could impede instead of encourage innovation. Strategic patenting is more likely to occur when innovation tends to be more incremental, when the expenses to get patents are reasonably low, and the creation of a product includes multiple patentable inventions (Hunt, 2006; Bessen and Hunt, 2007). For strategic patenting, large firms use the acquisition of many patents to hold up competitors, threatening litigation (Bessen and Hunt, 2007). Innovative firms might respond with a counter-threat, by creating a defensive patent portfolio. This might end up in a cross-licensing solution of the whole portfolios, with both firms abstaining from suing each other and the firm with the weaker portfolio paying fees (Grindley and Teece, 1997). Building a thick web of patents has been referred to as "patent thickets" (Shapiro, 2001), which has been measured by patent counts (Lerner, 1995; Cockburn and MacGarvie, 2011) or patent overlap (Hall et al., 2021). Another option would be merger and acquisition, for example with MNEs acquiring smaller innovative firms. There is recent empirical evidence for the US on strategic patenting (Akcigit and Ates, 2021) and a decline of entrants' patent share (De Loecker et al., 2021; Akcigit and Ates, 2021). For the UK, scholars also find increased patent entry costs due to patent thickets (Hall et al., 2021). Therefore, we might expect an increased number of patents to increase intra-regional patenting concentration as it reinforces the competitive advantage of firms and the entry costs for other firms.

3. Hypotheses

This study answers the research question to what extent the presence of MNEs affects patenting concentration. As firms that demonstrate relatively high productivity tend to be more likely to internationalise (Melitz, 2003; Helpman et al., 2004), we would expect them to become even more innovative through the market size effect (Smith, 1776; Aghion et al., 2021; Shu and Steinwender, 2019). By internalising R&D activities and benefiting from economies of scale (Coase, 1991; Williamson, 1965), (some) MNEs are likely to increase innovation. They are also more likely to locate in areas and sectors with higher concentration, which allows them to benefit from agglomeration effects (Marshall, 1890; Dunning, 1958; Caves, 2007). Therefore, we expect an increase in patenting of more innovative firms, which increases patenting concentration, as the patent share of innovative firms increases compared to firms that are less innovative. In addition, a positive competition effect among more innovative firms could contribute to innovative firms patenting more if it spurs neck-and-neck competition (Aghion et al., 2005). Thus, it is expected that the presence of MNEs is associated with higher levels of innovation concentration. Based on these considerations, the first hypothesis is formed:

Hypothesis 1. The level of patenting concentration between all firms is positively related to the patent share of all MNEs in a given technology sector and state.

To test this hypothesis, this paper estimates the baseline model and regresses the patenting concentration between all patenting firms, measured by the Gini coefficient, on the share of all patents by MNEs (domestic and foreign) within a technology class and state. The share of patents by MNEs describes the patents granted to MNEs relative to all patents, which signifies dividing the absolute number of MNE patents by the number of overall patents in a state and technology class.

However, the effect is likely to differ when it comes to the role of domestic-owned and foreign-owned MNEs. First, domestic-owned and foreign-owned MNEs are different in characteristics such as productivity, wages and skill mix (Nigh et al., 1998) and many domestic MNEs grow organically within the US and then decide to internationalise. Second, foreign MNEs choose to locate within the US for different reasons, often to benefit from local capacities while producing knowledge spillover to local firms (Marshall, 1890; Cantwell et al., 1995). Indeed, multiple papers have pointed out the role of foreign MNEs in creating local linkages and transferring knowledge (Anon-Higon and Vasilakos, 2008; Crescenzi et al., 2020), with some also describing a concentration decreasing effect (Rosenbluth, 1970; Dunning, 1974; Caves, 2007). Third, the majority of MNEs producing patents within the US are domestic-owned, making up around 80% of all MNEs. Thus, the majority of patents are from domestic-owned MNEs as I am not capturing the patents from foreign MNEs outside the US. For these reasons, I anticipate that the higher share of domestic-owned MNEs, not foreign-owned MNEs, to boost innovation concentration between all firms. As I expect the positive correlation between domestic MNEs and patenting concentration between all firms to be driven by a positive market size effect and a negative competition effect, it is more likely to observe a concentration enhancing effect in states where the share of MNE patents is high. Given these considerations, I form my second hypothesis:

Hypothesis 2. The positive relationship between patenting concentration and MNEs is driven by domestic-owned MNEs and more pronounced in states with higher MNE patent shares in a given technology sector and state.

To verify this hypothesis empirically, I am testing first the difference between domestic- and foreign-owned MNEs by regressing their share in separate regressions on the Gini coefficient. If the hypothesis of the effect being driven by domestic-owned MNEs is confirmed, I am splitting the domestic-owned MNE share into quartiles and include a dummy indicating whether a state has a low, middle, high or very high MNE share per technology class.

Finally, this paper is also interested in testing how the effect varies for other firms, for non-MNEs, as it has been shown that firms operating only in the home country are characterised by lower productivity than firms that internationalise (Melitz, 2003; Helpman et al., 2004). Multiple studies have empirically demonstrated that MNEs and foreign affiliates are larger in size, more capital-intensive, and invest more in R&D than domestic firms (OECD, 2019). Thus, firms that are not classified as MNEs tend to be less innovative, and we might expect them to respond adversely to increased pressure from internationalisation (Cohen and Levinthal, 1990; Aghion et al., 2005). With a negative competition effect, they might decrease their patent production due to more competitive pressure within a state and technology class. R&D activities can also act as barriers to entry, in particular if they are linked to the existence of economies of scale and if they create first-mover advantages (Mueller and Tilton, 1969; Klepper and Graddy, 1990). This negative effect on other firms' patenting activities is likely to be exacerbated if MNEs act strategically and foreclose other firms from technological fields (Gallini, 1984; Shapiro, 2001; Hall and Rosenberg, 2010; Hall et al., 2021). Other firms might not be able to enter established or new technological fields through patent thickets (Shapiro, 2001; Bessen, 2003), or only do so at high costs. Defensive patent portfolios might hinder other firms from innovating, thereby intensifying the adverse impact on other companies' patenting activities. This is tested in the third hypothesis:

Hypothesis 3. The level of patenting concentration of non-MNEs is positively related to the presence of domestic-owned MNEs in the same technology sector and region.

I start by testing the first hypothesis in the baseline model and investigate the impact of MNE presence on the overall intra-regional innovation concentration between firms. The results are shown in Table 1. The second hypothesis tests for the difference between foreign- and domestic-owned MNEs and the intensity of the effect. The results for heterogeneity in the effect are shown in Table 2. For the third hypothesis, for a negative competition effect, I focus on firms that tend to be less innovative by regressing the Gini coefficient consisting only of patents by non-MNEs on the share of domestic MNEs. I am also using different percentiles of the patent distribution of non-MNEs as outcome variables to identify how those firms are affected by increased competitive pressure. The results for this are shown in Table 3.

