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Mobilités inter-régionales de travailleurs hautement qualifiés et nouveauté technologique

Cet article propose une approche empirique pour étudier comment les régions introduisent une véritable nouveauté technologique en explorant l'effet des travailleurs géographiquement mobiles sur les nouvelles combinaisons de classes technologiques au sein des brevets déposés. Il a été démontré que les migrations augmentent l'activité d'innovation (quantité et entrée) à destination, mais la question de savoir si la mobilité des travailleurs permet de nouvelles combinaisons dans le portefeuille technologique est restée sans réponse. Empiriquement, nous cherchons à savoir si les travailleurs hautement qualifiés qui quittent des régions disposant d'un avantage comparatif révélé dans une classe technologique donnée suscitent de nouvelles combinaisons technologiques dans la région de destination. Nous testons cette hypothèse en utilisant à la fois des données administratives officielles sur la mobilité de la main-d'œuvre et des paires de combinaisons de codes technologiques présentes dans les données de brevets entre 1996 et 2017. Nous constatons que les travailleurs provenant de régions spécialisées dans une sous-classe technologique donnée stimulent la nouveauté technologique dans cette sous-classe dans la région de destination. Cet effet n'est présent que pour les sous-classes liées au portefeuille technologique local à destination et est présent à la fois pour les nouveautés de type réutilisation et création. Les résultats indiquent que la capacité d'absorption locale et la complémentarité entre les dynamiques internes et les moteurs exogènes sont importantes pour que les régions diversifient leur espace technologique.

Mots-clés : Nouveauté technologique, Mobilité de la main-d'œuvre, Connexité, Développement régional

JEL Code : O31, 033, J61, R11

Inter-regional highly skilled worker mobility and technological novelty

This article proposes an empirical approach to study how regions introduce true technological novelty by exploring the effect of geographically mobile workers on new technological classes combinations within patents filled. Migration has been shown to raise innovation activity (quantity and entry) at destination, but the question whether workers' mobility allows new combinations in technological portfolio remained unanswered. Empirically, we investigate if high skilled workers moving from regions with a revealed comparative advantage in a given technological class spark new technological combinations in the destination region. We test this hypothesis using both official administrative labor mobility data and pairs of combination of technological codes present in patent data between 1996 and 2017. We find that workers coming from regions specialized in a given technology subclass drive technological novelty in this subclass at destination. This effect is present only for subclasses related to the local technological portfolio at destination and is both present for reuse and creation-type novelties. Results imply that local absorptive capacity and a complementarity between internal dynamics and exogenous drivers are important for regions to diversify their technological space.

Keywords: Technological novelty, Labor mobility, Relatedness, Regional development

Code JEL : O31, 033, J61, R11

1. Introduction

Technological diversification is key in the economic development of regions and makes it possible both to create economic systems that are more resilient to shocks, particularly sectoral, and to develop new growth prospects. However, the technological diversification observed locally tends to follow path and place dependent processes (Martin and Sunley, 2006; Heimeriks and Boschma, 2014; Henning et al., 2013), mainly favoring the development of incremental refinements in technological domains already explored locally and an entry in new technological activities driven by their similarity, also called relatedness, with the current regional set of activities (Hidalgo et al., 2018). Innovation domains do not emerge randomly and are instead related to the set of existing activities already carried out in that region, making technological diversification difficult. Moreover, beyond the emergence of new technological domains (or classes), regional technological diversification can designate the way in which different technological domains are combined in new ways within the innovations filed. Indeed, following the schumpetarian tradition of knowledge recombination, innovations are defined as a set of technologies and components that are combined to create new product. When unfamiliar components are combined they increase the opportunity of breakthrough inventions (Arts and Fleming, 2018). These new combinations of previously uncombined technology classes, also labeled technological novelty, can be an important driver of technological diversification leading to radical innovations and economic growth (Arthur, 2007; Epicoco et al., 2022). Understanding the mechanisms behind this technological novelty is therefore of utmost importance. Technological novelty, defined as new combinations of technology subclasses (Fleming, 2007; Verhoeven et al., 2016) may either build on regional determinants such as technological specialization or build on external sourcing of new technologies.

On the latter, a large literature has shown that migrants, both international and inter-regional, had an impact on the level and pace of innovation carried out at their destination. Moreover, as they carry knowledge with them, they also act as drivers of its diffusion. Thus mobile workers are seen as agents of technological change at destination (Miguelez and Morrison, 2022). In this paper, we explore the role of inter-regional migration on technological change modeled as technological novelty. More precisely, we ask whether inter-regional mobility of high skilled workers spark the emergence of new combinations of technological subclasses in their host region.

We empirically test the question above combining two major datasets. On the one hand, we use the OECD Regpat database which provides information on patents, the regional location of inventors and technological content. With these data, we measure technological novelty which is defined as a new combination of a technological subclasses occurring for the first time in a given patent in a given year and region. The technology subclass is a four-digit code based on the International Patent Classification (IPC) enabling to classify the technological content of patents filed. On the other hand, we use BTS (”Base tous salariés”, All-Employee Basis) from INSEE (French national statistics office) which provides detailed information on the employment for all workers and their location in years t and t-1. We compute the bilateral inter-regional worker flows by socio-professional categories available in BTS. The dataset is a panel built at the Subclass x Region x Year level (Class-Region-Year, CRY). The dependent variable is the number of pairwise subclass combinations associated with a given subclass C that appears for the first time in a given year Y and region R. Following Bahar et al., (2020), the main independent variable is, for each CRY, the sum of incoming qualified workers coming from regions specialized in that given subclass C. In our empirical approach, we control for other external drivers of novelty, internal determinants and fine grained fixed effects.

Our contribution is threefold. First, we combine the literature on recombinant novelty, focusing on how new combinations of technology class emerges (Verhoeven et al., 2016), with that on the international mobility of workers (Bahar et al., 2020), and we extend findings of Boschma et al. (2022) by exploring the interregional linkages that allow technological breakthroughs. To our knowledge, this is the first study that analyzes the effect of within country mobility of workers on innovation measured with patent data. Movement of workers occur more within country than across international borders. Our aim here is to capture more detailed information on the whole sample of workers' mobility to better measure the effect on a within country (so less heterogeneous) technological space. Our second contribution is to build a dataset on the mobility of all workers (ant not only inventors), and focus on specific categories (high skilled workers) that might bring knowledge with them to their destination. We use official administrative data that measures all mobility of workers from year t-1 to year t when they change the location of their workplace. Third and last, we contribute to the novelty literature by focusing on a specific type of external contribution, i.e., the mobility of workers and the specific and knowledge they carry at a given technological subclass.

Our results extend previous knowledge in the aforementioned literature as we capture the effect of inter-regional mobility of skilled workers on novelty. We find that high skilled workers, such as scientists, engineers and technicians, when they carry an intensive technological knowledge, raise the creation of new combinations for this technological subclass in the region of their destination. This result is also true if the combinations are new to the country (France) or the World, and this result is robust when novelty is measured not as the number of new combinations but as their share or a dummy variable. Moreover, we find that the effect is higher when the destination region has a revealed comparative advantage in that technology, and when this technology is more related to the local technological space. This result highlights the fact that external drivers of novelty are complementary to and driven by the internal technological dynamic of the region.

The rest of the paper is organized as follows. In the next section we present our literature review and the hypothesis we test in the empirical section. The following section details the data we use, and section 4 presents our main variables. Section 5 unveils the main descriptive statistics and section 6 shows our empirical strategy. Section 7 presents the main econometric results, including heterogeneous effects, and Section 8 presents the robustness checks. The last section concludes.

2. Literature review

In order to study the relationship between highly skilled internal migration and the dynamics of technological change and novelty in host regions, we integrate three streams of literature. First, we build on contributions documenting the role of migrants and mobile workers on knowledge transfers and their impact on the technological composition of their host destination. Second, we consider the literature on regional diversification and how migrants may act as agents of technological change driving regions to diversify into new technologies. And finally, we draw on the Schumpeterian tradition of knowledge recombination to further investigate the conditions under which the inflow of non-local knowledge workers may drive technological novelty by recombining existing or new technologies.

2.1. Migration of knowledge workers and innovation

This section reviews the literature investigating how migration affects innovation by focusing on knowledge diffusion mechanisms. Like firm collaborations and interpersonal networks, migration helps knowledge to move across geographical boundaries (Henderson et al., 2005; Singh and Marx, 2013). Accessing extra-regional knowledge is key to overcome lock-in and renew the local knowledge base. It is a solution to the fact that knowledge is geographically bounded and difficult to transfer across firms and cities as it is tacit and sticky (Polanyi and Knowledge, 1958; Cowan et al., 2000). This phenomenon is even reinforced by the fact that mobile workers are not likely to relocate in space, therefore, mobility occurs primarily within cities (Agrawal and Cockburn, 2003; Almeida and Kogut, 1999; Breschi and Lissoni, 2009).

When highly skilled workers move across space, they tend to increase the efficiency of the innovation process by providing a renewed and wider access to knowledge at a reduced cost. They thus enable knowledge to be reused instead of re-created elsewhere and enables its recombination with local sources of knowledge (Oettl and Agrawal, 2008). As knowledge is mostly tacit, it is attached to the individuals, firms, and regions in which they have been developed and produced. Thus, knowledge is more easily transferred throughout space if it is carried by workers coming from regions and countries in which they were initially developed and produced (Breschi et al., 2010; Breschi et al., 2020; Coe and Bunnell, 2003).

Once these migrant workers have moved to their new location, they positively contribute to the level and growth of innovation at destination. These movers prove to be more productive than non-movers (Gagliardi, 2015) and once they have transferred their knowledge to their host regions, they tend either to develop new technologies on their own by creating new ventures (Bettin et al. 2019) or through collaborations with local teams (Choudhury and Kim, 2019). The recent literature provides increasing evidence of the positive role of migration on innovation at the host regions and countries (Lissoni, 2018; Bosetti et al., 2015; Kerr et al., 2016; Fassio et al., 2019; Cristelli and Lissoni, 2020): highly skilled migrants tend to patent proportionately more than native inventors (Kerr et al., 2016; Hunt and Gauthier-Loiselle, 2010; Fassio et al., 2019), their share in patenting is growing over time (Kerr and Lincoln, 2010) and they positively impact the patenting activity of natives (Kerr et al., 2016). They do also contribute to increase basic research as measured by the number of citations to published articles (Bosetti et al., 2015).

2.2. Migration, diversity, and technological evolution of regions

In addition to their impact on the level and pace of innovation, a more recent debate has questioned whether migrants modify the technological composition of economies by either reinforcing local specialization, or instead facilitating diversification of technological activities. This issue is part of a larger debate in the geography of innovation literature on how countries and regions diversify in new activities and industries. This capacity to diversify is key for the economic development to avoid technological lock-ins (Capone et al., 2019) and foster resilience (Frenken et al., 2007; Pasinetti et al., 1987), especially in case of a shock hitting specific activities (Boschma, 2017; Bathelt et al., 2004) or to enhance growth perspective (Pinheiro et al., 2018; Neffke et al., 2011). It is largely admitted that economies develop according to a branching process in which the entry of new activities are driven by their degree of relatedness to the existing set of activities (Hidalgo et al., 2007; Crespo et al., 2017; Hidalgo et al., 2018; Balland et al., 2019; Neffke et al., 2011). This dynamic has been first evidenced in the case of exports at the national level (Hidalgo et al., 2007) and then extended to the entry of industrial activities (Neffke et al. 2011) and new technological subclasses (Kogler et al., 2013; Rigby, 2015; Boschma et al., 2015). A similar pattern is also expected regarding the technological characteristics of skilled workers entering a region.

In this regard, the question is whether the knowledge transferred by migrants resemble or differ the local technological portfolio at destination. Two mechanisms not necessarily exclusive can be advanced to understand migrant's motivation and their impact at destination. First, migrants may be attracted to areas in which companies search for workers that have similar specialization as their region of origin in case of a shortage of highly skilled labor or rapid technological growth (Kerr and Lincoln, 2010). In this case, migration will tend to reinforce local specialization. Second, migrants may provide new and non-redundant knowledge thus increasing opportunities for technological diversification (Agrawal et al., 2003; Kc and Terwiesch, 2011; Breschi and Lissoni, 2009). In this case, they act as agents of structural change similarly to new firms entering a region and introducing new activities (Neffke et al., 2018; Miguelez and Morrison, 2022).

The recent literature tends to support this latter argument providing evidence that migrants affect the composition of receiving countries' technological portfolio. Bahar et al. (2020) find that the inflow of immigrant inventors coming from countries specialized in a given technology subclass[1] contribute to boost patenting and gain technological advantages

[1] *Technological subclasses are defined according to the international patent classification, https://www.wipo.int/classifications/ipc/en/ITsupport/Version20130101/transformations/viewer/index.htm*

in the same technology in the receiving countries. Concretely, migrants drive specialization when a country with no patent application in a technology gains a technological advantage in the subsequent years, *i.e.* when the share of innovations filed in the region belonging to this technology is higher than the average share this technology represents among all patents filed in all regions[2]. Akcigit et al. (2017) have also found that migration had modified the technological trajectory in the USA and Moser et al. (2014) found similar results for the specific technological field of chemistry in the USA. Bahar et al. (2020) generalize these findings by considering 95 countries and 651 technology subclasses.

