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# *Innovation in diversified cities: Evidence from Canada's urban areas*

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## Abstract

This paper examines the impact of cultural and industrial diversity on innovation across 152 Canadian urban areas from 2001 to 2021. By applying a knowledge spillover lens, it associates such diversity with enhanced knowledge variety and diffusion. Using inventor counts and Shannon indices as proxies for innovation and diversity, the authors show that cultural and industrial diversity fosters innovation. An increase of one standard deviation in cultural diversity raises innovation by 13.4% to 81.7%, while the same increase in industrial diversity raises it by 6.6% to 36.6%. Their interaction synergistically yields an additional 2.2% to 12.4% increase in innovation. Meanwhile, recent immigration diversity amplifies these effects, validating the knowledge mechanisms and highlighting significant theoretical and policy implications.


Keywords: Cultural diversity, immigration, industrial structure, innovation, knowledge spillovers

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# Introduction

Innovation is a central engine of economic growth, technological advancement and urban resilience (Balland et al., 2015). In an increasingly interconnected and competitive global economy, cities and regions must sustain innovative activity to remain productive and attractive (Florida, 2002). Among the most debated sources of urban innovation is diversity (Sorenson, 2023). Notably, cultural diversity and industrial diversity have been studied as distinct drivers of innovation. Cultural diversity, through ethnically heterogeneous cities, can expand the urban knowledge and skill pool, fostering creativity and problem-solving (Florida, 2002; Kemeny and Cooke, 2018; Saxenian, 2006). Meanwhile, industrial diversity, reflected in a city's varied industrial base, facilitates knowledge spillovers and adaptation in changing environments (Boschma and Frenken, 2006).

Intuitively, each diversity dimension is expected to foster innovation. However, evidence-based theory explicitly linking their combined effects remains limited, despite longstanding calls for more realistic, non-linear models of urban innovation (Shearmur et al., 2016; von Hippel, 2005). Even less is known about the temporal dimension of diversity's innovation effects (Kemeny & Cooke, 2018; Sorenson, 2023), meaning there is no definitive theory or evidence on whether cities realize more substantial innovation gains from the earlier or later stages of diversity. Thus, policy makers in developed countries lack the insights required to proactively respond to declining urban innovation from restrictive immigration policies and an eroding industrial base (Abramitzky et al., 2023; Balland et al., 2015; Clemens and Pritchett, 2019; Lincicome, 2021).

This paper addresses these gaps by asking: how does cultural and industrial diversity jointly influence urban innovation? A knowledge spillover perspective that builds on relevant insights from foundational research (e.g., Aghion and Jaravel, 2015; Audretsch and Feldman, 1996; Grossman and Helpman, 1991; Jaffe et al., 1993) was developed. Innovation is conceptualized as a process of knowledge recombination, dependent on the scope of knowledge variety and the speed of diffusion. Cultural and industrial diversity are theorized to synergistically amplify urban innovation by expanding knowledge variety without compromising the pace of knowledge diffusion. Additionally, incorporating the contingent effects of recent immigrant diversity introduces a temporal dimension that better identifies these mechanisms. The framework was validated by analyzing a unique dataset of 152 Canadian urban areas spanning the period from 2001 to 2021. This approach applies suitable econometric techniques and proxies for innovation and diversity, thereby mitigating endogeneity and other threats to the reliability of the estimates. Canada offers a particularly relevant context, as it is characterized by high multiculturalism—nearly one in four workers are foreign-born—and a diverse industrial landscape.

This study offers several contributions to the literature. First, it provides novel empirical evidence on the joint effects of cultural and industrial diversity on urban innovation, aligning with the mechanisms of knowledge variety and diffusion. It clarifies and affirms theories that emphasize innovation as a creative recombination process enabled by the interactions of co-located entities (e.g., individuals or firms) with diverse yet complementary knowledge (Boschma and Frenken, 2006; Asheim et al., 2011; Audretsch and Feldman, 2004). Second, by explicitly integrating the temporal dimension of immigration, it demonstrates how recent immigration disproportionately enhances the innovation returns to diversity, further corroborating the proposed mechanisms.

By identifying the recency of immigrant diversity as a critical contingent factor, this study also extends the established literature on immigrant innovation (Hunt & Gauthier-Loiselle, 2010; Kerr & Lincoln, 2010; Ottaviano & Peri, 2006; Saxenian, 2006) while supporting emerging work on immigrants as dynamizing conduits of new knowledge streams (Buchholz, 2021; Diodato et al., 2022; Kemeny and Cooke, 2018; Wigger, 2022). Finally, by leveraging a unique Canadian context and robust econometric methods, this paper offers actionable insights for regional or urban policies aimed at fostering innovation and resilience in diverse advanced economies. Specifically, its findings highlight the importance of harmonizing immigration, industrial and innovation policies to fully realize the potential of diversity-driven knowledge spillovers (Sorenson, 2023; Nathan & Lee, 2013).

The remainder of this paper is organized as follows. Section 2 develops the theoretical framework. Section 3 describes data sources and measures. In addition to describing the empirical approach, Section 4 reports the estimates for the relationship between innovation and cultural and industrial diversity and the contingent effects on recent immigrant diversity. Section 5 discusses robustness checks. Section 6 concludes with implications for theory and policy.

# Theoretical framework

Economic geography research has consistently emphasized the crucial role of agglomeration externalities in fostering innovation and economic growth (Grossman and Helpman, 1991), particularly when observing or acquiring external knowledge through interpersonal or interfirm interactions is possible (Aghion and Jaravel, 2015; Audretsch and Feldman, 2004; Glaeser et al., 1992; Jaffe et al., 1993). Building on this knowledge spillover perspective (Jacobs, 1969; Feldman and Audretsch, 1999), this study conceptualizes innovation as a creative exercise in commercially viable recombinations of existing knowledge (Schumpeter, 1939; Weitzman, 1998). This framework highlights two distinct but complementary mechanisms through which urban diversity, in its cultural and industrial dimensions, can foster innovation: the scope of knowledge variety and the speed of knowledge diffusion.

The scope of knowledge variety refers to the breadth and heterogeneity of knowledge, skills and heuristics available within a localized economy (Frenken et al., 2007; Weitzman, 1998). Intuitively, a greater scope of knowledge variety increases the potential for recombining disparate knowledge elements to generate new or improved solutions to existing and emerging problems (Asheim et al., 2011). Conversely, the speed of knowledge diffusion focuses on the rate at which ideas and practices spread across individuals or organizations operating in various sectors and urban areas (de Groot et al., 2016; Storper and Venables, 2004). Faster knowledge diffusion can accelerate the recombination process itself and the subsequent adoption and application of new knowledge, thereby converting the underlying knowledge base into innovations. These insights suggest that innovation depends on cultural and industrial diversity across urban areas in complex ways, requiring systematic theoretical and empirical clarification.

## Cultural diversity and innovation

Cultural diversity refers to the heterogeneity of ethnic, national and cultural backgrounds within an urban population (Ottaviano and Peri, 2006; Kemeny and Cooke, 2018). It can directly broaden the scope of knowledge variety available within a city's human capital pool (Kemeny and Cooke, 2018). Diverse cultural groups bring distinct cognitive frameworks, problem-solving heuristics and culturally embedded tacit knowledge (Gertler, 2003; Howells, 2002). This inherent heterogeneity enriches the stock of conceptual templates and informational inputs, fostering a wider array of perspectives on challenges and solutions, which is a critical precursor to novel recombination (Weitzman, 1998). For the ethnic dimension of cultural diversity, a diverse immigrant population can be a significant source of innovation-enabling knowledge variety (Buchholz, 2021). Compared with the native-born population, immigrants often embody fresh and internationally sourced knowledge, unique skill sets, and global networks, which can expand the scope of knowledge for innovation beyond what would be otherwise possible (Diodato et al., 2022; Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Wigger, 2022).