4. Data description

I construct a yearly panel dataset for US states from 1976 to 2010. All observations are at the state, technology and year level. I calculate multiple innovation indicators, different MNE measures and different concentration measures. The technology classes were developed by Hall et al. (2001) and are referred to as the NBER classification, which distinguishes between the six different classes Computers and Communications, Drugs and Medical, Electrical and Electronics, Chemical, Mechanical and Others. This patent classification system was chosen given that it establishes a classification that is economically relevant, spans over multiple decades and provides higher-level categories than for example the U.S. Patent Classification (Marco et al. 2015). However, for utility patents the NBER technology classes were discontinued shortly after 2010 (PatentsView, 2024), which is why the analysis is also limited to this period. To account for the differences in the nature of these technology classes, I construct the analysis also at the technology class level. This approach recognises that some technology classes are inherently more prone to concentration, such as through an incremental nature of innovation or different learning regimes. For example, Scherer (1983) highlights the differences in patenting patterns across industries and technology classes, while Breschi et al. (2000) emphasise learning regimes and Bessen and Hunt (2007) focus on the incremental nature of certain technologies.

The sample consists of 50 US states, excluding islands and other territories. Innovation is measured using data from PatentsView, using utility patents granted by the USPTO. As the focus of this study is to examine the distribution of patents between firms, the focus is on assignees. Every patent is linked to one or more assignees, which might be in the same or in a different region. To avoid multiple counting of multiple assignee patents, fractional counts are used, dividing each patent by the number of assignees and the number of regions. Thus, every assignee is assigned a patent value, which is equal to one if there is only one assignee in one state. Only data is kept where the assignee type is classified as private company or corporation. This signifies excluding patents from individuals, governments, and unassigned assignee types. After using the existing identifier to remove these patents, I manually take out patents assigned to organisations that are clearly not firms, such as universities, institutes, or foundations. In addition, observations with no assignee identifier are excluded as well, as it is not possible to identify the firm. The state level is chosen due to this study's interest in firm and spatial dynamics. From an innovation perspective, the state captures an aggregate level. Still, if a more granular level was chosen – such as county or metropolitan statistical area – firm concentration might be underestimated. Therefore, to balance the interest between firm and regional dynamics the state level seems to be a suitable compromise and can provide meaningful insights for policymakers and researchers.

4.1. Measuring innovation

Innovation can be measured in different ways. Earlier studies have proxied innovation by R&D activities, such as R&D expenditure or the amount of R&D laboratories, and thus focused on an input in the production of innovative activity (Feldman, 2000). Other papers have relied on the formation of new firms or start-ups (Audretsch and Vivarelli, 1994), investment related to innovative activity (Florida et al., 1994) or economic measures such as employment growth (Glaeser et al., 1992). In this study, innovation will be proxied by patents, as they are a measurable output of innovative activity.[1]

Location of assignees

The USPTO patent data provides information on the location of the assignee and the inventor. For firms that produce patents only in one location within the US, the location of the inventor, the assignee and the primary research location is the same. Thus, all patents will be assigned to that location. For firms producing research in different states within the US, the inventor's location is used, as this is the state where innovation is actually carried out and thus would influence other firms. In contrast, the assignee location refers to the legal headquarter, which might not reflect the innovative activities of the assignee.

I am identifying assignees based on the identification number provided by the USPTO, which is a disambiguated id number for every firm. However, the USPTO data does not account for dynamic changes in firm names and ownership structure. Arora et al. (2021) use the NBER patent database, which links US publicly listed firms and their patents, to account for dynamic changes. While they find that 40% of their sample is mismatched, this only provides a modest underestimation of the patent value. This substantial difference is explained by the mismatch between the NBER patent database and Compustat, the accounting for changes in names and better dynamic reassignment due to mergers and acquisitions. The study is relevant to assess the extent of a possible bias due to measurement error in firm dynamics that might not be accounted for in the USPTO database and thus apply to this study as well. Changes in firm names do not influence the results of this study, as it does not follow firms over time but creates an outcome variable based on the patent shares of the firms in the region. In the case of merger and acquisition, when a large company acquires a small one, and patents are still separately recorded for both firms, this would lead to an underestimation of the concentration within the state.

4.2. Independent variable

Identification of MNEs with R&D centres

MNEs are identified using patent data, following Crescenzi et al. (2020). By producing patents in multiple countries, an assignee can be identified as an MNE. However, as the focus is on MNEs with R&D centres, I only identify an MNE if it has at least five cross-border patents. To do this, I start by identifying which firm has engaged in cross-border research activities. Cross-border research activities are carried out if the country in which the assignee mainly conducts research differs from where the inventor has her residential location. The assignees' headquarters will not be considered as the main research location, as it refers to the legal headquarter, and it does not necessarily reflect where most of the research is conducted. Instead, it is the country where most of the inventors for each firm are located. A patent is categorised as an MNE patent if the country of the assignee's main research location differs from one of their inventors' location, with one of them required to be in the US. In addition, to capture MNEs with R&D centres, the restriction is imposed that an MNE has to have at least five cross-border patents. Orbis data is also used to validate the identification of MNEs, as described in the online Appendix.

The independent variable used in the analysis is the share of patents by MNEs. For every state, technology class and year, the *MNE patent share* is calculated. The absolute number of patents by MNEs is divided by the absolute number of patents within the state for every technology class in a given year. In addition to the patent share of MNEs, the share of firms that are MNEs is calculated, by dividing the absolute number of MNEs by the absolute number of firms in a state, technology class and year. Moreover, this study also considers the role of ownership. The USPTO provides a specific identifier that enables the distinction between foreign-owned and domestic-owned MNEs. This allows to construct the patent share by domestic and foreign MNEs similarly to the overall MNE patent share, dividing the number of patents for each respective group by the overall number of patents within a state, technology class and year. Finally, foreign patents are considered as well. Foreign patents are often produced in the form of MNEs setting up research labs in countries outside of the US. In this case, the inventor is based outside of the US, while the primary research location lies within the US. To measure the impact of foreign patents, the patents are reassigned to the primary research location within the US and are calculated as the share of foreign patents, which divides the foreign patent count by the overall number of patents for each respective state, technology class and year.