Moving from the country to the regional level, Diodato et al., (2022) find similar results showing that migration shapes the technological evolution of cities. They use a historical database on US data over the period 1870 and 1940 and find that native inventors benefit from the inventive activity of migrants which in turn contribute to the rise of new and previously non existing technological fields in the regions to which they moved to. Results are confirmed by Miguelez and Morrison (2022) on European regions which find again that migrants coming from regions specialized in a given technology contribute to increase natives' patenting and help regions to develop new technological specialization in these subclasses.

In contrast, Caviggioli et al., (2020) provide evidence for the second mechanism. They find that highly skilled migrants reinforce local specialization, especially in those fields that represent particular niches, that is, fields that are not frequently found across geographical areas. They do also show that the technological distance between migrants and natives contributes to diversify unless distance becomes too important hindering knowledge integration. However, these results in opposition to the previous contribution may be explained by the fact that they do not directly investigate the direction of specialization. Based on these arguments and applying it to internal migration, we propose to test the following hypothesis:

Hypothesis 1: The number of highly skilled mobile workers tend to drive technological specialization of technologies in which their originating region is already specialized.

2.3. Migrants as agents of technological novelty

Despite their important contribution, most of these papers remain rather agnostic regarding the process through which migrants contribute to diversify or reinforce existing specialization. This last section further investigates the underlying mechanisms through which knowledge transferred by migrants gets reused and recombined with local knowledge. Knowledge may not be easily absorbed, integrated, and recombined if it is dissimilar, distant, and unrelated to the local technological specialization as explained by the Schumpeterian tradition of knowledge recombination (Plunket and Starosta de Waldemar, 2023).

[2] *This index of the ratio of the share of a technology in a region to the share of this technology in all regions is called the Revealed Technological Advantage (RTA). See Appendix 1 for an example of technological novelty.*

Following this tradition, technological innovations can be defined as a set of technologies, components or artefacts that are combined to create new products (Martin, 1998; Fleming, 2001; Arthur, 2007; Verhoeven et al., 2016). Technological novelty corresponds to novel combinations of technological domains; they can be important drivers of radical innovations and economic growth (Arthur, 2007; Epicoco et al., 2022). When unfamiliar components are combined, they increase the risk of failure but also the opportunity of generating breakthrough inventions (Fleming, 2001; Arts and Fleming, 2018). Using patents to proxy innovation, novelty can be conceptualized as new combinations of technological subclasses. Moreover, following Carnabuci and Operti (2013) and applying their analysis to a regional portfolio, novelty can be characterized as *recombinant reuse* or *recombinant creation*. *Recombinant reuse* identifies new pairs of technological classes in which each of the two classes has already been used in the region in the past but for which the two classes have never been used in the same patent. *Recombinant creation* identifies new pairs of technology classes in which at least one of the two classes had never been used before in the region[3].

Based on this framework and focusing on the impact of skilled immigration shocks in the United States at the firm level, Choudhury and Kim (2019) investigate knowledge recombination when ethnic migrant inventors differ from locals and transfer undiscovered knowledge from their home regions to American firms. They find that migrants rather reuse the knowledge they mastered before migration when they collaborate within teams only composed of migrant workers and instead engage in recombinant creation when they collaborate within mixed teams including both native and migrant inventors. This suggests a need for knowledge integration by local inventors in order to enable combination with local knowledge. Miguelez and Morrison (2022) confirm these findings to a regional frame. Their result is interesting but does not explicitly test the impact of migrants on knowledge and technology classes recombination, which is the focus of this paper.

Building on previous findings, we can hypothesize that inter-regional migrants contribute to the recombinant process occurring in their host region. They are a source of external and potentially non-redundant knowledge and as such they feed the processes of distant search and exploration and offer higher opportunities for cross-fertilization and new combinations. We test the following hypothesis:

Hypothesis 2: The number of highly skilled workers coming from regions specialized in a given technology may increase the number of novel recombination based on that technology.

Further investigating the underlying recombinant process, two situations may be distinguished. First, if migrants introduce new technologies, they will tend to drive recombinant creation, that is, they will tend to generate innovation combining subclasses that are not yet part of the local portfolio with existing subclasses. It is probable that the integration of such new technologies will be easier if they are somehow related to the technological portfolio of the destination region. Second, if migrants reinforce local specialization, they will instead contribute to recombinant reuse, that is, combining in a new

[3] *See Appendix 1 for an example.*

way technologies included in the host region's portfolio. Thus, we propose two additional hypotheses, that we test with our data:

Hypothesis 2a: The number of highly skilled mobile workers tend to drive recombinant creation if they bring new and non-redundant knowledge.

Hypothesis 2b: The number of highly skilled mobile workers tend to drive recombinant reuse if they reinforce local specialization.

3. Data sources and sample construction

The objective of this paper is to study the logic presiding over the degree of novelty of the technological subclasses in the French regions, especially in relation to the inter-regional migration flows of skilled workers and the patent filers collaboration networks. To this end, two datasets are used.

3.1. Patent database

The patent data used are the OECD REGPAT database and the EPO (European Patent Office) and PCT (Patent Cooperation Treaty) patent filing data. Patents are classified according to the technological subclasses they mobilize. The classification system used is the International Patent Classification[4] (IPC) implemented by the World Intellectual Property Organization (WIPO). It is a nested classification system composed of 8 sections divided into classes, subclasses, groups and sub-groups. This study uses the 637 subclasses in order to define the technological components of each patent and characterize each regions technological portfolio. Subclasses are both disaggregated enough to identify heterogeneous patterns of technological specialization between French regions and aggregated enough to identify revealed technological comparative advantages. Using groups or sub-groups impede econometric estimations as patents within regions do not mobilize enough different IPC groups or sub-groups.

This study assigns patents to each French region based on the location of their inventors. When a patent includes inventors from multiple locations, the patent is assigned to each region. Considering the location of each inventor enables to map the inter-regional inventors' collaboration network. The geographic level used for the French regional breakdown uses the Nomenclature of Territorial Units for Statistics at its second level of disaggregation (NUTS2). The regions correspond to the 27 French administrative regions existing before the 2015 reform. For the purpose of this study, the 22 regions of metropolitan France have been selected.[5]

[4] The International Patent Classification system came into force in 1975 with the objective of standardizing and facilitating the understanding of the technological information contained in patents filed and to enable analysis and comparisons at an international level. It is subject to periodic revisions and improvements in order to better mirror latest technological developments.

[5] The 5 overseas departments and regions (Guadeloupe, Reunion, Mayotte, Guyana, Martinique) are not retained because of their low contribution to inter-regional migration flows and their peculiar innovation dynamics, characterized by a low number of patents filed. We also show robustness checks taking out important regions at a time.

Data cover the 1970 - 2017 period and thus provide historical depth relative to the technological development of regions.

3.2. Employment database

The employment data are extracted from the All-Employee Basis (BTS). These are administrative data provided by the French National Institute of Statistics and Economic Studies (INSEE). The data cover all French companies with employees. The information is provided at the establishment level. Establishments are production units corresponding to a single physical location of a firm.

The information provided encompasses the location of the establishment as well as the characteristics of each employee. For each year of BTS data, information on the employment situation in the previous year is provided. These data make it possible to quantify, year after year, the flows of occupational mobility of French employees. Worker flows are measured at the NUTS2 level and broken down by the socio-professional categories of employees. Employees socio-professional categories are based on the PCS-ESE classification (Professions and Socio-professional Categories of Salaried Employment of Private and Public Employers) at the second level of aggregation (29 categories). The employment data cover the 1996 – 2017 period.

Employment data are matched with the patent data so that the period of study corresponds to the years 1996 to 2017. Over this period, we identify new combinations of technology subclasses by relying on the whole history of European patent applications and their respective combinations since 1970.

4. Main variables

In order to study the impact of mobile workers on the evolution of each region's technological characteristics, we first need to develop a statistical indicator of regional technology spaces (i.e. the technological classes of filed patents). Thus, for each region, we determine their specialization and the subclass in which they have a comparative advantage. For each subclass in each region we determine whether it is related to the rest of the region's technological space. We also build a measure of similarity for each pair of existing technological subclasses. These indicators draw from the relatedness literature (Hidalgo et al., 2007; Hidalgo et al., 2018; Hidalgo, 2021; Boschma et al., 2015; Boschma, 2017).

4.1. Constructing technology spaces

Revealed Technological Advantage

First, it is necessary to identify the technological classes in which a region has a relative technological advantage. To this end, we identify, for each region, the technological classes for which the share of patents filed in this class is higher than the average share observed in all regions. We do this computing the Revealed Technological Advantage (RTA) index which measures the patenting intensity and specialization of a given NUTS 2 region r in a given subclass *c* as compared to the average intensity of patenting in this subclass in all the regions included in the sample[6] based on all patents filed between over the period [t-5;t-1]. Formally:

$$RTA_{c,r,y} = 1\left[\frac{patents_{c,r,(y-5)\to(y-1)} / \sum_{c} patents_{c,r,(y-5)\to(y-1)}}{\sum_{r} patents_{c,r,(y-5)\to(y-1)} / \sum_{c}\sum_{r} patents_{c,r,(y-5)\to(y-1)}} > 1\right] \quad (1)$$

The region is considered to be specialized in a subclass if its RTA = 1 and 0 otherwise. We do also compute this variable in a narrower sense, as the frequency of patenting in a given subclass and region compared to the same patenting intensity in this technology in all French NUTS 2 regions only. We label this index $RTA\_FR_{c,r,y}$.

Relatedness

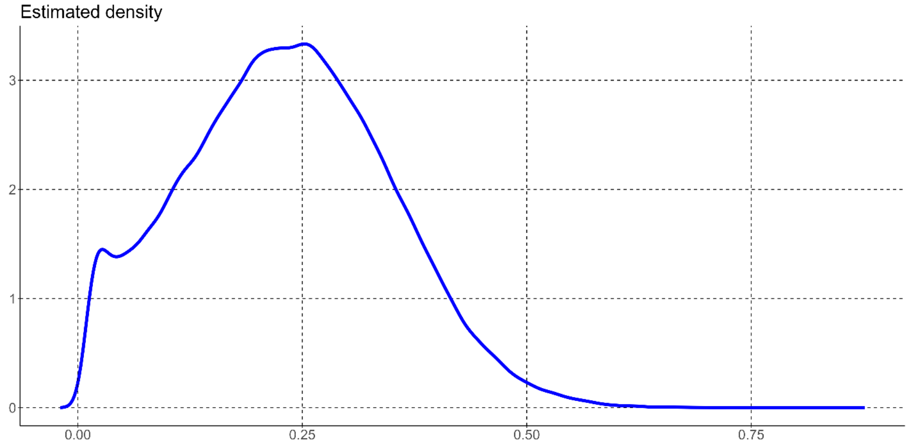
Using the RTA, it is possible to compute the relatedness $\phi_{c,c',y}$ for each pair of subclasses c and c'. Two subclasses are considered to be more related if regions with a RTA in one of these subclasses also had a RTA in the other one. The relatedness is computed by taking the minimum of the pair-wise conditional probabilities of regions having a comparative advantage in one technology subclass *c*, given that they have a comparative advantage in another technological subclass *c'* (Hidalgo et al. 2007, Boschma et al. 2015).

$$\phi_{c,c',y} = \min\left[\frac{\sum_{r}\left(RTA_{c,r,y} * RTA_{c',r,y}\right)}{\sum_{r} RTA_{c,r,y}}, \frac{\sum_{r}\left(RTA_{c,r,y} * RTA_{c',r,y}\right)}{\sum_{r} RTA_{c',r,y}}\right] \quad (2)$$

Relatedness is assigned to any pair of technology subclasses (c,c') and is therefore region-independent. The approach adopted in the construction of this indicator considers that if two technological subclasses are *close or related*, then they will tend to appear in patents filed in the same regions. More specifically, the relatedness measure relies on the assumption that related technologies will be used intensively in the same regions. Conversely, two *unrelated technology* subclasses are less likely to co-occur in the specialization bundles of many regions. The constructed indicator is based on this agnostic approach and is constructed in such a way that two IPC subclasses are all the closer as the regions having an RTA in one of these subclasses often have an RTA in the other subclass (Hidalgo et al. 2007). The average bilateral relatedness between IPC classes is 0.23, with a minimum at 0.007 and a maximum at 0.85. The probability density of the set of bilateral relatedness measured by kernel density estimation is shown in Figure 1.

[6] *18 European countries and the United States.*

Figure 1 - Estimated density of bilateral relatedness between IPC classes (2017)



Source: OECD REGPAT database. EPO and PCT patent filing data.