While the primary impact of cultural diversity on knowledge variety is straightforward, its influence on the speed of knowledge diffusion is ambiguous. On the one hand, the potential for ethnic enclaves or social distance across groups could impede the flow of knowledge and slow its diffusion rate (Alesina and La Ferrara, 2005; Reagans, 2011). On the other hand, a highly diverse population with potentially less integrated and more mobile individuals could foster dynamic social networks that increase the rate of knowledge exchange. Thus, even if cities face a trade-off between maximizing knowledge variety and optimizing diffusion speed, cultural diversity, particularly through its ethnic dimension, is expected to translate into a higher level of urban innovation. Consistent with this view, evidence indicates that greater immigrant diversity is robustly associated with increased worker productivity (Ottaviano and Peri, 2006; Kemeny and Cooke, 2018) and higher rates of innovation (Hunt & Gauthier-Loiselle, 2010).

## Industrial diversity and innovation

Beyond cultural heterogeneity, cities also exhibit industrial diversity, which refers to the variety and evenness of business sectors in an urban economy (Duranton and Puga, 2001; Frenken et al., 2007). The debate regarding the merits of industrial specialization versus diversification externalities has long been central to economic geography. While the Marshallian view emphasizes the performance-enhancing benefits of intra-industry knowledge deepening and economies of scale, the Jacobsian view highlights the potential for superior performance from industrial diversity through cross-sectoral knowledge spillovers (Beaudry and Schiffauerova, 2009; Jacobs, 1969; de Groot et al., 2016).

In line with the Jacobsian perspective, a heterogeneous industrial structure provides a greater number of distinct sectoral interfaces, thereby creating multiple cross-sectoral pathways through which knowledge can flow and be recontextualized (Audretsch and Feldman, 2004). This multiplicity of linkages within diverse industrial environments can accelerate knowledge diffusion by reducing the search and adoption costs associated with finding complementary knowledge and applications. Meta-analyses and microgeographic studies suggest that these diversity effects are especially salient at fine-grained spatial scales—where opportunities for unplanned, serendipitous interfirm and interindividual interactions are maximized, thereby boosting information exchange and innovation (Sorenson, 2023). Thus, industrial diversity is expected to foster urban innovation primarily by expanding the business or industrial knowledge stock and potentially improving knowledge diffusion for the average city.

## The joint effect: Amplifying knowledge variety and diffusion

The co-occurrence of cultural diversity and industrial diversity will be synergistic, as they jointly amplify the scope of knowledge variety and could facilitate a workable pace of knowledge diffusion. Culturally diverse cities contribute a broader range of heterogeneous ideas, problem-solving approaches and unique insights. When individuals are embedded within industrially diversified urban areas, their unique perspectives encounter a greater variety of complementary industrial contexts and applications (Buchholz, 2021; Diodato et al., 2022; Florida, 2002; Jacobs, 1969). This synergy is not merely additive. The diversified industrial structure provides the necessary channels and environments for the varied knowledge embodied in an ethnically diverse population to diffuse more rapidly and yield novel recombinations (Sorenson, 2023). This situation generates a creative dynamism greater than the sum of its parts, combining expansive raw knowledge inputs with an enabling industrial structure to accelerate urban innovation (Kemeny and Cooke, 2018; Sorenson, 2023).

### Identifying the mechanisms: The contingent influence of recent immigration diversity

If the knowledge spillover mechanisms articulated in this study are indeed at work, one would expect the joint impact of cultural and industrial diversity on innovation to be significantly influenced by the temporal dimension of ethnically driven cultural diversity. Specifically, recent immigration diversity can function as a crucial contingent factor, providing a unique validation for the theorized mechanisms of knowledge variety and diffusion. Recent immigrants—particularly those linked to economic-class immigration programs—embody fresh and internationally sourced knowledge, unique skill sets, and global networks that are distinct from those of the native-born or long-settled immigrant populations (Buchholz, 2021; Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010).

As they are initially less assimilated into the receiving country’s existing knowledge structures, their knowledge stocks are more differentiated, directly extending the scope of knowledge variety within the urban innovation system. This is a critical distinction, as established immigrant populations, while still contributing to diversity, may have knowledge bases that increasingly converge with those of the receiving country over time (Kemeny and Cooke, 2018). Moreover, recent immigrants often exhibit higher residential and occupational mobility and are strongly incentivized to build new social and professional networks (Kemeny and Cooke, 2018). This active network-building behaviour, spanning various urban areas and sectors, can significantly increase the speed of knowledge diffusion by forming new conduits for knowledge flow. Their global linkages also serve as “pipelines” for global knowledge, complementing local “buzz” by facilitating the inflow of new ideas from abroad (Diodato et al., 2022; Storper and Venables, 2020).

Taken together, this paper’s proposed knowledge spillover perspective suggests that the variation in innovation outcomes across urban areas partially reflects differences in the geographic dispersion and degree of cultural and industrial diversity. More ethnically and industrially diverse urban areas will generate more innovation because they foster a broader scope of knowledge variety without compromising the speed of knowledge diffusion. Because recent immigration diversity enhances these knowledge dynamics, innovation returns to cultural and industrial diversity are expected to be relatively high when immigrant diversity is recent.

# Methodology

## Data sources

This section describes the data used to examine how cultural and industrial diversity influences innovation across 152 Canadian urban areas from 2001 to 2021. It explains how innovation is measured using patent data, how diversity is quantified using census and business data, and what additional variables are included to control for other factors that may affect innovation.

## Measures and variables

### Patent data and measuring innovation

Innovation is measured by the number of inventors per 10,000 people in each urban area. An inventor is defined as an individual who applies for a patent, based on data from the Canadian Intellectual Property Office and Statistics Canada’s Canadian Employer–Employee Dynamics Database. These datasets are linked through the Social Data Linkage Environment (SDLE), which allows for the identification of inventors by location and time. The linkage rate is approximately 67% overall, improving to 70% to 75% after 2005, ensuring a reliable match between patent applicants and their demographic and geographic characteristics.[1]

Using inventors as a proxy for innovation is a common approach in the literature, as patent applications reflect the creation of new ideas, products or processes. While not all innovations are patented, and not all patents are granted or economically valuable, inventor counts offer a consistent and geographically specific measure of innovative activity. This approach is supported by studies such as those of Feldman (1994), who found a strong correlation between patenting and the introduction of new products, and Griliches (1990), who emphasized the role of patents in capturing inventive output. From 2006 to 2016, 46% of patent applications in urban areas in Canada were granted, suggesting that granted patents may have greater economic value. However, inventor counts remain a useful indicator of the overall level of innovation activity in a city.

Urban areas are defined as census metropolitan areas and census agglomerations, which are delineated based on commuting patterns and represent functional labour markets. These boundaries are fixed over time to ensure consistency in the analysis.[2] The dataset includes four five-year periods (2001 to 2006, 2006 to 2011, 2011 to 2016 and 2016 to 2021), resulting in 608 city–period observations. Innovation activity is calculated as the number of inventors divided by the total population of the urban area:

$$Innovation\,activity_c = \frac{\#inventors}{total\ population} x10,000 \quad (1)$$

This measure standardizes inventor counts by city size, allowing for meaningful comparisons across urban areas of different scales (Carlino et al., 2007). Averaging over five-year periods reduces yearly fluctuations, especially in smaller cities.

## Measuring diversity

Diversity is defined as the variety of characteristics within a population or economy, following Alesina and La Ferrara (2005), who describe it as the likelihood that two individuals differ in ethnicity or sector. This study examines two types—cultural diversity (ethnic variety) and industrial diversity (sectoral variety)—each measured with a Shannon index to capture both the number and the evenness of groups (Niebuhr, 2010).