4.3. Dependent variable

What does patenting concentration mean, and how can it be measured? This subsection answers these two questions and describes different concentration indicators. These indicators are constructed using patent counts to establish a distribution of innovation between firms. For every firm in a state, technology class and year, the number of patents is calculated and different indicators are computed to assess how concentrated patents are between firms. One limitation is that these indicators only include firms that produce patents. As the measures are based on the patent data from the USPTO, they only comprise firms that have registered their patent with this patent office. Therefore, it does not construct a measure of innovation for all firms, only for those producing patents, as highlighted by Griliches (1998). Thus, an interesting extension of this paper would be to include all the firms not producing patents (OECD, 2010).

Measuring patenting concentration

Concentration can be measured in multiple ways. Hirschman (1946) defines it in two different forms "Control of an industry by few producers can be brought about by an inequality of distribution of

[1] Despite being an imperfect way of measuring innovation, it is commonly applied in the literature. Some authors have used patent text as data (Griliches, 1981), Hall et al. (2001), others have used it to measure the value of innovation (Blundell et al., 1999; Kogan et al., 2017), innovation and competition (Aghion et al., 2005; Autor et al., 2020a; Bloom et al., 2016), knowledge spillovers (Jaffe et al., 1993; Moretti, 2004; Bloom et al., 2013), innovation networks (Branstetter et al., 2019) and rent distribution (Kline et al., 2019). Patent data has the advantage of being a measurable output, being commonly applied in the economic literature and being publicly available over a long period, which allows the assessment of how MNEs have affected intra-regional innovation concentration from 1976 to 2010. However, on the other hand, using patent data to measure innovation has certain limitations. Not only that not all patents possess the same economic or innovative value, but also that not all innovative activities are patented (Feldman, 2000). By creating inequality measures with the patent data, every patent receives the same weight and therefore assumes the same innovative value. Therefore, by using patent count data, it is not possible to assess the quality of innovative activity, just the quantity of patented innovative activity, where every patent contributes to higher innovative activity to the same extent. Despite these limitations, patent data fit the purpose of this study well and are a measurable output of innovative activity and thus should be used.

the individual output shares when there are many producers or by the fact that only few producers exist". The Gini coefficient (Gini, 1914) is calculated as the main variable of interest, which is a concentration indicator measuring the inequality of distribution of the firms' patent shares. This indicator is selected for multiple reasons. First, it is among the most commonly used measures in the economic inequality and concentration literature (Giles, 2004; Giorgi and Gigliarano, 2017; Forman and Goldfarb, 2020). Second, the degree of inequality in the distribution of innovative output across firms is expected to play a crucial role for other aggregate outcome variables. Third, it has the advantage of describing the whole distribution in one number. Fourth, it tends to focus more on the middle of the distribution (Sen, 1973) and thus on the average firm. The Gini coefficient takes on values between 0 and 1, with 0 signifying perfect equality of patenting activity, which means that patents are completely equally distributed across firms. In contrast, a Gini coefficient with a value of 1 displays maximum concentration, with all innovative activity being concentrated in one firm.

Concentration measures for robustness checks

Other patenting concentration measures are constructed to conduct robustness checks on patenting concentration. This includes the Herfindahl–Hirschman Index (HHI) (Herfindahl, 1950; Hirschman, 1946) and the four-firm concentration ratio (CR4). These measures are commonly used for measuring firm concentration and market power within an industry (Pavic et al., 2016). The HHI and CR4 measure innovation concentration with a particular focus on firms with large patent shares. The HHI is commonly applied in industrial economics to measure market concentration and assess the presence of an oligopoly or a cartel (Hannah and Kay, 1977; Tirole, 1988). It also measures economic diversity (Chen, 2020) as well as specialisation (Kemeny and Storper, 2015). The CR4 describes the patents accrued by the four largest firms within an industry.

4.4. Control variables

This paper uses control variables to account for confounding factors influencing patenting concentration within state and technology class, the MNE patent share and firm location. For this reason, two types of control variables are included; those varying by state and technology class and those only varying at the state level. The first type refers to the number of patenting firms and the patent count per state, which are constructed using USPTO data. To do so, the number of patenting firms and patents of every assignee in the region and technology class is calculated. Socio-economic variables at the state level include GDP, population and employment data. GDP data is collected from the Regional Economic Accounts of the Bureau of Economic Analysis, to control for the level of economic activity. To calculate GDP per capita, I divide it by population data, which is obtained from the United States Census Bureau. Employment data is added from the Business Dynamics Statistics. I am focusing specifically on employment within the Professional, Scientific, and Technical Services sector, rather than the overall employment level. Given that specialised human capital is an important factor for firm location (as described in Section 2.1), I am controlling for employment in R&D related sectors.

5. Model, methods and descriptive evidence

5.1. Baseline model

The baseline model takes the form of the following equation:

$$GINI_{i,j,t} = \beta MNE_{i,j,t-1} + \gamma X_{i,j,t-1} + \upsilon_i + \upsilon_j + \upsilon_t + \varepsilon_{i,j,t} \tag{5.1}$$

where *GINI* is the Gini coefficient for every state i in technology class j in period t, *MNE* is the MNE patent share in state i in technology class j for period t-1, *X* is a vector of controls in state i in technology class j for period t-1, υ_i, υ_j *and* υ_t are state, technology class and period fixed effects, and ε is the idiosyncratic error term. Period refers to three years, as I am creating three-year averages from 1976–2010. The control variables include the absolute number of patents, the absolute number of firms (both per technology class), GDP per capita, population, and employment. The standard errors are clustered at the state level.

Fixed effects are included to account for heterogeneity bias, which controls for unobserved time-invariant variation at the state, period, and technology class level. I therefore control for factors that are specific to each state that do not change over time, including geographic features such as access to a coast or harbour, the level of the institutional environment and the level of the regional innovation system. Given that the observation period spans over more than 30 years, during which there have been substantial changes in the regional innovation system, I am accounting for this by using the number of patents and patenting firms as controls. In addition, as described in Section 4, there are substantial differences across technology class by nature, which is why I include technology fixed effects. To account for shocks across states within a three-year period, period fixed effects are added. The results for this estimation are shown in Table 1.

Estimating a causal relationship is highly challenging in this case, as two main issues pose a challenge to estimating causal parameter estimates: selection and reverse causality. First, as described in Section 2.1, firm location is endogenous, as it is a highly selective process based on certain characteristics of a region. Thus, MNEs might be drawn to states that exhibit higher concentration levels. Second, there might be the issue of simultaneity, which refers in this study to MNE's patenting activities not only influencing the innovation concentration within the region, but also vice versa. The level of patenting concentration might influence the level of the MNE patent share. To account for the first concern, selective locational decision of firms, factors that influence this choice are used as controls, such as economic activity, firm dynamics, innovation and human capital. I do so by controlling for GDP per capita, scientific employment, population, the absolute patent count, and the absolute number of patenting firms. The second concern is related to simultaneity. In order for the MNE patent share to not simultaneously impact the patenting concentration, I am not analysing the effect in the same period, but instead use the lagged independent and controls variables.