Relatedness Density

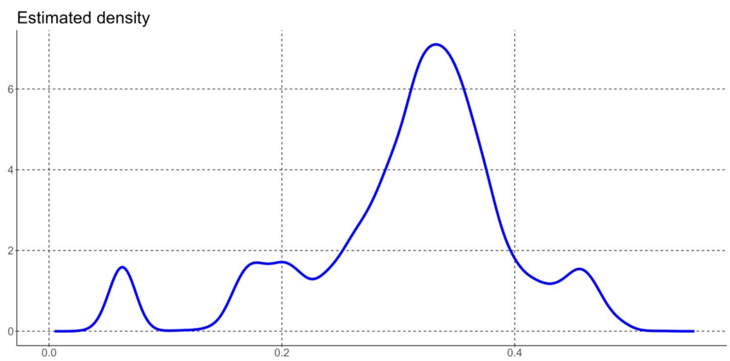
Finally, it is possible to measure the distance of any technology subclass from the specialization structure of a given region. Following the relatedness literature, we build the measure of *Relatedness Density*, specific to a technology subclass c in a region r in a year y. Regions are specialized in different technological subclasses, and every IPC subclass is more or less distant from the ones in which the region is already specialized. This distance between IPC classes is measured by the aforementioned pairwise proximity from equation (2). For a given class *c*, we therefore calculate its relatedness density to the technological portfolio of region *r* as the ratio of its pairwise relatedness with all the classes in which region *r* as a comparative advantage, divided by the sum of its pairwise proximities with all subclasses. Formally:

$$\text{Relatedness Density}_{\text{c,r,y}} = \frac{\sum_{c' \in RTA_{r,y}, c' \neq c} \phi_{c,c',y}}{\sum_{c' \neq c} \phi_{c,c',y}} \quad (3)$$

With $RTA_{r,y}$ the set of subclasses in which region r has a RTA during year y.

This indicator increases when a class gets closer to the specialization space of region r. The relatedness density of an IPC subclass in a region is independent of whether this subclass is actually used in the region considered. An IPC subclass can have a very high relatedness density in a region because it is similar to the IPC subclasses the region is specialized in, even though the region does not file any patent mobilizing this subclass yet. For all technology classes in all French regions, the average relatedness density is 0.31. The distribution of the density set is represented by the estimated probability density in Figure 2. This figure shows the estimated probability density for the set of relatedness density measures for all technology classes in all French regions. However, it should be noted that the distribution of relatedness densities of IPC classes varies from region to region.

Figure 2 – Estimated density of Relatedness Densities (All regions - 2017)



Source: OECD REGPAT database. EPO and PCT patent filing data.
Field: Metropolitan France. Regional Relatedness Densities for all technology classes built using patent data from all countries.

4.2. Constructing technology spaces

In order to study the impact of highly skilled mobile workers on the production of technological novelty, we build three main dependent variables, *Novelty, Recombinant creation and Recombinant reuse.*

4.2.1: Patent Novelty

Novelty is the number of new combinations, that is, the number of pairwise subclass combinations associated with a given subclass that appears for the first time in a given year and region. A new combination occurs when a subclass pair is combined for the first time in a patent. This new combination can be new to the region, new to France or new to the world. Unless otherwise stated, the reference level used is that of novelty at the regional level. The technological novelty measure follows the literature on recombinant novelty (Arts and Fleming, 2018; Fleming, 2001, Verhoeven et al., 2016) and is applied at the NUTS 2 level.

$$\text{Novelty}_{c,r,y} = \sum_{i=1}^{p_{c,r}} \left(\sum_{c_{i,c} \in n_{i,c}} 1_{[NewCombination_{c_{i,c},r,y}]} \right) (4)$$

With $p_{c,r}$ *the* total number of patents using subclass c in region r, $n_{i,c}$ the set of combinations in each patent *i* mobilizing the IPC subclass c. $1_{[NewCombination_{c_{i,c},r,y}]}$ takes the value 1 if combination $c_{i,c}$ from the set $n_{i,c}$ is new to the region *r* at year *y*.

In order to test the robustness of our estimates to the novelty indicator used, two other indicators are constructed and used in the robustness tests of our baseline estimations. *Novelty Binary* is a dummy variable which takes value 1 if at least one new combination is associated with a given subclass c in region r is observed in a given year y. *Novelty Share* is the share of new combinations over the total combination associated with a given subclass in a given year and region.

4.2.2: Novelty reuse and novelty recombination

In order to further explore the underlying recombinant process, we introduce two dependent variables that provide information on the status of the classes that are combined together for the first time. *Novelty reuse* counts the number of new combinations using subclasses that are already part of the region's technological portfolio and *recombinant creation* counts the number of new combinations when at least one of the subclasses is new to the region.

4.2.3: Class entry and specialization gain

Finally, following the literature (Boschma et al. 2015), we also build two dependent variables that capture the entry of a technological class or the gain of a technological specialization in a class for a given region and year.

$New\ IPC_{c,r,y}$ takes the value 1 if a technology subclass c appears in region r for the first time in year y.

$\text{Specialization}_{c,r,y}$ models the gains in RTA in a given c technology subclass in an r region. It takes the value 1 when a subclass enter the specialization set of a region a given year. It enables to consider whether mobile workers help a region become specialized and gain comparative advantage in a given subclass. Following the literature and in order to reduce the statistical noise around the 0 to 1 RTA switches, $\text{Specialization}_{c,r,y}$ is set to 1 if $RTA_{c,r,y-1} = 0$ and $RTA_{c,r,y-2} = 0$ and if $RTA_{c,r,y} = 1$, $RTA_{c,r,y+1} = 1$ and $RTA_{c,r,y+2} = 1$. In other words, gains in comparative advantage are only considered if the region had no RTA in the two preceding years of observation and if this gain in specialization is persistent, i.e., if it is observed over a period of at least three years.

4.3. Independent variables: highly skilled mobile workers

The aim of this paper is to investigate whether the flow of highly skilled workers coming from regions specialized in a given technological subclass c ($\text{RTA} = 1$) affects the production of new combinations using this technology. The socio-professional categories of the PCS-ESE nomenclature used to identify skilled workers correspond to professors and scientific professions (PCS-ESE 34), engineers and technical managers (PCS-ESE 38) and technicians other than service technicians (PCS-ESE 47)[7]. Thus, the flow of mobile workers coming from a region specialized in a given subclass is then computed as the sum of all highly skilled mobile workers $\text{Mob}_{r' \to r,y}$coming from other French regions r' moving into the region r in year y and weighted by the dummy variable whether RTA = 1 (Bahar and Rapoport, 2020).

$$\text{High Skilled Mobility (RTA)}_{\text{c,r,y}} = \sum_{r' \neq r} \text{Mob}_{r' \to r,y} \times RTA_{c,r',y} \quad (7)$$

[7] *This definition is similar to the one used by Harrigan et al. (2023) and Mayda et al. (2022): their definition is based on PCS categories 38 and 47, while we assume that category 34 can be attribute to the high skilled workers.*

As a robustness check, we use also three other weighting variables: *RTA_FR* is used to consider specialization in a narrower sense, using French regions only; *Relatedness density* is used to control whether mobile workers are coming from regions specialized in technologies related to this given subclass; *Size* controls for the fact that workers are coming from regions with a large patenting activity in a given subclass. *Size* is the share of patents in a given subclass, region, and year $n_{c,r',y}$ over the total number of patents applied for in the region and year $N_{r',y}$, $\text{Size} = n_{c,r',y}/N_{r',y}$.

4.4. Control variables

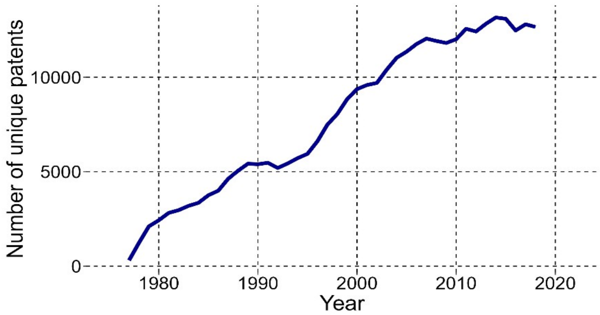
As novelty may also be explained by variables characterizing the region's technological portfolio, several controls are added to the regressions. *Relatedness density*, described above, may explain the occurrence of new combinations given the relatedness a given subclass to the rest of the technology space in the region (Plunket and Starosta de Waldemar, 2023). *New subclass* takes value one if the combination includes at least one subclass that enters the region for the first time. By definition, any combination including this subclass would be new. *Number of patents in the subclass* is the number of patents in which the subclass occurs in a given year and region. It is an indication of its technological importance in the region. The panel is completely balanced thus it may be that some classes do not occur in any patent. To control for this fact, we include a variable *Missing subclass* which takes value 1 if the subclass is missing in a given year and region. The flow of external knowledge can come from highly skilled workers, but it may also be explained by the collaborations with extra-regional inventors. The variable *Share of extra-regional patents* that is the share of patents in region r and subclass c which includes extra-regional inventors over the past five years to control for the fact that external knowledge brought by migrants do not catch the impact of external collaboration.

5. Descriptive statistics

5.1. Patenting activities and IPC subclass combinations

Each year, more than 12,000 EPO patents are filed in France, a figure that has been steadily increasing since the beginning of the study period and seems to have stabilized since the beginning of the 2010s (Figure 3).

Figure 3 - Number of yearly patents files in France

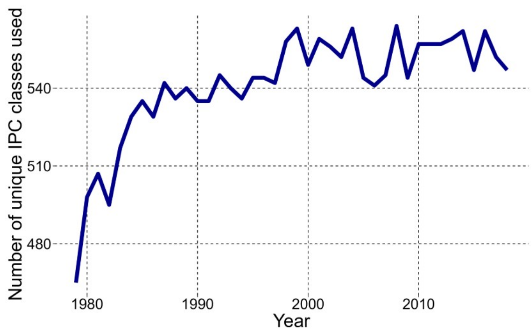


Source: OECD REGPAT database. EPO and PCT patent filing data.
Field: Metropolitan France patents.

However, patenting activity is not evenly distributed across French regions. In 2018, Île-de-France and the Rhône-Alpes region represented the two major innovation hubs in France with 5,088 and 2,489 patents filed respectively. The other French regions displayed very heterogeneous numbers of patents filed that same year, ranging from 66 filings for Limousin to 867 for the Midi-Pyrénées region.

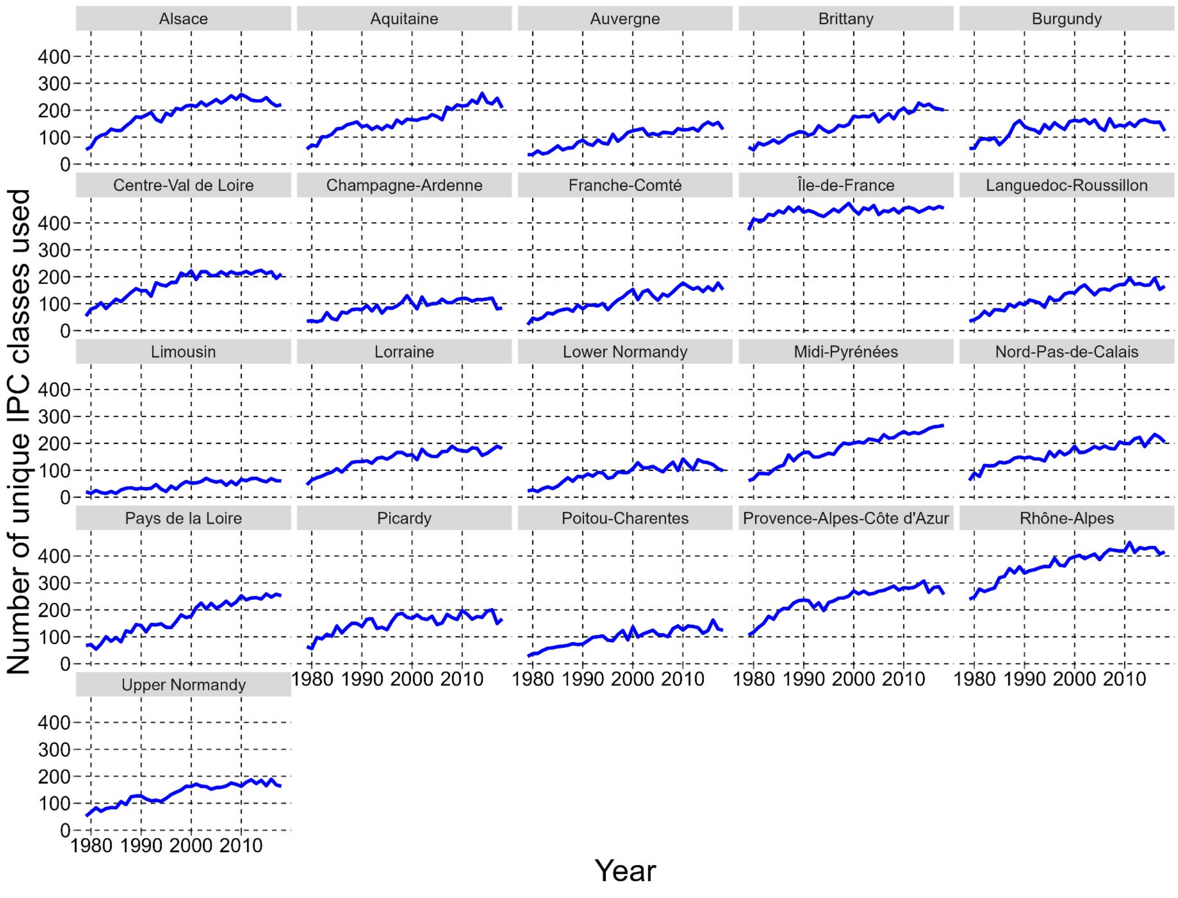
The number of technological subclasses used on average in each region has grown strongly until the end of the 1980s before stabilizing. In 2018, 547 different technological subclasses were found in patents filed in France, namely nearly 86 % of all technological subclasses in the nomenclature (Figure 4). Not all of these subclasses are mobilized in all French regions. In 2018, the Île-de-France region (FR10) used 455 subclasses and the Rhône-Alpes region 405, while the other regions used an average of between 100 and 250 subclasses (Figure 5).