**Cultural diversity:** Cultural diversity is calculated using Canadian census data (2001 to 2021), which record self-reported ethnicities, allowing multiple responses for nuanced identity capture (Statistics Canada, 2001–2021). The Shannon index is used because it accounts for the number of ethnic groups and their proportional balance, unlike simpler fractionalization indices that only measure difference probability (Ottaviano & Peri, 2006; Niebuhr, 2010; Ozgen, 2021). The formula is

$$CultDiv_c^t = -\sum_{i=1}^{N} s_{ic}^t \log\left(s_{ic}^t\right) \quad (2)$$

1. The linkage was done through Statistics Canada's SDLE. Of about 140,000 inventor records, 95,000 were successfully linked, a 67% linkage rate. After 2005, the linkage rate improved to 70% to 75%.
2. Urban area boundaries are fixed for consistency, as detailed in Appendix B.

where the share $s_{ic}^{t}$ represents the proportion of people from a specific ethnic group *i*, in an urban area *c,* during a given period *t*. Higher values indicate greater diversity. Self-reported ethnicities may introduce minor inaccuracies if individuals are unsure of their origins, but this does not systematically bias results (Statistics Canada, 2001–2021).

**Industrial diversity:** Industrial diversity is measured using firm-level data from Statistics Canada's T2-LEAP, which combines corporate income tax returns (T2) with the Longitudinal Employment Analysis Program (LEAP), covering all incorporated businesses in Canada. The analysis includes firms classified under North American Industry Classification System (NAICS) codes 111 to 939, representing a broad range of sectors. The Shannon index is applied to the distribution of firms across sectors in each urban area:

$$IndDiv_{c}^{t} = -\sum_{i=1}^{N} s_{ic}^{t} \log\left(s_{ic}^{t}\right) \tag{3}$$

where the share $s_{ic}^{t}$ represents the proportion of firms in a specific sector *i*, in an urban area *c,* during a given period *t*. Measuring firm counts better isolates the industrial structure, though firms operating in multiple sectors can complicate calculations (Audretsch & Feldman, 2004).

**Joint diversity:** The novelty of this study lies in examining cultural and industrial diversity simultaneously and exploring their interaction, rather than studying them in isolation. Cultural diversity brings together people with different backgrounds, ideas and perspectives, sparking creativity and innovation, as shown by Ottaviano and Peri (2006). Industrial diversity, on the other hand, fosters innovation by enabling knowledge exchange across varied business sectors, as demonstrated by Audretsch and Feldman (2004). However, few studies have investigated how these two forms of diversity interact to influence innovation. It is measured as follows:

$$CultDiv_{c}^{t} \times IndDiv_{c}^{t} \tag{4}$$

The intuition behind this interaction is that cultural diversity and industrial diversity may amplify each other's effects on innovation. A culturally diverse workforce in a city with many different industries could combine unique cultural insights with varied technical expertise, leading to more groundbreaking innovations. For instance, a diverse team in a city with tech and manufacturing sectors may develop novel products by blending global perspectives with cross-industry knowledge. This idea builds on Florida's (2002) concept of the "creative class," which suggests that diverse urban environments attract talent and foster innovation, but extends it by considering how industrial diversity provides the structural support for such ideas to flourish. In contrast, studies like that of Niebuhr (2010) focus primarily on cultural diversity's direct impact on innovation, often overlooking its interplay with industrial structures. By analyzing both types of diversity and their interaction, this study fills a gap in the literature, offering a more comprehensive understanding of how urban diversity drives innovation. This approach is particularly relevant in Canada, where cities exhibit varied combinations of cultural and industrial diversity (as illustrated in figures 2 and 3).

## Control variables

To isolate the effects of diversity on innovation, the analysis includes a set of control variables that capture other factors known to influence innovative activity. These variables are measured at the beginning of each five-year period to reduce the risk of reverse causality.

City size is controlled for by using the logarithm of the total population. The share of the largest ethnic group and the share of the largest industry are included to account for dominance effects, where a single group or sector may shape local dynamics. Human capital is measured by the share of residents with a university degree, reflecting the role of education in fostering innovation. Proximity to research institutions is captured by the logarithm of the distance to the nearest university, while local research capacity is measured by per capita research and development (R&D) expenditures from universities and businesses. Trade openness is included as the sum of imports and exports per capita, indicating a city's exposure to global markets and ideas.

These variables are drawn from multiple sources, including the Canadian Census of Population, the National Accounts Longitudinal Microdata File and Universities Canada. Descriptive statistics for all variables are presented in Table A.1. The data show substantial variation across cities and over time, supporting the identification of meaningful relationships in the regression analysis.

## Model specification

This section presents the empirical strategy used to estimate the effects of cultural and industrial diversity on innovation in Canadian urban areas. The baseline regression model is specified as follows:

$$\log\left(Innovation\ Activity_{cp}^{t}\right) = \alpha + \beta\, CultDiv_c^t + \delta\, IndDiv_c^t + \lambda\left(CultDiv_c^t \times IndDiv_c^t\right) + \gamma\, X_c^t + \theta_p + \tau_t + \varepsilon_{cpt} \quad (5)$$

This equation models the logarithm of innovation activity, defined as the average number of inventors per 10,000 people in urban area *c*, over four five-year periods (2001 to 2006, 2006 to 2011, 2011 to 2016 and 2016 to 2021). The logarithm transformation helps normalize the data, making it easier to interpret percentage changes in innovation. The key independent variables are cultural diversity $CultDiv_c^t$ and industrial diversity $IndDiv_c^t$, measured using the Shannon index, as described. These variables are designed to capture the scope of knowledge variety—cultural diversity reflects the heterogeneity of cognitive and social perspectives, while industrial diversity captures the breadth of sectoral knowledge bases. The interaction term $CultDiv_c^t \times IndDiv_c^t$ is included to reflect the synergistic amplification of innovation through the joint effect of knowledge variety and the speed of knowledge diffusion, where diverse perspectives embedded in varied industrial contexts enhance recombination and the transmission of ideas.

The model also includes a set of control variables $X_c^t$ to account for other factors that may affect innovation. These control variables, measured at the beginning of each period, include the logarithm of the urban area's population to account for city size, the share of the largest ethnic group to control for ethnic dominance, the share of the largest industry to control for sector concentration, the share of residents with a university degree to reflect human capital, the logarithm of the distance in metres to the nearest university to capture proximity to research hubs, the per capita sum of local university and business R&D expenditures to measure available research resources, and the per capita sum of exports and imports to measure an urban area's exposure to new ideas. The model also includes province fixed effects $\theta_p$ to account for regional differences and time fixed effects $\tau_t$ to capture changes over time. The error term $\varepsilon_{cpt}$ represents unexplained variation.

Multiple steps were taken to mitigate biases that could distort estimates. To reduce the risk of bias from reverse causality—where innovation might attract diverse populations or firms—the independent variables were measured at the start of each period (2001, 2006, 2011 and 2016). At the same time, using ordinary least squares (OLS) to estimate this model can lead to biased results because of endogenous choices. For instance, diverse populations or firms may strategically choose to locate in innovative cities to benefit from existing opportunities, inflating the estimated influence of diversity on innovation.