To check the robustness of the results, multiple checks are conducted that further support the results found in the main section of the paper. These tests are shown in the online Appendix. The relationship is not only estimated in *levels*, but also in *differences* as shown in Table 6. Another measure for the presence of MNEs is used in Table 7, applying the share of unique firms that are MNEs as independent variable. Moreover, as there has been substantial change regarding patenting in specific periods and technology classes over these multiple decades, technology class-period fixed effects are added in Table 7. Further, the results are also estimated in subsamples for periods that last around one decade in Table 10. Finally, more checks are also conducted using different measures of innovation concentration (Table 11), different weights in the OLS regression (Table 11) and sub-samples of states that are highly innovative (Table 9). However, despite these additional tests, this paper does not claim to capture a causal effect. It aims to lower potential biases stemming from multiple sources, including simultaneity and selection, but cannot rule out these might still affect the results. Despite these limitations, the paper captures a robust relationship showing consistent results after multiple tests.

5.2. IV strategy

As a next step, an instrumental variable (IV) approach that uses the information on the spatial networks of firms is applying. It exploits variation in patenting outside the state of interest to proxy variation within the state. It follows Moretti (2021), who constructs an IV that uses the geographical structure of firms that have laboratories in multiple locations within the US. The idea is to predict patenting activity within a US state from patenting activity in other locations where the firm is present. As the focus is on the impact of the presence of MNEs, a subsample of MNEs is used to predict their level of patenting within a state based on the innovative activity of laboratories of MNEs in other US states. For the state that the instrument is applied to, I am excluding the patents of the MNE and sum up the patents of all other MNEs within that state and technology class, normalised by the patents of all firms within the US for the same period and technology class. The intuition is that the level of innovative activity for one state can be predicted based on the innovative activity of firms of other states where the MNE has their spatial networks. Following Moretti (2021), the instrument is constructed as below:

$$IV_{j,t,i,f} = \sum_{s \neq j} D_{s,f,i} \frac{N_{s,f(-i)t}}{N_{ft}} \tag{5.2}$$

$D_{s,f,i}$ is a dummy variable that takes the value of 1 if MNE s has a minimum of 1 patent in state i and technology class f, $N_{s,f(-i)t}$ refers to the number of patents that an MNE j has in technology class f, year t in every state except for state i and N_{ft} is the number of nationwide patents in the technology class and year.

The aim of this IV strategy is to account for potential simultaneity bias. It predicts MNE patenting within a state from variation that originates from outside the state, from other states where the MNE is producing patents. The innovative activities of other MNEs states predicts the patenting activity of an MNE within a state. The rationale behind it is to isolate variation that is uncorrelated with innovation or productivity shocks within the MNE that is unobserved and varying over time within a state. Given that the instrument is constructed based on specific and external factors, it is expected to be exogenous on the assumption that firms localise their patent strategy per state. As discussed in Section 2.1, a large literature has pointed out how firms choose to locate in regions based on specific spatial characteristics. It is therefore likely that this condition is fulfilled. However, it might be also that an MNE would consider for example their rival's activity across location. In this scenario, the number of firms and patents is controlled for in all specifications, trying to account for activities of other firms. However, it might still be that the controls do not pick up all relevant activities of competitors. For these reasons, the paper does not claim to capture causal effects, but aims to reduce potential endogeneity bias through this IV strategy.

5.3. Development over time

This subsection explores the development of the main variables, the MNE patent share, as well as patenting concentration over time. As this research paper exploits their variation from 1976 to 2010, it aims at showing the change in both variables. It first focuses on the MNE patent share and then explores patenting concentration measured by the Gini coefficient over time.

MNE patent share

Fig. 1 plots the average MNE patent share across US states for every technology class from 1976 to 2010. A substantial long-run upward trend can be observed, showing an increase for all six technology classes. While the increase is flatter between 1976 and 1990, the slope becomes steeper from 1990 onward, showing a remarkable acceleration after 1994. The most notable change in patent share is for the category Drugs & Medication, where the share has been falling between 1983 and 1991, but risen from then onward for the rest of the period.

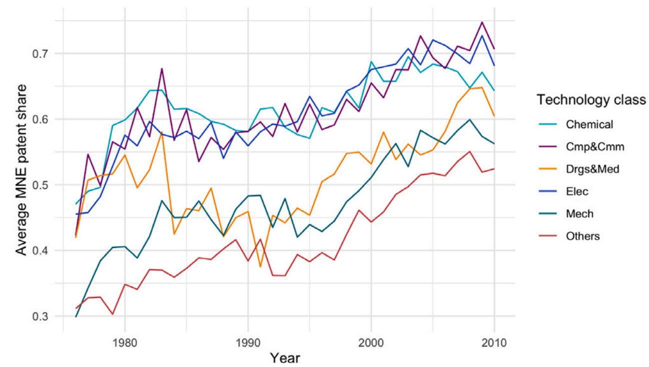

Fig. 1. Development of MNE patent share per technology class, average across US states, 1976–2010.

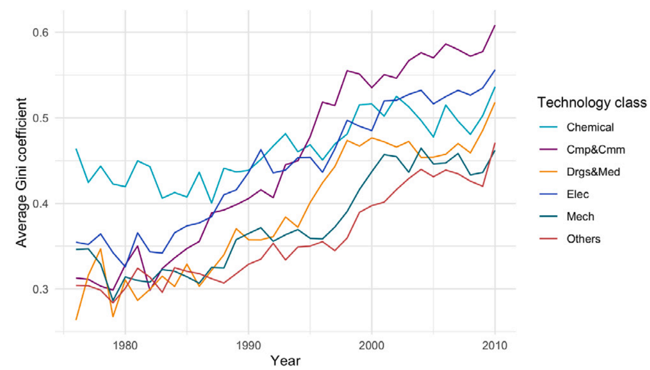

Fig. 2. Development of Gini coefficient per technology class, all patenting firms, average US state, 1976-2010.

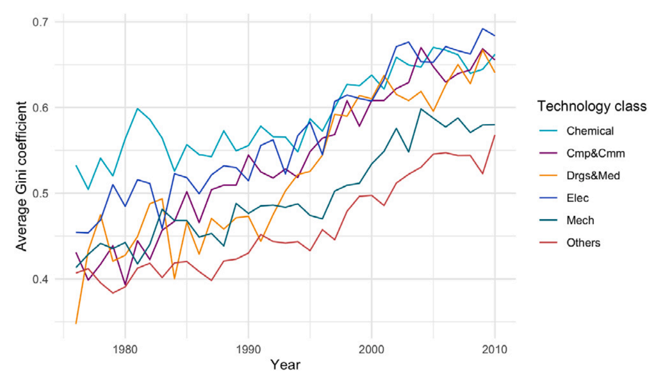

Fig. 3. Development Gini coefficient per technology class, non-MNEs, average US state, 1976-2010.