Figure 4 – Number of IPC subclasses used in France



Source: OECD REGPAT database. EPO and PCT patent filing data.
Field: Metropolitan France patents.

Figure 5 - Number of IPC subclasses used by French regions



Source: OECD REGPAT database. EPO and PCT patent filing data.
Field: Metropolitan France patents.

However, individual patents do not combine the same number of technology subclasses. Since 1996, half of the patents only use one IPC subclass (Table 1). Among the patents combining at least two subclasses and on which we focus, about 30 % combine only two subclasses. At the other end of the distribution, 0.4 % of patents are composed of at least 7 technology subclasses and thus have at least 21 pairwise IPC subclass combinations.

Table 1 – Number of IPC subclass by patent

Number of IPC subclasses (%)							
	1	**2**	**3**	**4**	**5**	**6**	**7+**
Total	50.3	29.4	13.2	4.6	1.6	0.6	0.40
2013	52	30	12.3	3.9	1.3	0.4	0.20
2014	52	30.1	12	4	1.3	0.5	0.10
2015	51.6	30	12.7	3.9	1.2	0.4	0.20
2016	51.7	30.1	12.4	4.1	1	0.4	0.20
2017	51.9	31.2	11.8	3.5	1	0.4	0.10

Source: OECD REGPAT database. EPO and PCT patent filing data.
Field: Metropolitan France patents.

The number of technological combinations used each year in France is around 5,000, which corresponds to 2.5 % of all the possible pairs of technology subclasses which include 637 individual subclasses in the nomenclature.

However, the technological combinations used each year are not necessarily the same from one year to another. The Table 2 indicates that over the period, 31,263 distinct combinations were used in France. Once again, Ile-de-France stands out, having mobilized 19,470 distinct combinations over the period, that is, 9.6 % of all theoretically possible combinations. Moving down the ranking, this figure decreases sharply. The Midi-Pyrénées region, fifth in the ranking of French regions having used the most distinct technological combinations since the 1970s, has exploited only 2.6 % of all theoretically possible technological combinations. While not all subclass combinations are comparable in practice, as the joint mobilization of highly unrelated domains would be complicated, it is noticeable that French regions still have a high potential to explore new technological domains by jointly mobilizing technological subclasses never before combined at the regional level.

Table 2 – Number of pairwise IPC combination used - Top 5 regions

Région	**Number of pairwise IPC combinations used (since 1970)**	**Share (%)**
Île-de-France	19 470	9.6
Rhône-Alpes	13 718	6.8
Provence-Alpes-Côte d'Azur	7 403	3.7
Alsace	5 348	2.6
Midi-Pyrénées	5 269	2.6
Total (France)	**31 263**	**15.4**
	Number of pairwise IPC combinations used yearly (2017)	
Île-de-France	2 341	1.2
Rhône-Alpes	1 389	0.7
Provence-Alpes-Côte d'Azur	597	0.3
Alsace	323	0.2
Midi-Pyrénées	594	0.3

Source: OECD REGPAT database. EPO and PCT patent filing data.
Field: Metropolitan France patents.

Across all technological classes, all French regions witness the emergence of new combinations (Table 3). The number of new combinations observed at the regional level in 2017 ranged from 35 (Limousin) to 315 (Île-de-France). New combinations at the national or global level are less common. For instance, in 2017, Île-de-France generated 187 new combinations at the national level and only 22 new combinations at the global level.

Table 3 – Technological novelty in French regions (2017)

Region	Distinct pairwise IPC combinations	Technological Novelty		
		New combinations (Region)	New combinations (France)	New combinations (World)
Île-de-France	2341	315	187	22
Rhône-Alpes	1389	270	95	7
Provence-Alpes-Côte d'Azur	597	176	54	6
Midi-Pyrénées	594	195	30	1
Aquitaine	496	169	45	3
Pays de la Loire	440	182	37	5
Alsace	323	84	11	0
Britanny	322	114	14	0
Nord-Pas-de-Calais	319	108	28	2
Auvergne	317	124	30	4
Centre-Val de Loire	291	108	22	4
Picardy	278	79	8	0
Upper Normandy	273	66	10	1
Lorraine	269	115	22	3
Languedoc-Roussilon	239	75	16	1
Franche-Comté	205	89	13	1

Burgundy	157	60	6	0
Poitou-Charentes	136	66	8	2
Lower Normandy	95	44	6	1
Champagne-Ardenne	79	35	5	0
Limousin	58	31	7	1

Source: OECD REGPAT database. EPO and PCT patent filing data.
Field: Metropolitan France patents. Patent data from all countries used to built 'novel to the world' index.

5.2. Technological Specialization and worker flows

The $RTA_{c,r,y}$ constructed in equation (1) are used to indicate the technology subclasses in which regions have a revealed relative technological advantage. On average over the period, the top patenting regions displayed a RTA in a given subclass in about 200 different technology subclasses each year (Table 4). However, the domains in which regions have an RTA are evolving over time. Over the period, the most innovative regions developed an RTA at least one year in nearly 500 different technology subclasses. In other words, technology spaces evolve, and the specialization structures of regions changes over time.

Table 4 – Number of RTA - Top 5 regions

Region	Total number of RTA (period)	Average yearly number of RTA
Île-de-France	575	208
Rhône-Alpes	544	253
Provence-Alpes-Côte d'Azur	522	199
Alsace	481	170
Midi-Pyrénées	496	186

Source: OECD REGPAT database. EPO and PCT patent filing data.
Field: Metropolitan France. RTA built using patent data from all countries.

For any year, the regions also present different specializations. Figures 6 to 9 compare, for example, the technological spaces of the Pays de la Loire and Brittany regions in 2017 by identifying 5 major technological sectors[8]. Each node represents an IPC subclass (figures 6 and 7) or a technological field (Figures 8 and 9) and each network's node's size represents the over-representation of this IPC class or technological field in the region under study compared with all patents filed in France. The networks are plotted using pairwise technological proximity for the edges. The graphic representation displays different specialization structure with the Pays de la Loire presenting a much more diversified technological space, with a marked specialization in mechanical engineering. Brittany, on the other hand, seems to specialize mainly in electrical engineering, with an important innovation cluster in chemicals as well. Figures 8 and 9 use the same graphical construction logic, aggregating IPC classes into 35 industrial sectors based on the CRIOS nomenclature. These two graphs provide a more synthetic visualization of regional technological spaces and

[8] *Chemistry, electrical engineering, instruments, mechanical engineering and other fields*

lead to similar observations.

Figure 6 – Pays de la Loire - 2017

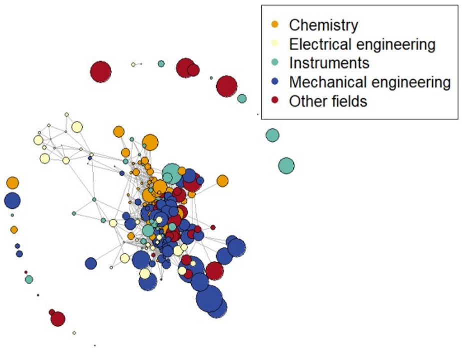


Figure 7 – Brittany - 2017

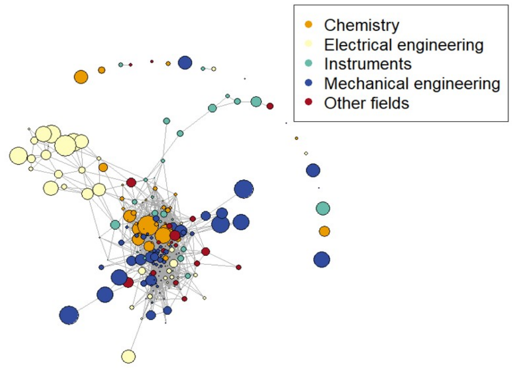


Figure 8 – Pays de la Loire – (Fields, 2017)

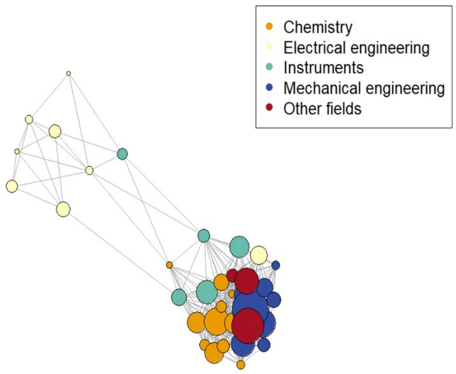
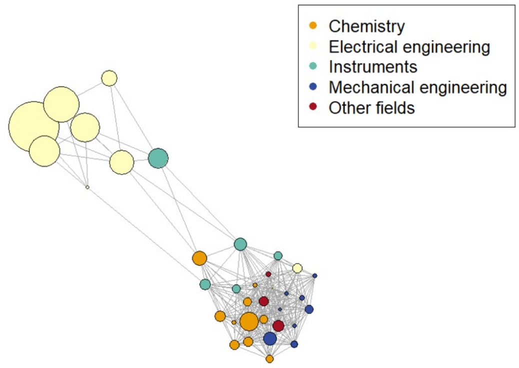


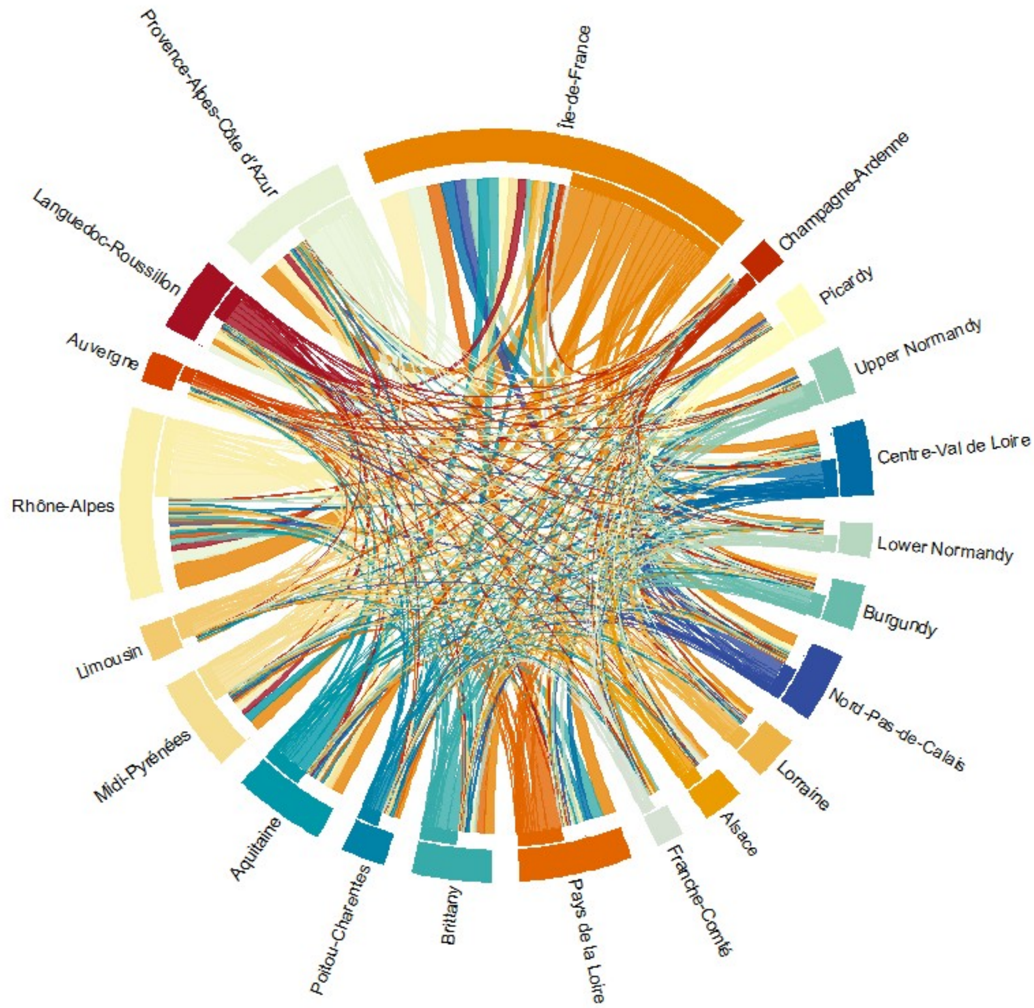
Figure 9 – Brittany – (Fields, 2017)



Note: Each circle represents an IPC class (Figures 6 and 7) or a CRIOS technology field (figures 8 and 9). The size of the circles represents the over-representation of the class or technological field in the patents filed in the region under consideration compared with its average occurrence in all French patents. The color of the circles corresponds to the 5 sectors identified in the nomenclature. The distance of the segments between two circles corresponds to their bilateral relatedness measure as presented in section 4.1. The further apart two circles are, the more different the technology classes they represent. By comparing the graphs of 2 regions, we can visually identify differences in the specialization of their technological areas.
Source: OECD REGPAT database. EPO and PCT patent filing data.
Field: Metropolitan France. Bilateral relatedness measures built using patent data from all countries.