To address this issue, the study employs an instrumental variable (IV) approach using a "shift-share" strategy. This method predicts local diversity by combining the initial shares of ethnic groups or firms in each urban area in a base year (1996) with their national growth rates over time (1996 to 2001, 1996 to 2006, 1996 to 2011 and 1996 to 2016). For each urban area in 2001, 2006, 2011 and 2016, the predicted share of each ethnic group or industry is calculated as:

$$\widehat{s_{ic}^{t}} = s_{ic}^{1996}\left[1+\left(g_{i}^{-c}\right)_{1996-t}\right] \tag{6}$$

Here, $s_{ic}^{1996}$ is the share of group *i* (ethnic group or industry) in urban area *c* in 1996, and $\left(g_{i}^{-c}\right)_{1996-t}$ is the national growth rate of that group from 1996 to year *t*, excluding the urban area's contribution to ensure exogeneity.[3] These predicted shares are used to compute predicted diversity indices for each urban area and period, which serve as instruments for cultural and industrial diversity, as well as their interaction. This approach isolates variation in diversity driven by national trends, thereby reducing bias from local innovations that influence diversity.

$$\widehat{Div_{ic}^{t}} = -\sum_{i=1}^{N}\widehat{s_{ic}^{t}}\log\left(\widehat{s_{ic}^{t}}\right) \tag{7}$$

The shift-share instrument is widely used in diversity studies, as it leverages historical patterns and national growth to predict local changes (Card, 2001; Ottaviano and Peri, 2006). By focusing on enterprise counts for industrial diversity, the study avoids confounding sectoral variety with workforce diversity, ensuring a clear analysis of the interaction between cultural and industrial diversity.

# Results

## Preliminary results

In this section, descriptive statistics from preliminary analyses illustrate the variation across cities and over time. Nationally, 67,969 inventors were identified from 2001 to 2021, with the highest concentrations in Ontario and Quebec. Table 1 shows that innovation activity varies widely across cities, ranging from 0 to 1.62 inventors per 1,000 people, with a national average of 0.86.

3. For industrial diversity, the growth rate is based on data from 1997 instead of 1996, as NAICS coding begins in 1997.

**Table 1**
**Distribution of inventors by province or territory, 2001 to 2021**

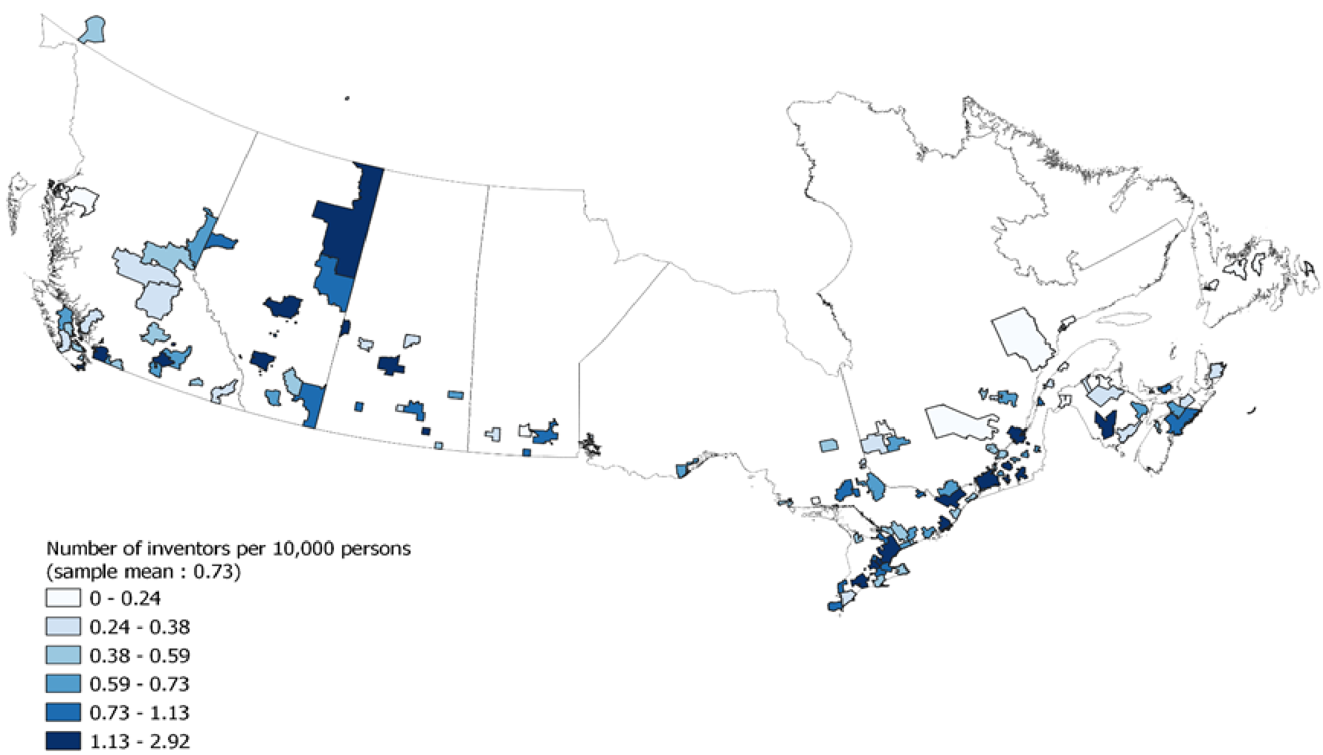
| | Inventors | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 2001 to 2006 | | 2006 to 2011 | | 2011 to 2016 | | 2016 to 2019 | | Total | |
| Province or territory | Total | Per capita | Total | Per capita | Total | Per capita | Total | Per capita | Total | Per capita |
| | number | ratio | number | ratio | number | ratio | number | ratio | number | ratio |
| Alberta | 2,429 | 1.57 | 2,539 | 1.45 | 3,163 | 1.62 | 1,855 | 0.9 | 9,986 | 1.39 |
| British Columbia | 2,514 | 1.27 | 2,079 | 0.98 | 2,389 | 1.05 | 1,811 | 0.76 | 8,793 | 1.01 |
| Manitoba | 527 | 0.93 | 481 | 0.81 | 405 | 0.65 | 302 | 0.46 | 1,715 | 0.7 |
| New Brunswick | 184 | 0.51 | 188 | 0.51 | 207 | 0.55 | 91 | 0.24 | 670 | 0.45 |
| Newfoundland and Labrador | 49 | 0.19 | 1 | 0 | 1 | 0 | 0 | 0 | 51 | 0.05 |
| Nova Scotia | 275 | 0.6 | 351 | 0.76 | 267 | 0.58 | 180 | 0.38 | 1,073 | 0.6 |
| Nunavut | 1 | 0.07 | 2 | 0.13 | 2 | 0.12 | 0 | 0 | 5 | 0.09 |
| Ontario | 9,033 | 1.55 | 8,016 | 1.28 | 7,725 | 1.17 | 4,968 | 0.72 | 29,742 | 1.18 |
| Prince Edward Island | 24 | 0.35 | 49 | 0.71 | 57 | 0.8 | 24 | 0.33 | 154 | 0.55 |
| Quebec | 4,604 | 1.25 | 3,492 | 0.9 | 3,483 | 0.86 | 2,519 | 0.61 | 14,098 | 0.91 |
| Saskatchewan | 488 | 1.01 | 431 | 0.86 | 445 | 0.83 | 281 | 0.51 | 1,645 | 0.81 |
| Territories | 14 | 0.41 | 6 | 0.16 | 6 | 0.16 | 11 | 0.28 | 37 | 0.26 |
| Total | 20,142 | 1.32 | 17,635 | 1.08 | 18,150 | 1.05 | 12,042 | 0.67 | 67,969 | 1.03 |

**Note:** Per capita is the total number of inventors per 10,000 people.

**Sources:** Statistics Canada, authors' calculations based on the Canadian Employer–Employee Dynamics Database and the Canadian Intellectual Property Office's Canadian Patents Database.

Interestingly, larger cities (population greater than 300,000) like Waterloo, Ontario, show higher innovation rates, while smaller cities like St. John's, Newfoundland and Labrador, have lower rates (see Figure 1). Alberta, Ontario and southern Quebec exceed the national average, while the Atlantic provinces lag.