Patenting concentration

Figs. 2 and 3 show the development of the Gini coefficient between 1976 and 2010. Since this study focuses on patenting concentration among all firms, as well as specifically among non-MNEs, both plots are presented. We can observe a substantial upward trend between 1976 and 2010, which holds for the two Gini coefficients and all six technology classes.

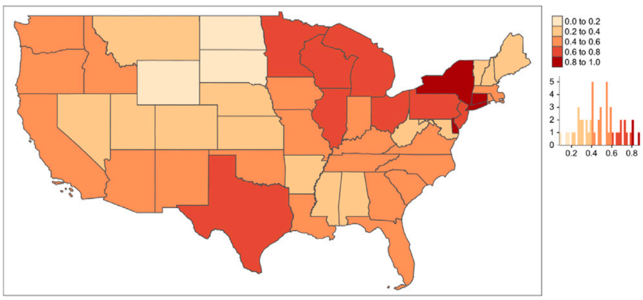

Fig. 4. Map of MNE patent share per state, average between 1976–2010 and technology class.

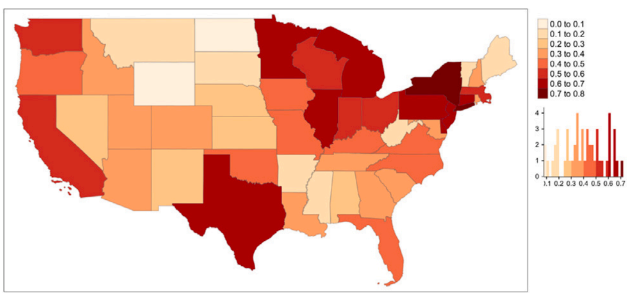

Fig. 5. Map of Gini coefficient per state, all firms, average between 1976–2010 and technology class.

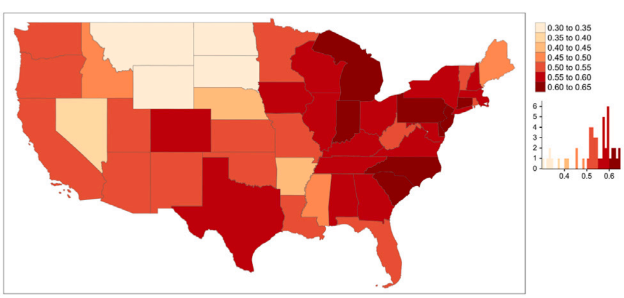

Fig. 6. Map of Gini coefficient per state, non-MNEs, average between 1976–2010 and technology class.

5.4. Development over space

MNEs patenting activity

This section describes the average MNE patent share and innovation concentration between 1976 and 2010, across technology classes for every state in the US. Fig. 4 shows the geographical distribution of the MNE patent share. At first glance, it becomes clear that a large number of states have, on average, an MNE patent share between 0.4–0.6, with around 19 states falling into this category. Less frequently, but still quite common, are average MNE patent shares between 0.2–0.4 and 0.6–0.8, while other categories occur scattered.

Intra-state Innovation Concentration

Fig. 5 plots the geographical distribution of intra-state innovation concentration, measured by the Gini coefficient. It summarises the average value of the Gini coefficient for all patenting firms within state across technology classes between 1976 and 2010. Fig. 6 does the same for the Gini coefficient for non-MNEs. While both maps depict similar patterns, with the West Coast, the Southern states and the Midwest showing high levels of concentration, these dynamics become even more pronounced for the non-MNE Gini coefficient. In particular, the East Coast tends to be more concentrated for non-MNEs, as well as in the Southwest.

6. Results

6.1. Overall results

Table 1 presents the results of the overall effect, regressing the Gini coefficient on the MNE patent share. The latter comprises all patents by MNEs, including patents by both foreign-owned and domestic-owned MNEs. All models are three-way fixed effects models, including state, technology, and period fixed effects. Standard errors are clustered at the state level. Model 1 exhibits the results of the three-way fixed effects model without any controls. Model 2 adds the control variables GDP per capita, population, scientific employment, the number of patenting firms and the absolute patent count. Models 3–5 look at different percentiles of the patent distribution of MNEs as dependent variables to understand at which part of the distribution we see the strongest effect. The results of Table 1 show that the estimated coefficients of the share of patents held by MNEs is statistically significant for all specifications at the 0.1% level. Models 1 and 2 provide evidence for a positive relationship between the Gini coefficient and the share of patents held by MNEs, suggesting that the presence of MNEs is linked to an increase in patenting concentration. In Model 2, the coefficient decreases in size after introducing the set of controls, indicating that a one standard deviation increase in the MNE patent share is associated with a rise in the Gini coefficient by 0.08 points. In Model 3–5, the effect on different parts of the patent distribution held by MNEs is examined. In line with expectations, the association between the MNE patent share and the percentiles of the MNE patent distribution is positive, with the largest coefficient size for MNEs at the top of the distribution (P75), followed by those in the middle (P50) and then by those at the tail of the distribution (P25).

The control variables include the number of patents and the number of firms in the region per technology class. As the distribution of these variables is highly right-skewed, a log transformation is used. The two variables are highly statistically significant for all model specifications. The number of patenting firms is negatively related to the Gini coefficient. This aligns with expectations, showing that an increase in patenting firms is linked to lower innovation concentration. For the number of patents and the Gini coefficient, a positive relationship is observed. With increasing patenting activity, innovation becomes increasingly concentrated across some firms. I also control for GDP per capita, population and scientific employment to control for market size, human capital that is specialised in R&D and the population structure. These controls are statistically insignificant.

This confirms the first hypothesis, showing that patenting concentration across all firms is positively associated with the share of patents held by domestic-owned and foreign-owned MNEs. A likely explanation for this increase in concentration is that MNEs at the top of the MNE patent distribution (P75) tend to produce more patents than at the middle or the tail of distribution. However, while this relationship between highly innovative MNEs and concentration is expected, the effect might be also driven by changes in the patenting distribution of non-MNEs. Moreover, the relationship is also expected to differ depending on the type of MNEs. Both of these aspects will be looked at in the next sections.