Finally, the flows of qualified mobile workers are significant. In 2017, one million salaried workers changed their regions of employment, among which around 161 000 high-skilled workers identified by the socio-professional categories used to build our $\text{High Skilled Mobility}_{c,r,y}$ variable. These mobility flows are particularly intertwined as shown in Figure 10. The most significant region in terms of mobility flows is Île-de-France, which had 39,107 incoming skilled employees and 32,646 outgoing skilled employees in 2017. Other regions show less significant and less balanced flows between inflows and outflows. For instance, in 2017, the inflow of skilled employees in Limousin was 1,564 individuals, while the outflow was 5,272 employees.

Figure 10 – Skilled worker flows between regions - 2017



Note: The segments around the circle are proportional in width to the sum of incoming and outgoing flows received by each region. For a given region, outflows are the color associated with the region around the circle. Inflows to each region are colored according to their region of origin.
Source: BTS database.
Field: Metropolitan France patents.

Crossing these inter-regional mobility flows with the regions Revealed Comparative Advantages, both varying over time, provides class x region x year specific high-skilled workers flows with sufficient heterogeneity to study the effects of mobility flows from regions specialized in a technological subclass in a given year on the novelty of innovations mobilizing this subclass in the host regions. Detailed descriptive statistics for our main variables can be found in the appendix Table A2.

6. Empirical strategy

6.1. Estimated equation and identification strategy

Our aim is to estimate the impact of the inflow in a region *r* of highly skilled workers coming from all regions specialized in a given technological subclass *c* on the number of new combinations (Novelty$_{c,r,y}$) associated with this given subclass (*High Skilled Mobility$_{c,r,y-1}$*). The basic econometric equation to be estimated is given by:

$$\text{Novelty}_{c,r,y} = \beta_0 + \beta_1 \text{High Skilled Mobility}_{c,r,y-1} + \beta_2 X_{c,r,y-1} + \varphi_{c,r} + \psi_{r,y} + \alpha_{c,y} + \epsilon_{c,r,y} \quad (8)$$

In our three-dimensional panel, $X_{c,r,y-1}$ is a set of control variables as defined in the previous section and constructed at the Class-Region-Year (CRY) level. We include fixed-effects $\varphi_{c,r}$, $\psi_{r,y}$ and $\alpha_{c,y}$. Indeed, group-specific effects may exist at region $\times$ technological subclass, region $\times$ year or technological subclass $\times$ year levels. The inclusion of fixed effects enables us to control for inter-group variability by adding dummy variables that absorb the effects specific to each group considered. This identification strategy, based on high dimensional fixed effects, allows us to be confident in the estimation of our β_1 coefficient. Note that the inclusion of these three groups of high-dimensional fixed effects absorb much of the correlation between regressors and unobserved variables.. In order to incorporate all these fixed effects, we use the high-dimensional fixed effects methodology proposed by Correia (2016; 2019) and based on the adaptation of the general solution proposed by Guimaraes and Portugal (2010) and Carneiro et al. (2012). $\varepsilon_{c,r,y}$ are robust standard errors clustered at the fixed effects level (multiway).

Since the subclass $\times$ region $\times$ year panel used in the study is balanced, the number of observations is constant each year[9], for each region and for each technological subclass, and the number of categories for each of these variables. To put it differently, the sample size does not depend on the number of patents filed and therefore the number of groups used to estimate the fixed effects is constant. Having a balanced panel therefore prevents inconsistency problems that might arise with high-dimensional fixed effects modeling in an unbalanced setting. Our independent variables are lagged one year, in order to diminish risks of reverse causality in the estimations.[10] This is true for all variables except new subclass and missing subclass, which share contemporaneous information on the status of the subclass in that region and year.

Estimates are conducted in a linear framework. Nevertheless, the three versions of the independent variable proposed are the number of new combinations, a binary indicator and a proportion. Therefore, a Poisson regression for the count data, a Probit model for the binary indicator and a Tobit model could therefore intuitively be considered. However, with (high-dimensional) fixed-effects, the probit estimator is not well behaved because of the incidental parameter problem. Tobit model are also affected in a high-dimensional fixed-effects setting by the disturbance variance estimator (Greene, 2002). Therefore, in this setting, linear models are preferable. Regarding the Poisson model, incidental parameter

[9] *In total, the dataset contains 22 regions x 22 years x 637 classes: 308308 observations. Since we used lagged variables, the number of observations drops to 294 294 observations in our baseline estimations.*

[10] *One-year lagged are widely used in the literature (Balland et al., 2019; Caviggioli et al., 2020; Boschma et al. 2022; Miguelez and Morrison, 2022). In related but not similar literature, Wang and Hagedoorn (2014) show a significant effect of (y-1) internal R&D on patenting, and also long-run effects. They show that the effect of R&D activity on the number of patents at the firm level has a U-shaped lag structure: the share of more contemporaneous R&D accounts for 36% on the total R&D. We follow their approach and we add a previous lag to the (y-1) lag of our main variable of interest. We provide results in section 7.2. A robustness test is also presented in the appendix, including flows in y+1 to check for the absence of reverse causality.*

problems and caution about mobilizing fixed effects are less central. The use of the Poisson model with high-dimensional fixed-effects could therefore be considered. It is used in this paper as a robustness tool for the linear baseline regression using Poisson pseudo-maximum likelihood regressions (PPML) with multi-way fixed effects (Correia et. al., 2020). The result is presented in the appendix (Table A4).

An instrumentation strategy is employed to control for possible omitted variable or reverse causality problems. The instrumentation strategy and the subsequent results are used as robustness tests for the main estimates and are presented in section 8.2.

7. Results

7.1. Entry: new subclass to the region and on the specialization basket

Before addressing the impact on recombinant novelty, it is interesting to study simpler issues, namely whether mobility flows affect the occurrence of a new subclass (*New IPC*) or a new specialization.

In Table 5, column (1) reproduces the main model presented in equation (1) using the binary variable $New\ IPC_{c,r,y}$ as the dependent variable. Results indicate that the occurrence of a new technological subclass in French regions is positively and significantly correlated with the inflow of highly skilled workers coming from regions specialized in this specific technological subclass c at year (y-1). The proximity of a technological subclass to a region portfolio, measured by its relatedness density in this region, is associated with a non-linear effect. It is only at a high relatedness density level (around 0.75) that an increase in the relatedness density of a class in a region has a positive effect on the propensity of this subclass to enter the region's technological portfolio.

Table 5 - Impact of labor mobility on the occurrence of new IPC classes and level of specialization

	New IPC	Specialization
	(1)	(2)
High Skilled Mobility (RTA) (y-1)	0.0016***	0.0145***
	[0.0003]	[0.0008]
Relatedness density	-0.0150***	-0.0359***
	[0.0042]	[0.0067]

Relatedness density sq	0.0103**	-0.0136+
	[0.0043]	[0.0074]
New subclass		0.1504***
		[0.0034]
# of patents in the subclass	-0.0087***	-0.0010
	[0.0004]	[0.0012]
Missing subclass	-0.0696***	-0.0167***
	[0.0023]	[0.0017]
Share of extra-regional inventors	-0.0196***	-0.0380***
	[0.0008]	[0.0019]
Constant	0.0585***	-0.0979***
	[0.0028]	[0.0049]
Observations	294294	294294
R-Squared	.1517	.1916

*Note: Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01. Estimation method: Linear regression with high-dimensional fixed effects.*
Source: OECD REGPAT database. EPO and PCT patent filing data. BTS database.
Field: Metropolitan France patents and workers flows.

Similarly, column (2) uses the variable $\text{Specialization}_{c,r,y}$ as the dependent variable in order to test whether mobility helps a region to gain a comparative advantage in a given subclass. This is a binary variable indicating a region's gain in specialization in a technological class. In other words, the variable indicates whether a region goes from a RTA of 0 to a stable RTA of 1 on year *y*. Again, the flow of skilled workers from regions specialized in a subclass is associated with a RTA gain in those same technology subclasses in the host regions. *Relatedness density* has again a non-linear effect, the share of extra-regional inventors is negative, whereas *New subclasses* has a positive effect.

These preliminary results confirm hypothesis 1 regarding the role of occupational mobility and are consistent with the existing literature (Bahar and Rapoport, 2020), showing previous results highlighted in the literature to be robust when considering intra-national occupational mobility.

7.2. Technological novelty: the number of new combinations

Beyond the emergence of new subclasses or specialization, the aim of this study is to investigate whether highly skilled mobile workers boost the production of new combinations in subclasses in which their regions of origins is already specialized.

Table 6 presents the result of the main equation with four different weights. The effect associated with the mobility flows weighted by the RTA (i.e. the variable is equal to zero when the originating region is not specialized in technology *c*, otherwise it is equal to the number of migrants) are statistically significant, both when the RTA is computed with reference to the regions in 18 countries (column 1, baseline specification) or uniquely all French regions (column 2). The inflow of workers from regions specialized in a technology subclass *c* is therefore associated with a higher number of novel combinations of technology subclasses involving this subclass in the host region. This result is robust to weighting by the size of the technology subclass in the region of origin (column 3). These results thus indicate that skilled worker mobility from regions in which innovation activity in a given technology subclass is intense are strongly associated with more technological novelty in this specific subclass in the patents filed in the host region. This important result is corroborated by a number of robustness tests presented in the appendix.[11]

Table 6 - Impact of highly skilled labor mobility on novelty

	Novelty (region)			
	(1)	(2)	(3)	(4)
High Skilled Mobility (RTA) (y-1)	0.0034***			
	[0.0012]			
High Skilled Mobility (RTA FR) (y-1)		0.0037**		
		[0.0015]		
High Skilled Mobility (Size) (y-1)			0.0127***	
			[0.0033]	
High Skilled Mobility (Related Density) (y-1)				0.0021
				[0.0019]
Relatedness density	-0.0111	-0.0111	-0.0113	-0.0113
	[0.0134]	[0.0134]	[0.0134]	[0.0134]
Relatedness density sq	0.0076	0.0076	0.0075	0.0078
	[0.0155]	[0.0155]	[0.0155]	[0.0155]
New subclass	0.2904***	0.2904***	0.2906***	0.2905***
	[0.0125]	[0.0125]	[0.0125]	[0.0125]
# of patents in the subclass	-0.0103***	-0.0103***	-0.0095***	-0.0103***
	[0.0030]	[0.0030]	[0.0030]	[0.0030]
Missing subclass	-0.5774***	-0.5774***	-0.5773***	-0.5774***
	[0.0049]	[0.0049]	[0.0050]	[0.0049]
Share of extra-regional inventors	-0.0066***	-0.0066***	-0.0068***	-0.0067***
	[0.0024]	[0.0024]	[0.0024]	[0.0024]
Constant	0.5807***	0.5782***	0.5843***	0.5900***
	[0.0083]	[0.0097]	[0.0059]	[0.0106]
Observations	294294	294294	294294	294294
R-Squared	.5552	.5552	.5552	.5552

*Note: Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01. Novelty is measured as the number of distinct combinations associated with a given ipc code found in all patents in a year and region. Estimation method: Linear regression with high-dimensional fixed effects.*
Source: OECD REGPAT database. EPO and PCT patent filing data. BTS database.
Field: Metropolitan France patents and workers flows.

In contrast, when weighted by the relatedness density of class *c* in the region of origin, the result is not significant (column 4). Relatedness density indicates how close a technology subclass is to the core of a region's technological specialization, whether or not this subclass is used in the region. Therefore, the fact that a region is specialized in technological fields does not imply that labor mobility flows from this region would be associated with higher novelty indexes in related technological subclass in the host region if these subclasses are not used intensively in the sending region. Therefore, with workers flows, the key determinant of technological novelty in technology subclasses at destination lies in their intensive usage in

[11] *Table A3 shows that the main result is robust when using alternative novelty indicators (novelty binary and novelty share). Table A4 shows that the result is robust when using a PPML regression with multi-ways fixed effects instead of a linear setting. Table A5 shows that the main result is robust to the removal of either one of the two largest patenting regions (Île-de-France, Rhône-Alpês) or the region with the lowest level of patenting activity (Corsica). Table A6 tackles the issue of bad controls (Angrist and Pischke, 2009) and shows that reproducing the benchmark specification including controls one by one does not alter the positive and statistically significant effect of our main independent variable. Table A7 reproduces Table 5 adding lag (y-2) in the regression following the methodology of Wang and Hagedoorn (2014). Our main result remains robust: the effect of lagged high skilled mobility occurs when there is a lag of one year, while the effect of the second lag is non-significant. Table A7bis reproduces equation from Table 5, including forward mobility flows (y+1) to test for the absence of reverse causality.*

the region of origin, rather than simply being related with the specialization portfolio of this region. These results confirm **hypothesis 2**.