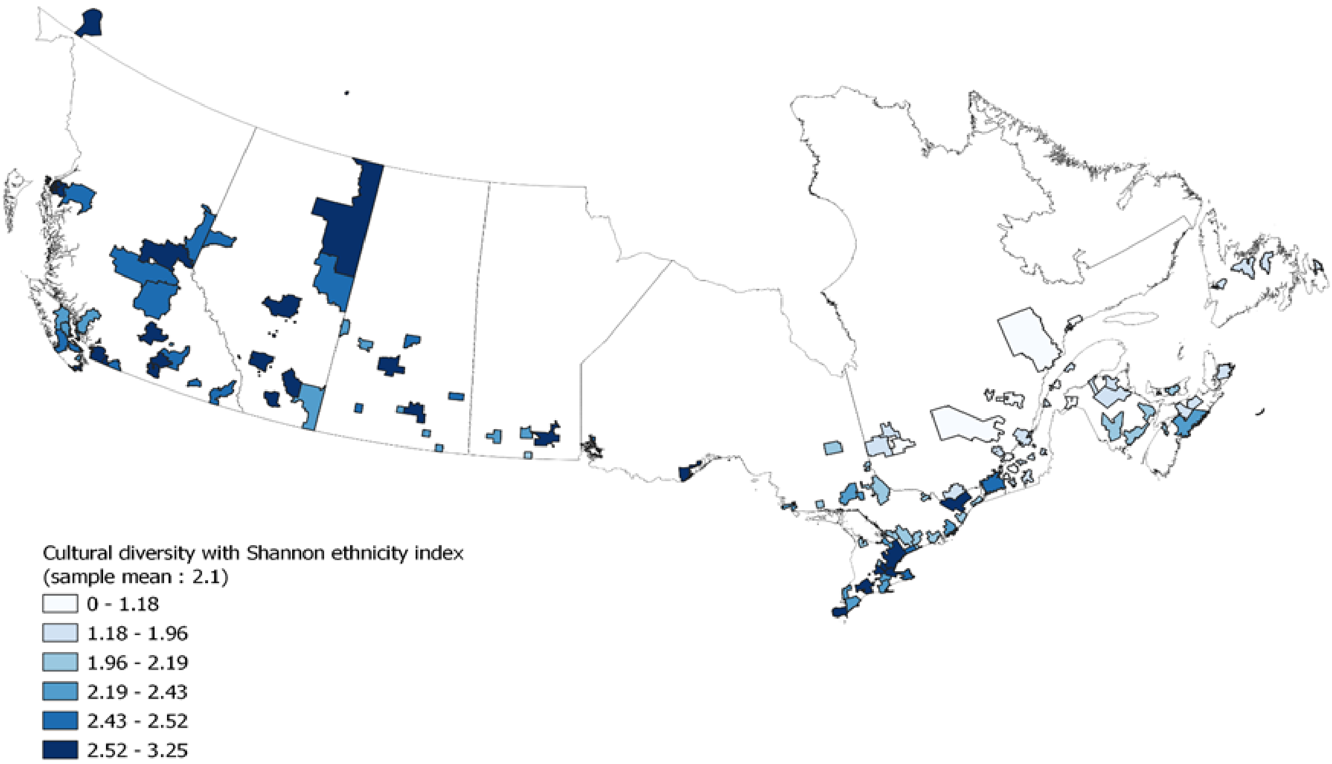
**Figure 1**
**Innovation activity in Canadian urban areas, 2001 to 2021**




**Note:** Innovation activity is the average number of inventors per 10,000 people from 2001 to 2021.
**Sources:** Statistics Canada, authors' calculations based on the Canadian Employer–Employee Dynamics Database and the Canadian Intellectual Property Office's Canadian Patents Database.

Toronto, Ontario, consistently ranks as the most culturally diverse city in Canada, while smaller cities in Quebec and Atlantic Canada tend to have lower diversity scores (Figure 2). Western provinces, such as British Columbia and Alberta, also exhibit high levels of cultural diversity, reflecting recent immigration trends and historical settlement patterns.

**Figure 2**
**Cultural diversity in Canadian urban areas, 2001 to 2021**

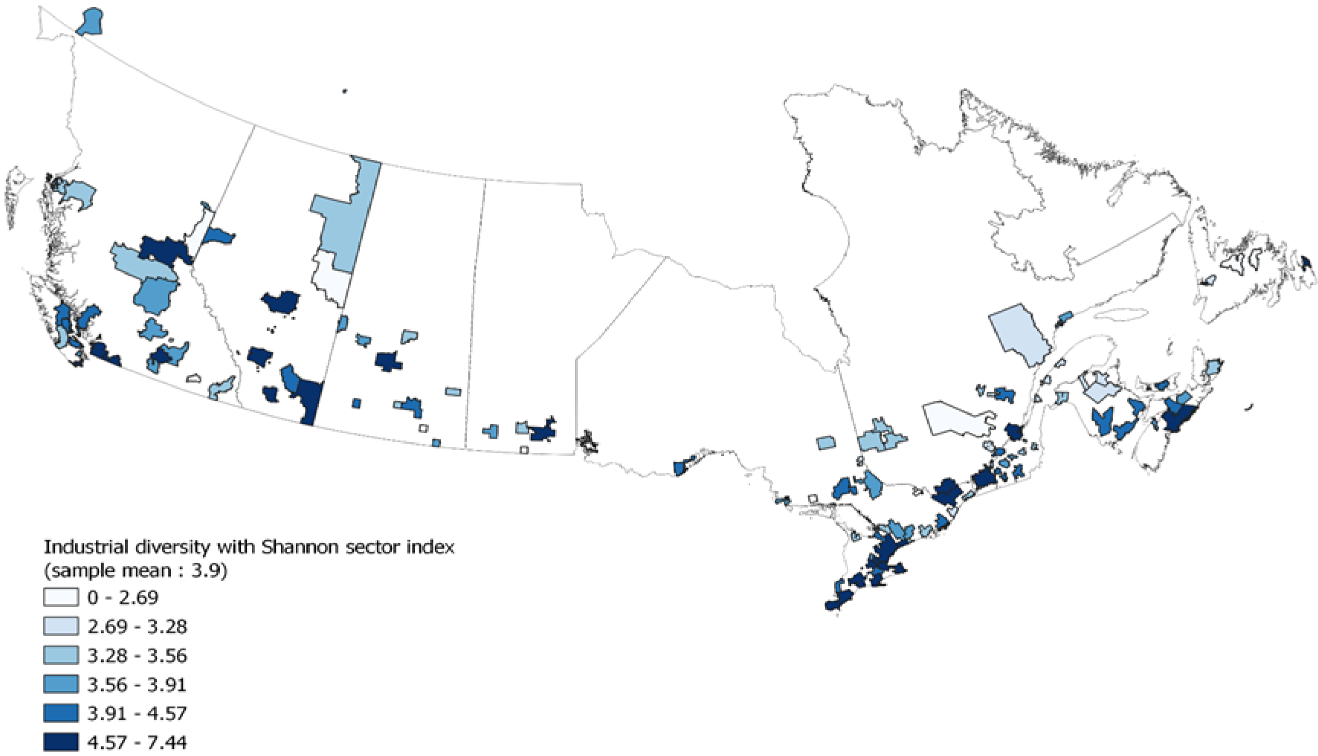



**Note:** Cultural diversity is measured as the average of the Shannon ethnic diversity indices calculated for the years 2001, 2006, 2011, 2016 and 2021.
**Source:** Statistics Canada, authors' calculations based on the Census of Population database.