One major concern might be that the share of non-patenting firms would differ substantially. As the measure of concentration solely rely on firms that patent, it might be that the proportion of non-patenting firms differs across states and technology classes, which could introduce bias to the results. Therefore, further checks are conducted with a subsample consisting of the top patenting states and technology classes. To strengthen the results of the paper, a subsample with more homogeneous states is created, including only innovative states as well only technology classes that are more prone to patenting. The results are shown in Table 9, demonstrating similar results for states with a more complete distribution.

Table 1
Regression results for patenting concentration of all firms and for different percentiles of the patenting distribution.

Dependent Variables:	Gini		MNEs P75	MNEs P50	MNEs P25
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
MNE	0.3530***	0.1101***	0.8119***	0.3544***	0.1835***
	(0.0506)	(0.0182)	(0.1230)	(0.0528)	(0.0355)
Log (patents)		0.1929***	0.2299***	0.0019	−0.0279**
		(0.0152)	(0.0687)	(0.0237)	(0.0120)
Log (firms)		−0.1361***	−0.1901***	−0.0551**	−0.0093
		(0.0198)	(0.0698)	(0.0264)	(0.0166)
GDP pc		0.2604	−2.743	−0.9570	−0.6265
		(0.3274)	(4.565)	(1.411)	(0.8905)
Log (popul.)		−0.0135	−0.3335	−0.0147	0.0619
		(0.0342)	(0.2499)	(0.1035)	(0.0518)
Emp Scient		−0.000	−0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Fixed-effects					
State	Yes	Yes	Yes	Yes	Yes
Period	Yes	Yes	Yes	Yes	Yes
Technology class	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	2,924	2,913	2,913	2,913	2,913
R^2	0.70350	0.85430	0.29132	0.33210	0.23961
Within R^2	0.22329	0.62222	0.11376	0.06626	0.04654

Clustered (state) standard-errors in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

6.2. Ownership and regional heterogeneity

In this subsection, the second hypothesis is tested, exploring whether the relationship between the patent share held by MNEs and patenting concentration is driven by domestic-owned or foreign-owned MNEs. It also tests for regional heterogeneity, investigating which states contribute most to this effect. To test for the type of MNEs, I am exploring the effect for both by running two separate regressions, with the patent share of domestic-owned and foreign-owned MNEs as regressors. The results are presented in Table 2. Model 1 and Model 2 show that the patent share held be domestic-owned MNEs is positively and significantly associated with innovation concentration. As depicted in Model 3 and 4, the coefficient for foreign-owned MNEs is also positive, but statistically insignificant. This suggests that the overall positive link is driven by domestic MNEs.

To test for regional heterogeneity, Models 5 and 6 show how the effect varies across space. This is done in two different ways. First, the MNE patent share is interacted with the absolute patent count. Second, a categorical variable for the MNE patent share is created, and categorised as low, middle, high and very high intensity. Low intensity means a patent share between 0–0.25, middle between 0.25–0.50, high between 0.50–0.75 and very high between 0.75–1. In Model 5, when interacting with the patent count, the main effect of the MNE patent share and the interaction term are positive and statistically significant. Thus, states with more innovation are expected to see higher patenting concentration. When focusing on the intensity of patents held by MNEs, a positive and significant effect for all groups (relative to the low patent share) is found. Larger coefficients are shown for the high and very high group. This suggests that the overall effect is driven by regions with a higher share of patent held by MNEs and by regions where more patents are produced.

These findings support the second hypothesis, showing evidence that the increase in patenting concentration is driven by domestic-owned MNEs. This could be explained by innovative domestic MNEs benefiting from a positive market size effect, increased specialisation and economies of scale. However, it could be also partly explained by changes in patenting by firms that are not MNEs. The role of non-MNEs will be explored in the next subsection. In contrast, the role of foreign MNEs has been typically described as creating knowledge spillovers and thus rather linked with a negative effect on concentration. While the estimated coefficient is negative in Model 3, it becomes positive when including controls. However, in both cases the coefficient is not statistically significant. Therefore, this paper cannot draw any conclusions on the role of foreign MNEs, but finds evidence regarding the presence of domestic MNEs in being linked to higher innovation concentration. Moreover, when looking at heterogeneity across space, it becomes clear that the effect is more pronounced in states with higher shares of patents held by MNEs. These findings are in line with a positive market size effect and a negative competition effect, which would predict to observe a concentration enhancing effect in states where the share of MNE patents is high.

This paper also tests for further heterogeneity regarding technology classes. To understand whether the effect of MNEs on patenting concentration differs by technology, an interaction term between the MNE patent share and technology is added. The results are presented in Table 8. While it shows that there are significant differences between technology classes affecting patenting concentration, the effect is not significant when interacted with the MNE patent share. Additionally, the role of foreign patents is explored, by adding it as a regressor as share of all patents per state and technology class. The estimated coefficient is not statistically significant, results are shown in Table 8.

6.3. Effect on non-MNEs

To test the third hypothesis, the effect on patent concentration of non-MNEs is estimated. The Gini coefficient is calculated using only the patents of firms that are not classified as MNEs. I then regress the Gini coefficient for non-MNEs on the share of patents held by MNEs. The results are presented in Table 3. The first specification shows the effect without control variables, while Model 2 incorporates the same set of controls used in the previous table. In both models, we can observe a positive and statistically significant effect on patenting concentration for the link between the patent share held by MNEs and patenting concentration for firms that are not MNEs. It shows a larger effects than for the concentration measure consisting of all firms. A one standard deviation increase in the MNE patent share is linked to a raise in the Gini coefficient by 0.14 points. These findings are in line with the hypothesis on a negative competition effect. A potential explanation of these findings might be the technological distance to the frontier as well as competitive pressure. Non-MNEs tend to be less innovative, and due to lower absorptive capacity and higher cognitive distance to more innovative firms, technological diffusion might be less common.

Table 2
Testing for differences between domestic- vs. foreign-owned MNEs and patenting intensity.