Regarding variables controlling the technology space of the host region, relatedness density is associated with a negative and non-significant coefficient. The fact that a technology subclass is closer to the core of a region's technological specialization does not have an impact on the technological novelty produced in that technology subclass. This result may be related to the fact that regions do not explore diversification via novel combinations of technological subclasses in their inventive activity, especially in subclasses close to the fields in which the region is already specialized. This first regression table therefore suggests that mobility flows play a significant role in the dynamics of invention.

Table 7 - Technological novely at national and international level

	Novelty	
	France	World
High Skilled Mobility (RTA)	0.0031***	0.0015***
	[0.0009]	[0.0004]
Relatedness density	-0.0136	-0.0048
	[0.0085]	[0.0038]
RelatedDens_sq	0.0190+	0.0057
	[0.0102]	[0.0045]
New subclass	0.1164***	0.0399***
	[0.0104]	[0.0052]
# of patents in the subclass	0.0045**	0.0011+
	[0.0020]	[0.0007]
Missing subclass	-0.1581***	-0.0317***
	[0.0037]	[0.0014]
Share of extra-regional inventors	0.0010	0.0006
	[0.0014]	[0.0006]
Constant	0.1510***	0.0233***
	[0.0058]	[0.0025]
Observations	294294	294294
R-Squared	.3666	.1683

*Note : Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01. Estimation method: Linear regression with high-dimensional fixed effects.*
Source: OECD REGPAT database. EPO and PCT patent filing data. BTS database.
Field: Metropolitan France patents and workers flows.

This influence of skilled worker flows on technological innovation is all the more important as the regional technological novelty they enable is not a mere imitation of what is being done in their region of origin or in other French regions. By adopting a broader definition of technological innovation to identify IPC subclasses combinations appearing for the first time, not only in the host region but also in France or globally, the results in Table 7 indicate that the mobility of skilled workers continues to have a significant and positive impact on the emergence of new technological combinations at their destination. The effect of mobility on technological novelty therefore enables the emergence of combinations of technological classes never before seen in the country, and sometimes in the world, underlining the pivotal importance of worker flows on innovation dynamics.

7.3. Worker flows and regional specialization complementarity

Previous results shows that on average, workers flows trigger technological novelty at the destination region in the IPC classes in which the workers' regions of origins are specialized. What remains unanswered is whether this effect is observed for every IPC class in every host region, regardless of the host region previous technological portfolio.

Table 8 explores the mechanisms through which mobile workers affect novelty given the characteristics of the regional technology space. Columns 1 and 2 estimate the impact of mobile workers when they come from regions specialized in a subclass and enter a region in which the given subclass relatedness density is lower (respectively higher) than the median. To put it differently, the first column is estimated as a sub-sample consisting of half of the technologies closest to the destination region's specialty fields, and the opposite for the second column. The effect appears higher and significant for subclasses characterized by high relatedness density at destination, that is, when the subclass is strongly related to subclasses in which the host region is already specialized. This result suggests a form of complementarity between the technologies conveyed by mobile workers and that embodied in the technological space at destination.

Table 8 - Disentangling the effects

	Novelty (region)				Recombinant Reuse	Recombinant Creation
	(1) RD < med.	(2) RD > med.	(3) RTA = 0	(4) RTA = 1	(5)	(6)
High Skilled Mobility (RTA) (y-1)	0.0022+	0.0058**	0.0003	0.0130***	0.0024+	0.0015***
	[0.0012]	[0.0029]	[0.0014]	[0.0045]	[0.0012]	[0.0005]
Relatedness density	-0.0200	-0.0163	-0.0005	-0.0760+	0.0024	-0.0198***

	[0.0171]	[0.0248]	[0.0135]	[0.0410]	[0.0133]	[0.0062]
Relatedness density sq	0.0146	0.0144	-0.0070	0.0681+	-0.0023	0.0137**
	[0.0194]	[0.0272]	[0.0152]	[0.0410]	[0.0154]	[0.0064]
New subclass	0.2836***	0.2763***	0.2437***	0.0000		
	[0.0156]	[0.0206]	[0.0128]	[0.0000]		
# of patents in the subclass	-0.0123**	-0.0122***	-0.0016	-0.0118***	-0.0042	-0.0091***
	[0.0050]	[0.0034]	[0.0042]	[0.0038]	[0.0030]	[0.0008]
Missing subclass	-0.6032***	-0.5651***	-0.6298***	-0.5020***	-0.5149***	-0.0962***
	[0.0072]	[0.0053]	[0.0058]	[0.0057]	[0.0045]	[0.0034]
Share of extra-regional inventors	-0.0044	-0.0097***	-0.0016	-0.0074	0.0060**	-0.0184***
	[0.0038]	[0.0034]	[0.0032]	[0.0055]	[0.0024]	[0.0011]
Constant	0.6015***	0.5676***	0.6367***	0.4926***	0.5252***	0.0867***
	[0.0088]	[0.0192]	[0.0092]	[0.0319]	[0.0081]	[0.0039]
Observations	138970	150890	212185	80482	294294	294294
R-Squared	.6309	.5467	.611	.5557	.5323	.1716

*Note : RD < (resp. >) med is a split sample when Relatedness density is < (resp. >) median; RTA =1 (resp. = 0): split sample when RTA = 1 (resp. =0). Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01. Estimation method: Linear regression with high-dimensional fixed effects.*
Source: OECD REGPAT database. EPO and PCT patent filing data. BTS database.
Field: Metropolitan France patents and workers flows.

Columns 3 and 4 replicate the analysis by considering whether the region is or not already specialized in a given subclass. The impact is significant only for subclasses in which the region is already specialized confirming the results in column 2 and the relationship with the regional technology space. These results support hypothesis 2a rather than 2b. If the technological subclasses in which the originating region is specialized are too distant from the specialization of the host region, then the effects of workers' mobility flows between these regions will not be significant.

Does this mean that the inflow of workers only generate novelty recombining technological subclasses already used in the host region? To answer this question, we consider the characteristics of novelty. We remind that recombinant reuse are combinations that associate subclasses that are already in the region's portfolio whereas recombinant creation includes at least one new subclass. In both equations, the coefficients associated with skilled worker flows are significant, even though the magnitude of the elasticity is 1.6 times higher for recombinant reuse. From what precedes, the effect of specialized workers flows on recombinant reuse is rather intuitive. It shows that when skilled workers enter a new region, they help produce new technology combinations gathering in the same patents IPC classes that were previously already used in the host region but in separate patents.

Explaining the impact on recombinant creation seems more challenging. When mobile workers come from regions specialized in a given subclass, they enable the production of a combination which includes at least one new subclass at destination. Either this subclass is new to the region, or it is associated with a subclass that is new to the region. Technological complementarity between origin and destination regions can therefore be needed for only one of the two IPC subclasses of the new technology combinations observed: one subclass close to the innovation already carried out at destination, and the second one having never been used in the host region. Hypotheses 2a and 2b are therefore not opposed.

Table 9 - Reuse and Creation

	Recombinant Reuse (region)				Recombinant Creation (region)			
	RD < med.	**RD > med.**	**RTA = 0**	**RTA = 1**	**RD < med.**	**RD > med.**	**RTA = 0**	**RTA = 1**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Skilled Mobility (RTA)	0.0013	0.0050+	-0.0002	0.0128***	0.0011+	0.0013	0.0005	0.0000
	[0.0012]	[0.0028]	[0.0014]	[0.0045]	[0.0006]	[0.0009]	[0.0007]	[0.0010]
Relatedness density	-0.0008	-0.0164	0.0105	-0.0742+	-0.0267***	-0.0011	-0.0141+	-0.0087
	[0.0169]	[0.0249]	[0.0133]	[0.0408]	[0.0091]	[0.0093]	[0.0075]	[0.0096]
Relatedness Density sq	-0.0026	0.0174	-0.0166	0.0701+	0.0230**	-0.0045	0.0121	0.0022
	[0.0192]	[0.0272]	[0.0150]	[0.0408]	[0.0100]	[0.0090]	[0.0083]	[0.0096]
# of patents in the subclass	-0.0014	-0.0086**	0.0047	-0.0111***	-0.0167***	-0.0055***	-0.0092***	-0.0008
	[0.0050]	[0.0034]	[0.0043]	[0.0038]	[0.0017]	[0.0008]	[0.0013]	[0.0009]
Missing subclass	-0.5002***	-0.5214***	-0.5353***	-0.4812***	-0.1547***	-0.0676***	-0.1367***	-0.0331***
	[0.0063]	[0.0051]	[0.0051]	[0.0057]	[0.0062]	[0.0030]	[0.0049]	[0.0017]
Share of extra-regional inv.	0.0136***	-0.0010	0.0120***	-0.0072	-0.0259***	-0.0127***	-0.0183***	0.0003
	[0.0039]	[0.0033]	[0.0032]	[0.0053]	[0.0019]	[0.0014]	[0.0015]	[0.0016]
Constant	0.5053***	0.5309***	0.5496***	0.4729***	0.1460***	0.0577***	0.1280***	0.0346***
	[0.0080]	[0.0190]	[0.0089]	[0.0318]	[0.0060]	[0.0065]	[0.0053]	[0.0073]
Observations	138970	150890	212185	80482	138970	150890	212185	80482
R-Squared	.5902	.5337	.5741	.5515	.2686	.2025	.234	.2614

*Note: Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01. Estimation method: Linear regression with high-dimensional fixed effects.*
Source: OECD REGPAT database. EPO and PCT patent filing data. BTS database.
Field: Metropolitan France patents and workers flows.

To further explore the results of columns 5 and 6, we estimate, for each of our dependent variables (*recombinant reuse and recombinant creation*), the same split samples as in columns 1 to 4 in Table 9. The first 4 columns of Table 9 support the result that high skilled mobility supports technological novelty at destination only if the technological class is highly related to the technological space (column 2) or the technological specialization set at destination (column 4). Columns 5 to 8 sheds light on the fact that while there is evidence of an effect of high skilled mobility on recombinant creation, there is only an effect on classes which are below the median of the local relatedness density. This indicates that high skilled mobility indeed (also) bring new and non-redundant knowledge to the local economy.

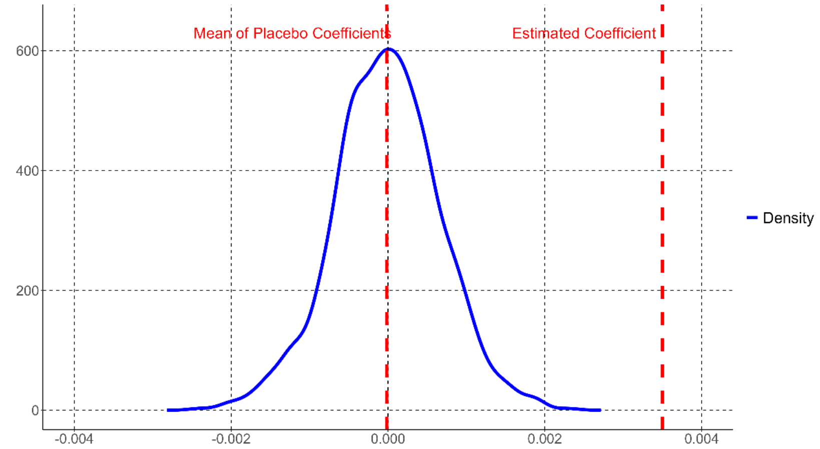
8. Robustness checks

8.1. Placebo test: randomizing specializations

Three main additional robustness tests have been carried out. First, we perform a placebo test to see if the estimated coefficient associated with our main explanatory variable may have been a result of chance, namely a positive random effect of skilled labor on novelty. To verify that this is not the case, we performed a test that involves randomly assigning Revealed Technological Advantages (RTA) to origin regions while maintaining the same proportion of class x region dyad with an RTA. These randomly assigned RTA are then used to calculate the mobility flows of skilled employees weighted by the specialization of the region of origin using the formula presented in the methodology section. We then estimate our benchmark specification (column 1 of Table 6) using these randomly assigned comparative advantages to capture the coefficients, standard errors, and p-values associated with the skilled labor flow built with the random RTAs. The simulation is replicated 1000 times. The coefficients from the 1000 regressions are used to calculate the probability density of the distribution of coefficients associated with the mobility variable when the technological advantages of the regions are randomly distributed. The coefficient of our benchmark equation from the result section is then compared to the estimated probability distribution to assess the robustness of our main result.

Figure 11 below plots the probability density of the estimated coefficients in the 1000 placebos. This distribution is symmetrical and centered at 0. In contrast, the coefficient estimated in the reference equation is positive and of very large magnitude compared with the estimated distribution of coefficients estimated by Placebo. The value of this coefficient is greater than the maximum value observed in the 1000 placebo regressions. The result of the main analysis is therefore not statistically attributable to statistical chance. The weighting of mobility flows by the observed technological advantages leads to a positive effect of a magnitude that is out of all proportion to that of the estimated coefficients when the technological advantages are randomly attributed. In other words, the effect of mobility on technological novelty is indeed linked to the technological specialization of the host region and thus to the fact that mobile workers convey knowledge specific to their region of origin and that can be mobilized in the host regions to create technological novelty.