Figure 3 provides a snapshot of industrial diversity. Notably, Wasaga Beach, Ontario, has the highest industrial diversity, and Calgary, Alberta, has the lowest. Meanwhile, Quebec shows high industrial but low cultural diversity, while the Western provinces exhibit the opposite, suggesting unique regional interactions.

Several patterns are evident from further analysis of figures 2 and 3. Notably, a city with high cultural diversity but low industrial diversity, such as Toronto, may generate innovative ideas through diverse perspectives but lack the variety of industries needed to implement them effectively. Conversely, a city like Québec, with high industrial diversity but lower cultural diversity, may benefit from sectoral variety but miss out on the creative spark provided by a diverse population.

**Figure 3**
**Industrial diversity in Canadian urban areas, 2001 to 2021**




**Note:** Industrial diversity is measured as the average of the Shannon sector diversity indices calculated for the years 2001, 2006, 2011, 2016 and 2021.
**Source:** Statistics Canada, authors' calculations based on the T2-Longitudinal Employment Analysis Program database.

## Baseline results: Estimated effects of cultural and industrial diversity on urban innovation

This section presents the findings from the baseline regression analysis examining how cultural diversity, industrial diversity and their interaction affect innovation activity in Canadian urban areas. The results are estimated using OLS and IV methods, with the table below showing the coefficients and their significance levels based on robust standard errors. The regression model tests the logarithm of innovation activity (average inventors per people) against cultural diversity (measured by the ethnic diversity index), industrial diversity (measured by the sector diversity index), their interaction (ethnic–industry interaction) and a set of control variables. The OLS results provide a baseline estimate, while the IV approach addresses potential biases from reverse causality, where innovative cities may attract diverse populations or firms. The IV method uses a shift-share instrument, as described previously, to predict diversity levels based on national growth trends, offering a more reliable estimate of the true effects.

**Table 2**
**Regression results for innovation activity, 2001 to 2021**

| | Inventors per capita (OLS, all patents) (log) | | | Inventors per capita (IV, all patents) (log) | | | Inventors per capita (alternative IV, all patents) (log) | | | Inventors per capita (IV, granted patents) (log) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | coefficient | | standard deviation | coefficient | | standard deviation | coefficient | | standard deviation | coefficient | | standard deviation |
| Ethnic diversity index | 0.193 | ** | (0.061) | 0.179 | ** | (0.061) | 0.817 | ** | (0.341) | 0.134 | ** | (0.048) |
| Sector diversity index | 0.095 | * | (0.039) | 0.108 | ** | (0.042) | 0.366 | ** | (0.172) | 0.066 | ** | (0.031) |
| Ethnic–sector interaction | 0.041 | ** | (0.014) | 0.039 | ** | (0.014) | 0.124 | † | (0.067) | 0.022 | † | (0.011) |
| Share of largest industry | 0.865 | ** | (0.407) | 0.775 | † | (0.404) | 0.185 | | (0.610) | 0.645 | ** | (0.301) |
| Share of largest ethnic group | -0.016 | | (0.076) | -0.018 | | (0.075) | -0.005 | | (0.185) | -0.057 | | (0.051) |
| Total population (log) | 0.012 | | (0.016) | 0.003 | | (0.020) | -0.051 | | (0.043) | 0 | | (0.015) |
| R&D expenditures per capita (log) | 0.064 | ** | (0.011) | 0.063 | ** | (0.010) | 0.054 | ** | (0.011) | 0.033 | ** | (0.008) |
| Trade per capita (log) | -0.004 | | (0.009) | -0.005 | | (0.009) | -0.005 | | (0.011) | -0.002 | | (0.007) |
| Share of graduates | 1.325 | ** | (0.392) | 1.337 | ** | (0.382) | 1.325 | ** | (0.426) | 0.294 | | (0.272) |
| Distance to university (log) | -0.003 | | (0.008) | -0.003 | | (0.008) | -0.006 | | (0.009) | 0.01 | † | (0.006) |
| Province fixed effects | Yes | | Yes | Yes | | Yes | Yes | | Yes | Yes | | Yes |
| Year fixed effects | Yes | | Yes | Yes | | Yes | Yes | | Yes | Yes | | Yes |
| Number of observations | 568 | | 568 | 568 | | 568 | 506 | | 506 | 568 | | 568 |
| Adjusted R-squared | 0.49 | | 0.49 | ... | | ... | ... | | ... | ... | | ... |
| **IV first-stage results** | | | | | | | | | | | | |
| Historical ethnic diversity | ... | | ... | 0.91 | ** | ... | 0.31 | ** | ... | 0.91 | ** | ... |
| Kleinbergen-Paap F-statistic | ... | | ... | 726 | | ... | 10 | | ... | 726 | | ... |
| Historical sector diversity | ... | | ... | 0.94 | ** | ... | 1.56 | ** | ... | 0.94 | ** | ... |
| Kleinbergen-Paap F-statistic | ... | | ... | 112 | | ... | 30 | | ... | 112 | | ... |

... not applicable

* significantly different from reference category ($p < 0.05$)

** significantly different from reference category ($p < 0.01$)

† significantly different from reference category ($p < 0.10$)

**Notes:** OLS = ordinary least squares. IV = instrumental variable. R&D = research and development. The table presents the coefficients obtained from OLS estimation and two-stage IV estimation according to equations (5) and (6) using the initial cultural and industrial diversity of each period analyzed. The dependent variable is the logarithm of the average number of inventors per 10,000 people in urban area *c* , over four five-year periods (2001 to 2006, 2006 to 2011, 2011 to 2016 and 2016 to 2021). The lower part of the table presents the following first-stage IV statistics. The standard deviations in parentheses are robust.

**Sources:** Statistics Canada, T2-Longitudinal Employment Analysis Program database, Canadian Employer–Employee Dynamics Database and Census of Population database; Canadian Intellectual Property Office, Canadian Patents Database; and Universities Canada.

Table 2 shows that the estimated coefficients are not only statistically significant but also economically meaningful. Cultural diversity has a positive and highly significant effect (coefficient 0.193, $p < 0.01$), suggesting that a one-unit increase in the ethnic diversity index raises innovation activity by about 19.3%. Industrial diversity also shows a positive and significant effect (0.095, $p < 0.05$), indicating a 9.5% increase in innovation per unit increase in the sector diversity index. The interaction term is positive and significant (0.041, $p < 0.01$), meaning that the combined effect of cultural diversity and industrial diversity boosts innovation more than their individual contributions, supporting the study's hypothesis of synergy. Among control variables, the share of the largest industry (0.865, $p < 0.01$) and the share of graduates (1.325, $p < 0.01$) have strong positive effects, showing that cities with dominant industries or highly educated residents tend to innovate more. R&D expenditures per capita (0.064, $p <0.01$) also significantly increase innovation, reflecting the importance of research resources. Other controls, such as population size, trade per capita and distance to a university, show no significant effects.

The IV results, which correct for endogeneity using the shift-share instrument, provide a more reliable estimate by addressing reverse causality—where innovative cities may attract diverse populations or firms. For all patents, the IV estimate for cultural diversity (0.179, $p < 0.01$) is slightly lower than the OLS estimate but remains strongly positive, suggesting a 17.9% increase in innovation per unit of diversity. Industrial diversity increases to 0.108 ($p < 0.01$), a 10.8% rise, indicating a stronger effect when controlling for endogeneity. The interaction term remains positive and significant (0.039, $p < 0.01$), reinforcing that cultural and industrial diversity together enhance innovation, with a combined effect of about 3.9% per unit interaction. These IV estimates are larger in some cases and smaller in others compared with OLS estimates, reflecting the correction of biases such as measurement error and simultaneity. The alternative IV specification shows larger coefficients (0.817 for cultural diversity, 0.366 for industrial diversity and 0.124 for the interaction, all significant), and this may result from differences in instrument strength or sample composition. For granted patents, the effects are smaller but still significant (0.134, 0.066 and 0.022, respectively, all $p < 0.01$ or $p < 0.10$), suggesting that the interaction holds across patent types.