Dependent Variable:	Gini					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Domestic MNE	0.3422***	0.1009***				
	(0.0463)	(0.0182)				
Foreign MNE			−0.0319	0.0192		
			(0.0435)	(0.0267)		
Log (patents)		0.1932***		0.2162***	0.1657***	0.2008***
		(0.0153)		(0.0157)	(0.0196)	(0.0177)
Log (firms)		−0.1355***		−0.1609***	−0.1193***	−0.1465***
		(0.0202)		(0.0205)	(0.0217)	(0.0226)
GDP pc		0.1819		−0.1381	0.1838	0.2489
		(0.3067)		(0.2854)	(0.3696)	(0.3232)
Log (popul.)		−0.0110		−0.0033	−0.0080	−0.0052
		(0.0338)		(0.0363)	(0.0375)	(0.0345)
Emp Scient		−0.000***		−0.000**	−0.000***	−0.000**
		(0.000)		(0.000)	(0.000)	(0.000)
MNE					0.0718***	
					(0.0236)	
MNE ×Log (patents)					0.0231**	
					(0.0090)	
MNE middle						0.0140**
						(0.0061)
MNE high						0.0440***
						(0.0076)
MNE very high						0.0618***
						(0.0121)
Fixed-effects						
State	Yes	Yes	Yes	Yes	Yes	Yes
Period	Yes	Yes	Yes	Yes	Yes	Yes
Technology class	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,924	2,913	2,924	2,913	2,913	2,842
R^2	0.70256	0.85349	0.61842	0.84825	0.85536	0.84937
Within R^2	0.22082	0.62013	0.00041	0.60654	0.62496	0.62661

Clustered (state) standard-errors in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Table 3
Regression results for patenting concentration of non-MNEs and for different percentiles of the patenting distribution of non-MNEs.

Dependent Variables:	Gini Non-MNE		Non-MNE P75	Non-MNE P50	Non-MNE P25
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
MNE	0.1773***	0.1300***	−0.2948***	−0.4221***	−0.2475***
	(0.0247)	(0.0206)	(0.0418)	(0.0515)	(0.0414)
Log (patents)		0.0287***	0.0795***	0.0306	0.0308**
		(0.0080)	(0.0171)	(0.0183)	(0.0140)
Log (firms)		0.0312**	−0.0758**	−0.0043	−0.0979***
		(0.0141)	(0.0292)	(0.0283)	(0.0261)
GDP pc		0.7893	2.087***	1.658	1.983
		(0.6874)	(0.7215)	(1.765)	(1.744)
Log (popul.)		−0.0661	0.0017	0.0184	−0.1003
		(0.0598)	(0.0545)	(0.1030)	(0.1105)
Emp Scient		−0.000**	0.000*	−0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Fixed-effects					
State	Yes	Yes	Yes	Yes	Yes
Period	Yes	Yes	Yes	Yes	Yes
Technology Class	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	2,921	2,910	2,913	2,913	2,913
R^2	0.60401	0.64147	0.38977	0.60447	0.51102
Within R^2	0.07894	0.17910	0.05713	0.08486	0.11410

Clustered (state) standard-errors in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Model 3–5 look at the effect of the presence of MNEs on different parts of the non-MNE patenting distribution. It clearly shows a negative link between the patent share of MNEs and the patents produced of non-MNEs at all parts of the distribution. The strongest negative effect is for non-MNEs in the middle of the distribution. Firms in the middle and the tail of the patent distribution are those the furthest away from the technological frontier, with the lowest absorptive capacity and those more affected by a negative competition effect. It could be in particular economies of scale related to internationalisation and from centralising R&D that create or increase barriers to patent, discouraging less innovative firms from producing patents in general or from entering novel technological areas. This effect is expected to be even larger if MNEs are early movers linked to successful technological innovations.

To verify the robustness of the results, multiple checks are conducted that are presented in the online Appendix. First, in addition to estimating the relationship in *levels*, this paper also shows the results in *differences*. They are shown in Table 6, demonstrating that the results are consistent with those shown in Tables 1 and 3. The estimated coefficient is equal in size for the results linked to the concentration of all firms and larger for the concentration of non-MNEs. Second, this paper also tests the robustness of the results when applying another measure for the presence of MNEs. Instead of using the share of patents held by multinational enterprises, the share of firms that are MNEs is used as independent variable. The results are presented in Table 7, which confirm a positive and significant effect. The estimated coefficient size is smaller for the Gini coefficient and larger for the Gini non-MNEs. Third, another concern might be that the effects could be driven by certain technology-period specific trends. As there has been substantial change regarding patenting in specific periods and technology classes over these more than three decades, it is essential to rule out that these dynamics are driving the overall results. Therefore, technology class-period fixed effects are added in Model 3 and 4 in Table 7, showing consistent results. Fourth, the sensitivity of the results is also verified when using other measures of patenting concentration. Instead of the Gini coefficient, the HHI and CR4 are shown in Table 8.8, confirming the positive relationship between the presence of MNEs and innovation concentration. Finally, the relationship is estimated by introducing different weights in the regression. Running a population weighted regression is also done in Table 8.8, strengthening the validity of the findings.

6.4. Two-stage least squares estimations

In this section, I estimate the impact of the presence of MNEs on the patenting concentration for all firms but also for non-MNEs using 2SLS. As discussed in Section 5.2, an IV is used that is built upon the prediction of the patenting activity of an MNE within a state using spatial firm networks. Table 4 shows the results of the 2SLS estimations, including the first and the second stage estimates.

Panel A in Table 4 reports the first stage regression results, which are the same for both specifications, as it regresses the MNE patent share on the instrument and the control variables. The instrument is correlated with the MNE patent share, with the coefficient being highly significant, fulfilling the relevance condition. In the second stage, the coefficient of Model 1, estimating the effect on innovation concentration of all firms, is not statistically significant. A likely explanation is that patents of MNEs are also included in the dependent variable, in contrast to Model 2. The results of the second stage of Model 2 show a positive and significant effect regarding the effect of MNEs on innovation concentration for non-MNEs. Thus, the IV estimate support the conclusions derived from the main results linked to innovation concentration for non-MNEs, but does not find significant results for all firms, where exogeneity is likely not fulfilled.

Table 4
Two-stage Least Squares estimations for the MNE patent share and both patenting concentration measures.

Model:	(1)	(2)
Panel A: First Stage		
IV	3.163***	3.163***
	(0.5417)	(0.5417)
Panel B: Second Stage		
Dependent Variables:	Gini	Gini non-MNEs
MNE	−0.0006	0.2870**
	(0.0841)	(0.1289)
Fixed-effects		
State	Yes	Yes
Period	Yes	Yes
Technology Class	Yes	Yes
Controls	Yes	Yes
Fit statistics		
Observations	3,207	3,204
R^2	0.91621	0.69216
Within R^2	0.78160	0.29974

Clustered (state) standard-errors in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

7. Conclusion and discussion

For more than three decades, the US has seen patenting concentration increase in different technology classes, measured by the Gini coefficient. Yet, it is not clear what the drivers of rising innovation concentration are. For this reason, this paper analyses the effect of the presence of domestic-owned and foreign-owned MNEs on innovation concentration between all firms and non-MNEs within US states from 1976 to 2010. While there is substantial literature covering the effect of trade on domestic patenting, see e.g., Verhoogen (2008), Aghion et al. (2018), Shu and Steinwender (2019), the effect of the presence of MNEs, and in particular on patenting concentration, remains less explored. Research on patenting concentration within the US (Akcigit and Ates, 2019; Forman and Goldfarb, 2020) or on the role of MNEs in market concentration, see e.g., Caves (2007), does not cover the impact of MNEs with R&D centres on innovation concentration. Therefore, the contribution of this paper is to provide evidence to what extent the presence of domestic-owned and foreign-owned MNEs affects patenting concentration within US states and to shed light on which part of the distribution is the most affected. Using patent data from the USPTO, I construct the Gini coefficient as measure of patenting concentration and different measures of the presence of MNEs. Overall, I find evidence for a positive link of the MNE patent share and innovation concentration. This study uses OLS and IV estimates to approximate the relationship. To verify the robustness of the results, further estimations including applying more measures of patenting concentration and running a population-weighted regression are carried out.