Figure 11 – Estimated density of Placebo coefficient distribution



Source: OECD REGPAT database. EPO and PCT patent filing data. BTS database.
Field: Metropolitan France patents and workers flows.

8.2. Instrumentation strategy

Instrumentation strategy: method

In quantifying the effect of skilled labor mobility flows on novelty, panel estimates could still be biased as a consequence of endogeneity issues from two sources: omitted variables and reverse causality. We use an instrumentation strategy as robustness test of our main estimation presented in section 6.1.

First, an omitted variables issue could arise if unobserved class-region time-varying determinants (such as a productivity shock in a given CRY) shapes both the flow of workers and also the novelty activity. The question of causality is particularly relevant in the context of knowledge spillovers. The professional mobility of workers between different regions is not random. On the one hand, the size of flows studied may be partly correlated with the size of the population of the host regions. For example, structurally, the Île-de-France region receives larger flows of workers than the other regions because it represents the largest employment area in France. If the novelty indicator is correlated with the size of the region, an endogeneity problem may arise, since regions hosting more mobile workers will also have on average higher novelty indicators for all technological subclasses. The inclusion of three sets (class-region, region-year, class-year) of fixed effects mitigates much of this issue, but still some time-varying variable could be omitted, even when we take into account the standard determinants of novelty.

Second, there may also be a reverse causality, as mobility choices may be affected by the dynamics of specialization of regions in certain technological subclasses. For example, a region developing an innovation activity in one or more technological subclasses may resort to recruiting skilled workers with previous experience in the field. The recruitment of these workers may take place in firms already innovating in these technologies, and these firms are likely to be located in regions specializing in these technologies. This endogeneity issue is widespread in the migration literature (Jaeger et al., 2018) and the identification strategy builds on a more canonical approach that is applied in different branches of the economic literature. This general approach is called shift-share instruments or Bartik instruments (Bartik, 1991), and it has become quite prevalent in the immigration and labor market literature following the work of Altonji and Card (1991) and Card (2001), and more recently on migration and innovation (Bahar et al. 2020; Diodato et al., 2022).

We propose an IV strategy to address the aforementioned issues by utilizing the shift-share methodology and the employment data, based on bilateral flow of skilled workers outlined above. The aim is to create a predicted flow of workers $\widehat{\mathrm{MOB}}_{r' \to r,y}$ that is less dependent on the local demand for workers specialized in a subclass *c*, who are moving to a particular region r and year y. This would neutralize the reverse causality problem as in the shifts we take out the workers going from region r' to region r of the calculation. To do so, for each PCS category, we first calculate the percentage of workers who originated from a specific region r' and ended up in region r in the reference year y^0 (share). Next, for a given PCS category, we calculate the yearly sum of high-skilled workers in this PCS category who migrated from r' to every other r'' region (shift) than the region r we are focusing on. Using this information, we can determine an imputed measure $\widehat{\mathrm{MOB}}_{r' \to r,y}$ that accurately reflects the migration patterns of high-skilled workers across different regions:

$$\widehat{\mathrm{MOB}}_{r' \to r,y} = \underbrace{\left(\frac{\mathrm{Mob}_{r' \to r,y^0}}{\sum_{r \neq r'} \mathrm{Mob}_{r' \to r,y^0}} \right)}_{\text{Share}} * \underbrace{\left(\sum_{r' \neq r''} \mathrm{Mob}_{r' \to r'',y} \right)}_{\text{Shift}} \quad (9)$$

The idea behind the predicted flow of workers $\widehat{\mathrm{Mob}}_{r' \to r,y}$ used in the instrument is to use the total mobility flows measured a given year arriving in region r, under the assumption that these total flows are not correlated with the region's specific needs in a technological class, on a give year *y*. Indeed, the reverse causality problem may be linked to the fact that the innovation dynamic observed in a given technology class induces temporary and targeted recruitment in regions with a comparative advantage in that technology class. Taking inflows from all regions cleanses the flow variables of this potential endogeneity problem. The bilateral flow proxy between r' and r is then calculated by weighting the total flows into region r by the share of flows into region r from region r' in a given reference year y_0. Taking a reference share distant in time helps to hedge against reverse causality, and is based on the assumption that the regions of origin of incoming flows are experiencing a stable trend, beyond the potential shocks that may arise when the region recruits specifically from regions specializing in the technological classes in which it files a patent.

The predicted bilateral measure $\widehat{\mathrm{Mob}}_{r' \to r,y}$ is then weighted by the RTA in the origin region r' and then summed across all regions r'≠r. The resulting imputed instrument $\mathrm{High\ Skilled\ Mobility\ IV}_{c,r,y}$ is formally computed as follow:

$$\text{High Skilled Mobility IV}_{c,r,y} = \sum_{r' \neq r} \widehat{\text{MOB}}_{r' \rightarrow r,y} * RTA_{c,r',y} \quad (10)$$

The variable calculated in equation 10 is then used as an instrument of the variable detailed in equation 7 in a two-stage least squares estimation. Tests for under-identification (Kleibergen-Paap), over-identification (Sargan-Hansen) and weak instruments (Cragg-Donald) are used to investigate the robustness of the identification strategy.

Instrumentation strategy: results

The shift and share strategy used in a two-stage least squares does not alter the significance of the results. The coefficients associated with skilled worker flows remain positive and significant (Table 10, column 1).

Table 10 - Instrumentation

	Second Stage Novelty	1st stage regression High Skilled Mobility
High Skilled Mobility (RTA)	0.0043**	
	[0.0018]	
Relatedness density	-0.0250**	-0.0035
	[0.0120]	[0.0081]
RelatedDens_sq	0.0063	-0.0055
	[0.0136]	[0.0087]
New subclass	0.3499***	0.0033
	[0.0112]	[0.0043]
# of patents in the subclass	0.4328***	-0.0024+
	[0.0047]	[0.0013]
Missing subclass	-0.1840***	-0.0031**
	[0.0049]	[0.0015]
Share of extra-regional inventors	-0.0023	0.0064***
	[0.0023]	[0.0013]
External instrument		0.9411***
		[0.0024]
Observations	2.78e+05	
R-Squared	0.2777	
Weak identification Kleibergen-Paap Wald F		1.52e+05

*Note: Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01. Estimation method: Linear regression with high-dimensional fixed effects.*
Source: OECD REGPAT database. EPO and PCT patent filing data. BTS database.
Field: Metropolitan France patents and workers flows.

8.3. Placebo tests: the effect of police forces and clergy on innovation

One last robustness is presented below. Indeed, our estimates focus on the effect of the arrival of skilled workers from regions specialized in a technological subclass. It is interesting to test whether these effects remain when the workers considered are not skilled workers but workers belonging to socio-professional categories from which no effect on innovation is expected. The mobility of the police force and the clergy is used as a placebo test, keeping the weighting by the RTAs. These flows are not associated with any significant effect as show in Table 11 below. This result also reinforces the robustness of the previous results.

Table 11 - Identification strategy validity		
	Second Stage Novelty	1st stage Cops and Clergy Mobility
Police and Clergy mobility	0.0021	
	[0.0014]	
Relatedness density	-0.0170**	-0.0137
	[0.0083]	[0.0145]
Relatedness density sq	0.0223**	-0.0429***
	[0.0097]	[0.0156]
New subclass	0.1023***	0.0180**
	[0.0088]	[0.0083]
# of patents in the subclass	0.0038***	-0.0013
	[0.0014]	[0.0015]
Missing subclass	-0.1558***	-0.0035+
	[0.0016]	[0.0018]
Share of extra-regional inventors	0.0005	-0.0045+
	[0.0014]	[0.0023]
External Instrument		0.4253***
		[0.0023]
Observations	2.78e+05	
R-Squared	0.0300	
Weak identification Kleibergen-Paap Wald F		3.56e+04

*Note: Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01. Estimation method: Linear regression with high-dimensional fixed effects.*
Source: OECD REGPAT database. EPO and PCT patent filing data. BTS database.
Field: Metropolitan France patents and workers flows.

9. Conclusion

The literature analyzing the link between migration and innovation dynamics emphasizes the external knowledge source represented by migration, thereby contributing to the diversification of local knowledge bases. The transfer of knowledge made possible through worker mobility offers an opportunity to broaden the technological portfolio of host regions. This not only facilitates innovation in new technological fields but also enables specialization in previously untapped technological domains at the regional level. In essence, mobile workers serve as agents of structural technological change, promoting technological diversification by facilitating patenting in the specialized fields of their regions of origin. However, the integration and recombination of knowledge imported by mobile workers may prove challenging if it deviates significantly from the activities carried out within the host region. Recent literature also suggests that the utilization of external knowledge brought in by mobile workers varies depending on the composition of work teams. Teams comprising both local and migrant inventors tend to blend local knowledge with the newly acquired external knowledge, whereas teams consisting solely of migrant inventors drive unrelated diversification by relying exclusively on external knowledge.

Our study aims to comprehensively investigate the mechanisms through which knowledge transfers, facilitated by the inter-regional mobility of skilled workers, are integrated and recombined within their host regions and can lead to technological novelty. A first important contribution lies in adopting the lens of national inter-regional mobility to analyze the impact of professional mobilities on innovation. This approach acknowledges that migration primarily occurs at the regional level and that technological specialization is regional before being national. Our findings reveal that the mobility of skilled workers fosters the emergence of novel technological combinations in the technological classes in which the mobile workers' region of origin is specialized in. Furthermore, the influence of inter-regional migration on technological novelty extends beyond mere replication of existing technological combinations found in other regions, as new combinations are new not only at the regional but also at the national and sometimes international level.

However, not all forms of knowledge are integrated the same way within host regions. If mobile workers originate from regions with specialized areas that significantly differ from the technological activities prevalent in the host region, their mobility will not have a statistically significant effect on technological novelty. This suggests the presence of an enhancement effect between worker inflows and the local technology space in the host region. However, technological novelty enabled by workers mobility not only reinforces specialization and encourages patenting in technological classes already used within host regions but can also enable the introduction of new technological classes. The technological novelty linked to migration is thus driven by the complementarity of the specialization structures of both regions of departure and arrival but can also lead to the exploration of technological classes that are new to the host region through the technological combinations being observed.

Our study therefore enables us to study in greater detail the role of professional mobility on the technological development of regions, taking into account the specificities of the technological spaces of the regions from which mobile workers originate and those in which they are received. This approach sheds light on the mechanisms of knowledge transmission enabled by occupational mobility, looking specifically at the technological fields in which they occur and the conditions under which they generate new technological combinations.

However, our study suffers from some limitations. Focusing on the inflow of workers coming from regions specialized in a technology impedes to study the characteristics of the second class associated with the new combination. Our analysis shows that mobility does indeed enable the emergence of both reuse and creation-type novelties, but it might be interesting to extend the analysis by measuring the relatedness between the two classes making up each new combination, as well as the relatedness density of each of these two classes in relation to the technological space of the regions of departure and arrival. Indeed, our study does not allow to conclude whether the new combinations favored by the arrival of workers are subclasses that are distant from each other. It is possible that the necessary condition allowing innovation leads to the emergence of new combinations in which one class is close to the specialization of the host region and the other is only close to the specialization of the region of departure. It is therefore possible that the complementarity between technological areas can create combinations between distant domains. These questions, which relate more to the characteristics of the technological innovation produced than to the mechanisms by which this innovation emerges, deserve to be characterized thoroughly and should be the focus of future research.

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Apprendix 1

The paper uses the International Patent Classification (IPC) to characterize the technology subclasses in which regions are specialized. Each patent is characterized and classified according to the technologies combined to form an invention. As an example, consider Patent EP19980933721 applied for by the company Pernod-Ricard in 1997 for "making a composition for producing corks", by two inventors, and one is located in the Paris region (FR10). The patent is assigned to three four-digit IPC codes B27J (Mechanical working of cork), B27N (Manufacture made from particles or fibers of wood) and C08L (Composition of macromolecular compounds)[12].

The novelty of a subclass or its combination is considered at the regional level, based on the location of inventors, and over the whole European patent history.

- Regarding single subclasses, B27J appears for the first time in the region in year 1997 and in this patent, whereas the others were already used in the past (see table below).
- Regarding combinations, the patent can be decomposed as three distinct pairwise combinations: (B27J;B27N), (B27J;C08L) and (B27N;C08L).

This patent has a high degree of novelty as each of the three combinations appear for the first time in the region. However, novelty can be characterized differently. (B27J;B27N) and (B27J;C08L) are combinations that include a subclass B27J previously unknown in the region, and thus they are characterized as "Recombinant creation" whereas (B27N;C08L) is characterized as "Recombinant reuse" as both subclasses are already part of the technological portfolio, that is, they have appeared previously in a patent but never together. Thus, this patent is the first to combine both of these subclasses. Recombinant reuse corresponds to the situation where both codes already exist in the region's portfolio but are combined for the first time. Recombinant creation is the situation in which at least one of the codes did not occur in any patent applied by local inventors and thus not present in the regions' portfolio.