The IV approach improves on OLS by tackling endogeneity, where diverse groups or firms may move to innovative cities, inflating diversity's apparent effect. The shift-share instrument uses national growth trends to predict local diversity, isolating exogenous variation and reducing bias. The high F-statistics (726 for cultural diversity and 112 for industrial diversity) indicate strong instruments, confirming their validity. Compared with OLS estimates, IV estimates are more consistent with true causal effects, though they can differ in magnitude because of corrected biases. For example, the IV interaction term (0.039) is slightly lower than the OLS (0.041), suggesting that some of the OLS effect may reflect reverse causality. However, the positive sign persists, supporting the synergy hypothesis.

The magnitude of this paper's coefficients aligns with previous studies. The positive and significant coefficients for cultural diversity (0.179 to 0.817) align with Ottaviano and Peri (2006), who found that diverse populations foster innovation through varied perspectives. Industrial diversity (0.108 to 0.366) supports Audretsch and Feldman (2004), showing that diverse industries enhance knowledge spillovers. The interaction term (0.039 to 0.124) is the study's novel contribution, confirming that cultural diversity and industrial diversity amplify each other's effects. For instance, a city like Waterloo, with high levels of both, likely benefits from diverse ideas being applied across varied sectors, as hypothesized in Section 2.4. The smaller coefficients for granted patents (e.g., 0.022 for the interaction) suggest that the synergy is stronger for patent applications than granted patents, possibly because of stricter approval processes filtering out some innovations.

Several control variables show significant effects. R&D expenditures per capita (0.033 to 0.064, $p < 0.01$) consistently boost innovation, highlighting the role of research investment. The share of graduates (1.325 to 1.337, $p < 0.01$ in most models) indicates that education drives innovation, consistent with Lee (2011). The share of the largest industry (0.645 to 0.865, $p < 0.01$ or $p < 0.10$) suggests that dominant sectors can anchor innovation, though this effect weakens in some IV models. Distance to a university shows a weak positive effect for granted patents (0.010, $p < 0.10$), possibly reflecting remote innovation hubs.

## Mechanism identification: Estimates for contingent effects of recent immigrant diversity

To more comprehensively identify the proposed knowledge-based mechanisms, the baseline analysis was extended by accounting for the recency of immigrant diversity as a contingent factor. Specifically, recent immigrant diversity, measured as an index that captures the ethnic composition of immigrants who arrived in the five years preceding each census year, was considered. As theorized, recent immigrants were expected to predominantly bring new skills, ideas and risk-taking behaviour that contribute directly to innovation (Buchholz, 2021; Diodato et al., 2022; Kemeny and Cooke, 2018), particularly in science, technology, engineering and mathematics (STEM) fields. When these attributes are combined with their potentially elevated occupational or geographic mobility, recent immigrants stand out as vital sources of knowledge variety and diffusion. As previously established, studies show that skilled immigrants, especially in STEM, increase innovation by filing more patents and introducing new ideas (Hunt & Gauthier-Loiselle, 2010; Kerr & Lincoln, 2010). In Canada, where the longstanding economic-class immigration programs favour skilled workers, this effect may be significant. As recent immigrants are part of the ethnic diversity measured earlier, it is difficult to determine whether the impact of diversity primarily comes from these newcomers or the overall ethnic mix.

The new measure focusing on recent arrivals resolves this issue and validates the mechanisms. The results in Table 3 show that recent immigrant diversity has a positive and statistically significant effect on innovation. The IV estimate is 0.151, indicating that a one-unit increase in the recent immigrant diversity index leads to a 15.1% increase in innovation activity. The model also includes an interaction term between recent immigration diversity and industrial diversity, which is positive and significant at 0.048. This interaction further supports the proposed knowledge-based mechanism: recent immigrants are more likely to contribute to innovation when embedded in a diverse industrial environment that enables cross-sector knowledge flows.

## Table 3
## Regression results for innovation activity, 2001 to 2021

| | Inventors per capita (OLS, all patents) (log) | | | | Inventors per capita (IV, all patents) (log) | | | | Inventors per capita (recent immigrants, IV, all patents) (log) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | coefficient | | standard deviation | | coefficient | | standard deviation | | coefficient | | standard deviation |
| Ethnic diversity index | 0.193 | ** | (0.061) | | 0.179 | ** | (0.061) | | … | | … |
| Immigration diversity index | … | | … | | … | | … | | 0.151 | * | (0.065) |
| Sector diversity index | 0.095 | * | (0.039) | | 0.108 | ** | (0.042) | | 0.07 | † | (0.039) |
| Ethnic–sector interaction | 0.041 | ** | (0.014) | | 0.039 | ** | (0.014) | | … | | … |
| Immigration–sector interaction | … | | … | | … | | … | | 0.048 | ** | (0.017) |
| Share of largest industry | 0.865 | ** | (0.407) | | 0.775 | † | (0.404) | | 0.500 | | (0.443) |
| Share of largest ethnic group | -0.016 | | (0.076) | | -0.018 | | (0.075) | | … | | … |
| Share of largest immigrant group | … | | … | | … | | … | | 0.047 | | (0.088) |
| Total population (log) | 0.012 | | (0.016) | | 0.003 | | (0.020) | | -0.031 | | (0.023) |
| R&D expenditures per capita (log) | 0.064 | ** | (0.011) | | 0.063 | ** | (0.010) | | 0.069 | ** | (0.011) |
| Trade per capita (log) | -0.004 | | (0.009) | | -0.005 | | (0.009) | | -0.002 | | (0.009) |
| Share of graduates | 1.325 | ** | (0.392) | | 1.337 | ** | (0.382) | | 1.250 | ** | (0.408) |
| Distance to university (log) | -0.003 | | (0.008) | | -0.003 | | (0.008) | | -0.002 | | (0.009) |
| Province fixed effects | Yes | | Yes | | Yes | | Yes | | Yes | | Yes |
| Year fixed effects | Yes | | Yes | | Yes | | Yes | | Yes | | Yes |
| Number of observations | 568 | | 568 | | 568 | | | | 506 | | |
| **IV first-stage results** | | | | | | | | | | | |
| Historical ethnic diversity | … | | … | | 0.91 | ** | … | | 0.97 | ** | … |
| Kleinbergen-Paap F-statistic | … | | … | | 726 | | … | | 198 | | … |
| Historical sector diversity | … | | … | | 0.94 | ** | … | | 0.72 | ** | … |
| Kleinbergen-Paap F-statistic | … | | … | | 112 | | … | | 95 | | … |

… not applicable

* significantly different from reference category ($p < 0.05$)

** significantly different from reference category ($p < 0.01$)

† significantly different from reference category ($p < 0.10$)

**Notes:** OLS = ordinary least squares. IV = instrumental variable. R&D = research and development. The table presents the coefficients obtained from OLS estimation and two-stage IV estimation according to equations (5) and (6) using the initial cultural and industrial diversity of each period analyzed. The dependent variable is the logarithm of the average number of inventors per 10,000 people in urban area $c$, over four five-year periods (2001 to 2006, 2006 to 2011, 2011 to 2016 and 2016 to 2021). The lower part of the table presents the following first-stage IV statistics. The standard deviations in parentheses are robust.

**Sources:** Statistics Canada, T2-Longitudinal Employment Analysis Program database, Canadian Employer–Employee Dynamics Database, Census of Population database; Canadian Intellectual Property Office, Canadian Patents Database; and Universities Canada.