I first examine the effect of the presence of (domestic- and foreign-owned) MNEs on the patenting concentration of all firms and find a positive relationship that is highly statistically significant. This overall effect is driven by the presence of domestic-owned MNEs. Foreign-owned MNEs, in contrast, are not significantly related to higher patenting concentration. These effects differ across space: regions with a high patent share held by MNEs experience a higher increase in patenting concentration, compared to regions with only a low share. Crucially, the effect on patenting concentration for non-MNEs is more pronounced than for all patenting firms. A one standard deviation increase in the MNE patent share is linked to an increase in the Gini coefficient for all firms by 0.08 points and 0.14 point for the Gini coefficient for non-MNEs. This effect is mostly driven by an adverse effect on firms that are not MNEs, with those in the middle of the patenting distribution of non-MNEs producing fewer patents. Non-MNEs tend to be less innovative than MNEs, are further away from the technological frontier and have a lower absorptive capacity. Therefore, having a higher share of MNEs can be linked to other less-innovative firms producing fewer patents. Still, there appears to be evidence of a small number of highly innovative MNEs that become more innovative.

These findings are in line with a negative competition and a positive market size effect that have been previously found in the literature on internationalisation and domestic patenting within the US. Internationalisation allows MNEs to increase the "extent of the market", which fosters the division of labour and reinforces the realisation of economies of scale (Smith, 1776). In particular, internalising R&D activities and benefiting from economies of scale (Coase, 1991; Williamson, 1965), has rendered (some) MNEs more innovative. Economic globalisation can play a crucial role by reinforcing existing effects due to a considerable rise in the potential gains from innovation due to a market size effect while at the same time heightening losses due to a competition effect (Aghion et al., 2021). R&D activities can also act as barriers to entry, in particular if they are linked to the existence of economies of scale and if they create first-mover advantages (Mueller and Tilton, 1969; Klepper and Graddy, 1990). This negative effect on other firms' patenting activities is likely to be exacerbated if MNEs act strategically and foreclose other firms from technological fields (Gallini, 1984; Hall and Rosenberg, 2010). However, these findings could be also partly explained by other dynamics, such as mergers and acquisitions or changes in patenting law.

Questions related to globalisation, innovation and concentration are highly relevant for public policy. This paper provides evidence on the role of domestic MNEs in shaping innovation concentration dynamics in the last three decades within US states. Traditionally, it has been highlighted that the presence and growth of domestic MNEs taking advantage of economies of scale in R&D results in technological advantages for the country of origin, as well as foreign MNEs to create spillovers to domestic firms (Caves, 2007). This paper finds no evidence for a potential concentration decreasing role of foreign MNEs through spillovers. However, it highlights the role of domestic MNEs and their growth through scale economies in domestic R&D. Whether this is beneficial for technological development in the home economy is an important question. Innovation concentration has been on the rise for multiple decades and patterns of lacking knowledge diffusion, market concentration as well as wage polarisation concentration have become apparent (Akcigit and Ates, 2021; Autor et al., 2020b, 2019). This automatically raises the question of how much innovation concentration is beneficial for the domestic economy. While certain levels of concentration have been shown to be efficient, some have argued that a tipping point has been reached if not overstepped (Covarrubias et al., 2020). In the last three decades, US industries have been shown to have switched from "good" to "bad" concentration: In the 1990s, concentration has been found to be efficient, while since the 2000s it has been linked to decreased growth in productivity, reduced investment and increased prices due to lower competition as well as higher entry barriers (Covarrubias et al., 2020). Recent evidence has also pointed out that technology leaders are producing fewer spillover effects than smaller firms (Crescenzi et al., 2020), which could also be linked lower productivity dynamics. Considering this context, it might be sensitive to question the benefits for the home economy and call for policy measures that limit the concentration of innovation, while at the same time encouraging the diffusion of knowledge and innovation.

There are multiple limitations in this study. First, patent data is used to measure innovation. It is well known that patents are an imperfect measure of innovation and that not all innovation is patented. Therefore, only innovation created by firms that produce patents is captured, which likely provides an underestimation of innovation concentration between firms. Robustness checks are conducted with subsamples of top patenting states and selected technology classes where the distribution is expected to be more complete. These further tests underline the validity of the results. Second, I am only measuring patenting concentration, which does not need to be the other coin of knowledge diffusion. It would be highly interesting to conduct a further study focusing on knowledge diffusion as outcome variable and to understand the role of domestic-owned MNEs. Third, I identify MNEs with R&D centres through patent data, which means that I only capture a subset of MNEs that produce patents internationally and have at least five cross-border patents. This also implies excluding MNEs that do not patent as well as MNEs that do not patent internationally but produce goods and services across borders. I am trying to account for this by verifying the MNE identification with Orbis data. However, this does not allow me to verify the status of all MNEs. Fourth, this study uses an aggregated measure of MNE presence, which entails a lot of heterogeneity across firms. As the goal of this research is to explore overall dynamics of the presence of MNEs, this aggregated measure is used. However, it would be highly interesting to look more into the heterogeneity across firms and gain a better understanding why this effect is observed. In general, looking more into the mechanisms of the effect could be an interesting area of future work. Despite these limitations, this paper provides an important contribution to the increasing literature on patenting concentration. It shows how the presence of domestic-owned MNEs is positively linked to an increase in patenting concentration within states and how less innovative firms are adversely affected and produce fewer patents. Given other trends such as declining knowledge diffusion (Akcigit and Ates, 2021), declining productivity in R&D investment (Bloom et al., 2020) and increasing market power (Autor et al., 2020b), it is vital to look at patenting dynamics and provide a better understanding how the distribution of innovation between firms has changed over time.

CRediT authorship contribution statement

Martina Pardy: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Martina Pardy reports financial support was provided by European Commission.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.respol.2025.105235.

Data availability

Data will be made available on request.

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