Table A1 - Characterizing novelty

IPC subclass	Year of IPC entry in the region	Combination	Year of novel combination in the region	Already existing combination	Recombinant reuse	Recombinant creation
Example 1: Patent EP19980933721 Priority year 1997						
B27J	1997	B27J ; B27	1997			B27J ;B27
C08L	1978	B27J ; C08L	1997		B27J ; C08L	
B27N	1978	B27N ; C08L	1997		B27N ; C08L	
Example 2: Patent EP19970401843 Priority year 1996						
C07C	1978	C07C ; C12F	1978			C07C ; C12F
C11B	1978	C07C ; C11B	1978	C07C ; C11B		
C12F	1996	C11B ; C12F	1996			C11B ; C12F

Another example is given by Patent applied for by Pernot Ricard by inventors located in the Paris Region and in year 1996 for "extracting 2-phenylethanol from residues obtained

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during alcohol production by fermentation". Among the three combinations (see table below), two are new to the region and enter the category Recombinant creation as they combine subclass C12F which occurs for the first time in a patent in the region whereas the combination C07C ; C11B has already been used in the region in 1978[13].

Appendix 2

Table A2 – descriptive statistics

	Mean	SD	Min	Max
Novelty	0.38	1.07	0.00	25.00
Novelty (France)	0.11	0.48	0.00	18.00
Novelty (World)	0.02	0.15	0.00	6.00
Novelty Binary	0.17	0.38	0.00	1.00
Novelty Binary (France)	0.07	0.25	0.00	1.00
Novelty Binary (World)	0.01	0.11	0.00	1.00
Novelty Share	0.10	0.26	0.00	1.00
Novelty Share (France)	0.02	0.11	0.00	1.00
Novelty Share (World)	0.00	0.04	0.00	1.00
Novelty Reuse	0.35	1.02	0.00	25.00
Novelty Creation	0.03	0.26	0.00	18.00
New subclass	0.01	0.09	0.00	1.00
Specialization	0.03	0.16	0.00	1.00
High Skilled Mobility (RTA)	1165.30	1963.84	0.00	34235.00
High Skilled Mobility (RTA_FR)	1163.23	1849.68	0.00	30351.00
High Skilled Mobility (RD)	1095.46	1804.71	0.00	27477.00
High Skilled Mobility (Size)	10.61	40.58	0.00	3042.27
Relatedness density	0.27	0.26	0.00	1.00
# of patents in the subclass	1.66	9.74	0.00	773.00
Missing subclass	0.71	0.45	0.00	1.00
Share of extra-regional inventors	0.23	0.35	0.00	1.00
Observations 308 308				

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Table A3 - Robustness Checks : alternative novelty indicators

	Novelty (Binary)	Novelty (Share)
High Skilled Mobility (RTA)	0.0019+	0.0018**
	[0.0010]	[0.0007]
Relatedness density	-0.0157	-0.0199**
	[0.0106]	[0.0077]
RelatedDens_sq	0.0143	0.0105
	[0.0123]	[0.0086]
New subclass	0.2236***	0.3551***
	[0.0088]	[0.0091]
# of patents in the subclass	-0.0118***	-0.0313***
	[0.0022]	[0.0015]
Missing subclass	-0.5724***	-0.4401***
	[0.0037]	[0.0035]
Share of extra-regional inventors	-0.0052***	-0.0046***
	[0.0020]	[0.0017]
Constant	0.5751***	0.4194***
	[0.0064]	[0.0051]
Observations	294294	294294
R-Squared	.5925	.5217

Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01

Table A4 - Robustness Checks
Poisson pseudo-maximum likelihood regressionswith high-dimensional fixed effects

High Skilled Mobility (RTA)	0.025**
	[0.0103]
Relatedness density	-0.062
	[0.0898]
RelatedDens_sq	0.017
	[0.0931]
New subclass	0.2235***
	[0.0325]
# of patents in the subclass	-0.0414***
	[0.0078]
Share of extra-regional inventors	-0.0089
	[0.0161]
Constant	-0.3725***
	[0.077]
Observations	80630
R-Squared	0.1048

Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01

Table A5 - Robustness checks

	Novelty		
	Excluding Ile de France	**Excluding Rhône-Alpes**	**Excluding Corsica**
High Skilled Mobility (RTA)	0.0023+	0.0031**	0.0037***
	[0.0013]	[0.0013]	[0.0013]
Relatedness density	-0.0160	-0.0094	-0.0123
	[0.0131]	[0.0136]	[0.0138]
RelatedDens_sq	0.0136	0.0049	0.0089
	[0.0153]	[0.0155]	[0.0159]
New subclass	0.2874***	0.2902***	0.2981***
	[0.0126]	[0.0127]	[0.0127]
# of patents in the subclass	-0.0134***	-0.0127***	-0.0107***
	[0.0030]	[0.0030]	[0.0030]
Missing subclass	-0.5811***	-0.5783***	-0.5771***
	[0.0050]	[0.0051]	[0.0050]
Share of extra-regional inventors	-0.0060**	-0.0076***	-0.0068***
	[0.0024]	[0.0024]	[0.0024]
Constant	0.5863***	0.5795***	0.5796***
	[0.0085]	[0.0086]	[0.0088]
Observations	280917	280917	280917
R-Squared	.5486	.55	.5532

Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01

Table A6 - Robustness check regarding the issue of bad controls

	Main result									
L.High Skilled Mobility (RTA)	0.0034***	0.0075***	0.0075***	0.0057***	0.0075***	0.0040***	0.0072***	0.0072***	0.0056***	0.0039***
	[0.0012]	[0.0016]	[0.0016]	[0.0016]	[0.0016]	[0.0012]	[0.0016]	[0.0016]	[0.0016]	[0.0012]
Relatedness density	-0.0111		-0.0108					-0.0063	0.0049	-0.0154
	[0.0134]		[0.0164]					[0.0164]	[0.0158]	[0.0135]
RelatedDens_sq	0.0076		0.0036					0.0020	-0.0055	0.0106
	[0.0155]		[0.0183]					[0.0183]	[0.0178]	[0.0156]
New subclass	0.2904***			0.8096***					0.8089***	
	[0.0125]			[0.0128]					[0.0128]	
# of patents in the subclass	-0.0103***				0.0036			0.0033	0.0088***	-0.0128***
	[0.0030]				[0.0033]			[0.0033]	[0.0033]	[0.0030]
Missing subclass	-0.5774***					-0.5974***				-0.5976***
	[0.0049]					[0.0051]				[0.0051]
Share of extra-regional inventors	-0.0066***						-0.0270***	-0.0267***	-0.0095***	-0.0123***
	[0.0024]						[0.0033]	[0.0033]	[0.0032]	[0.0025]
Constant	0.5807***	0.1424***	0.1452***	0.1465***	0.1410***	0.5861***	0.1502***	0.1506***	0.1454***	0.5977***
	[0.0083]	[0.0092]	[0.0095]	[0.0092]	[0.0092]	[0.0080]	[0.0092]	[0.0096]	[0.0096]	[0.0084]
Observations	294294	294294	294294	294294	294294	294294	294294	294294	294294	294294
R-Squared	.5552	.3798	.3798	.4044	.3798	.5521	.38	.38	.4045	.5522

Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01

Novelty is measured as the number of distinct combinations associated with a given ipc code found in all patents in a year and region

Table A7 - Impact of hilly skilled labor mobility on novelty including lag of y-2

	Novelty			
	(1)	(2)	(3)	(4)
High Skilled Mobility (RTA)	0.0043***			
	[0.0015]			
High Skilled Mobility (RTA) (lag 2)	-0.0016			
	[0.0016]			
High Skilled Mobility (RTA FR)		0.0035**		
		[0.0017]		
High Skilled Mobility (RTA FR) (lag 2)		0.0008		
		[0.0016]		
High Skilled Mobility (Size)			0.0108***	
			[0.0032]	
High Skilled Mobility (Size) (lag 2)			0.0088***	
			[0.0029]	
High Skilled Mobility (Related Density)				0.0024
				[0.0019]
High Skilled Mobility (Related Density) (lag 2)				-0.0010
				[0.0018]
Relatedness density	-0.0033	-0.0034	-0.0036	-0.0035
	[0.0138]	[0.0138]	[0.0138]	[0.0138]
Relatedness density sq	-0.0004	-0.0003	-0.0002	-0.0002
	[0.0160]	[0.0160]	[0.0160]	[0.0160]
New subclass	0.2976***	0.2975***	0.2978***	0.2977***
	[0.0130]	[0.0129]	[0.0130]	[0.0130]
# of patents in the subclass	-0.0113***	-0.0113***	-0.0108***	-0.0113***
	[0.0030]	[0.0030]	[0.0030]	[0.0030]
Missing subclass	-0.5761***	-0.5761***	-0.5760***	-0.5762***
	[0.0050]	[0.0050]	[0.0050]	[0.0050]
Share of extra-regional inventors	-0.0068***	-0.0069***	-0.0071***	-0.0069***
	[0.0025]	[0.0025]	[0.0025]	[0.0025]
Constant	0.5830***	0.5729***	0.5739***	0.5916***
	[0.0096]	[0.0112]	[0.0071]	[0.0130]
Observations	280280	280280	280280	280280
R-Squared	.5561	.5561	.5562	.5561

Note: Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01

Novelty is measured as the number of distinct combinations associated with a given ipc code found in all patents in a year and region

TABLE A7bis - Impact of hilly skilled labor mobility on novelty including lag of y+1

	Novelty	
	(1)	(2)
High Skilled Mobility (RTA) (y+1)	-0.0025	
	[0.0013]	
High Skilled Mobility (RTA FR) (y+1)		0.0017
		[0.0015]
Relatedness density	0.0214	0.0215
	[0.0136]	[0.0155]
RelatedDens_sq	-0.0101	-0.0101
	[0.0155]	[0.0155]
New subclass	0.2852***	0.2853***
	[0.0122]	[0.0122]
# of patents in the subclass	0.0292***	0.0292***
	[0.0030]	[0.0030]
Missing subclass	-0.5744***	-0.5745***
	[0.0049]	[0.0049]
Share of extra-regional inventors	0.0280***	0.0281***
	[0.0028]	[0.0028]
Constant	0.5846***	0.5800***
	[0.0083]	[0.0098]
Observations	294294	294294
R-Squared	.3666	.1683

Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01
Estimation method: Linear regression with high-dimensional fixed effects.

Table A8 - Disentangling the effects including lag y-2

	Novelty				Recombinant Reuse	Recombinant Creation
	(1)	(2)	(3)	(4)	(5)	(6)
	RD < med.	RD > med.	RTA = 0	RTA = 1		
High Skilled Mobility (RTA)	0.0036**	0.0055	0.0018	0.0110**	0.0032**	0.0013**
	[0.0016]	[0.0034]	[0.0015]	[0.0051]	[0.0015]	[0.0006]
High Skilled Mobility (RTA) (lag 2)	-0.0031+	0.0034	-0.0033**	0.0069	-0.0014	0.0001
	[0.0018]	[0.0033]	[0.0016]	[0.0047]	[0.0015]	[0.0006]
Relatedness density	-0.0076	-0.0154	0.0051	-0.0719+	0.0072	-0.0167***
	[0.0174]	[0.0255]	[0.0139]	[0.0424]	[0.0138]	[0.0061]
Relatedness density sq	0.0014	0.0126	-0.0125	0.0631	-0.0072	0.0108+
	[0.0197]	[0.0278]	[0.0155]	[0.0424]	[0.0160]	[0.0063]
New subclass	0.2918***	0.2879***	0.2532***	0.0000		
	[0.0160]	[0.0214]	[0.0133]	[0.0000]		
# of patents in the subclass	-0.0118**	-0.0140***	-0.0024	-0.0133***	-0.0058+	-0.0085***
	[0.0051]	[0.0034]	[0.0043]	[0.0039]	[0.0030]	[0.0008]
Missing subclass	-0.5992***	-0.5650***	-0.6265***	-0.5021***	-0.5156***	-0.0935***
	[0.0072]	[0.0054]	[0.0058]	[0.0059]	[0.0045]	[0.0034]
Share of extra-regional inventors	-0.0043	-0.0109***	-0.0012	-0.0085	0.0054**	-0.0181***
	[0.0039]	[0.0035]	[0.0032]	[0.0056]	[0.0024]	[0.0012]
Constant	0.6057***	0.5482***	0.6436***	0.4613***	0.5293***	0.0840***
	[0.0101]	[0.0224]	[0.0104]	[0.0379]	[0.0092]	[0.0043]
Observations	132413	143584	201927	76747	280280	280280
R-Squared	.6324	.5477	.6127	.5569	.5339	.171

RD < (resp. >) med is a split sample when Relatedness density is < (resp. >) median; RTA =1 (resp. = 0): split sample when RTA =1 (resp. =0)

Robust standard errors clustered at fixed effects level (multiway) are shown in brackets. + 0.10 ** 0.05 ***0.01

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