Meanwhile, the IV estimates for cultural and industrial diversity remain robust in this extended model, with coefficients of 0.179 and 0.070, respectively. The interaction between cultural and industrial diversity remains significant at 0.039, reinforcing the conclusion that diversity in both people and industries enhances innovation. The instruments used in this model are strong, with F-statistics well above conventional thresholds, confirming the validity of the identification strategy.

To summarize, the regression analysis provides strong evidence that cultural diversity and industrial diversity contribute to innovation in Canadian cities. Their interaction produces a synergistic effect, and recent immigration adds another layer of impact. Crucially, the findings on recent immigration validate the theoretical mechanisms of knowledge variety and diffusion, rather than representing a separate channel. These results are robust across multiple specifications and estimation methods, supporting the conclusion that diversity is a key driver of urban innovation.

## Robustness checks

To ensure the robustness of the main estimated effects of diversity on innovation, a series of methodological checks addressing potential biases and limitations was conducted. These robustness tests focus on the validity of the IVs, the quality of patent data, the influence of agglomeration effects and the timing of the instruments used in the shift-share approach.

### Instrument validity

First, the validity of the Bartik instruments is evaluated using criteria from the recent econometric literature (Adão et al., 2019; Borusyak et al., 2020; Goldsmith-Pinkham et al., 2020). These instruments are constructed using 1996 baseline shares of ethnic and industrial groups and national growth rates, excluding the focal city to avoid endogeneity. The predicted diversity indices show sufficient variation, with coefficients of variation around 0.1 for cultural diversity and 0.2 for industrial diversity. The 84 percentage point spread between the first and fourth quintiles for ethnic diversity further supports the instruments' relevance. To address concerns about potential national shocks that could simultaneously influence national group growth rates and local innovation—such as federal immigration policy changes or sector-specific booms—province and time fixed effects are included. While these controls mitigate broad regional and temporal confounders, residual correlation with unobserved shocks cannot be fully ruled out, a limitation common to shift-share designs.

### Alternative instrument specification

Second, to test whether the instruments are influenced by highly concentrated groups that may correlate with unobserved city-specific factors, an alternative Bartik instrument was developed. This version excludes groups in the top quartile of geographic concentration. The results using this alternative remain statistically significant and consistent with the main findings, reinforcing the robustness of the estimates. However, the alternative IV specification in Table 2 yielded substantially larger coefficients for diversity measures. This difference likely reflects two factors: (1) the exclusion of highly concentrated groups reduces potential attenuation bias caused by endogenous clustering, as these groups may themselves be influenced by local innovation, and (2) the alternative instrument also places greater weight on more spatially dispersed groups, which are more plausibly exogenous to local innovation dynamics. These properties suggest that the larger coefficients may reflect a cleaner identification of the causal effect, though they also highlight the importance of interpreting the main IV results as conservative estimates.

### Patent quality

Third, the study examines patent quality by distinguishing all patent applications from those that were granted. As 46% of applications in urban areas from 2006 to 2016 were granted, and granted patents are more likely to reflect economically meaningful innovation (Harhoff et al., 1999), the model is re-estimated using only granted patents. The results remain positive and significant, though slightly smaller in magnitude, indicating that the diversity–innovation relationship holds even when focusing on higher-quality innovations.

### Agglomeration effects

Fourth, the potential for productivity externalities resulting from inventor agglomeration is considered. Previous research (Moretti, 2021) suggests that inventors may become more productive when located near others in the same field. However, in this dataset, inventors are rarely co-located within the same postal code and sector unless they are co-applicants, minimizing the risk of agglomeration bias.

### Instrument timing

Finally, the timing of the instruments is tested. While the baseline uses 1996 as the reference year, an alternative specification using 2001 and focusing on the 2006-to-2021 period yields similar results, though some coefficients lose significance at the 10% level.[4] This suggests that the results are not driven by a specific base year while highlighting the trade-off between temporal proximity and instrument strength.

### Summary

Overall, these checks confirm that the observed effects of diversity on innovation are not artifacts of model specification, instrument weakness or data limitations. The alternative IV results, while larger, reinforce the direction and significance of the main findings and provide additional support for the causal interpretation of diversity's role in urban innovation.

## Discussion and conclusion

This study provides new evidence on the role of diversity in shaping innovation across Canadian cities. By analyzing data from 152 urban areas from 2001 to 2021, cultural diversity and industrial diversity are shown to significantly enhance innovation, as measured by the number of inventors per total population. The results are robust across multiple specifications, including models that account for endogeneity using a Bartik IV approach. The findings also highlight the importance of recent immigrant diversity, which independently contributes to innovation beyond the broader effects of ethnic diversity.

These evidence-based insights make three key contributions to the literature on urban diversity and innovation, each of which deepens theoretical understanding and provides empirically grounded policy insights. First, the findings provide new empirical evidence of the joint effects of cultural and industrial

4. For industrial diversity, the growth rate is based on 1997 rather than 1996 data, as NAICS coding begins in 1997 (Adão, R, et al., 2019; Borusyak et al., 2020). Using a 10-year period may reduce this variation, particularly for industrial diversity, where dominant sectors change slowly (Kemeny & Cooke, 2018). While longer periods can stabilize estimates, as in the work of Ottaviano and Peri (2006), they may also obscure short-term migration dynamics—an important consideration in Canada's evolving immigration context.

diversity on urban innovation, clarifying the synergistic nature of these two dimensions. This reinforces a knowledge spillover view of urban innovation, emphasizing the need for sustained interactions among co-located entities with diverse but complementary knowledge (Boschma and Frenken, 2006; Audretsch and Feldman, 2004; Asheim et al., 2011). Second, this analysis extends previous studies by explicitly incorporating the temporal dimension of immigration into a knowledge spillover framework. Specifically, it demonstrates that recent immigrant diversity amplifies the innovation returns to overall urban diversity. This contribution extends the literature on the economic benefits of immigrants or multicultural environments (Kerr & Lincoln, 2010; Ottaviano & Peri, 2006; Rodríguez-Pose and Lee, 2020; Saxenian, 2006) by identifying recency as a contingent factor. Moreover, this finding is theoretically consistent with the mechanisms of external knowledge variety and accelerated diffusion (Buchholz, 2021; Diodato et al., 2022).

Recent immigrants not only expand the scope of available knowledge pools but also accelerate the recombination and transmission of ideas, as they introduce new perspectives and maintain active knowledge pipelines to other regions (Saxenian, 2006). The empirical evidence aligns with emerging research on exposure effects and interactive problem-solving (Buchholz, 2021), suggesting that innovation benefits from the dynamic interactions and fresh knowledge streams introduced by recent immigrants. This also supports the view that immigrants are carriers of origin-specific knowledge, fostering novel technological trajectories (Wigger, 2022; Diodato et al., 2022). Thus, cities that combine a diverse population with a varied industrial base are better positioned to generate and implement innovative ideas.

Finally, by leveraging the Canadian context as an ideal setting for testing its framework, this study provides actionable policy insights for fostering innovation and resilience in diverse, advanced urban economies. The findings highlight the importance of harmonizing immigration, industrial and innovation policies to realize the full potential of diversity-driven knowledge spillovers (Sorenson, 2023; Nathan & Lee, 2013). While Canada's immigration system and urban structure are distinctive, the mechanisms identified in this study are not context specific. The mechanisms of knowledge variety and diffusion apply to other advanced economies with diverse populations and complex industrial ecosystems. For example, cities in the United States, Australia and parts of Europe with similar immigration inflows and sectoral diversity may experience comparable innovation dynamics (Florida, 2002; Nathan and Lee, 2013).

The generalizability of this paper's findings is partially reflected in the superior innovation ecosystems found in regions such as Silicon Valley and London, where the necessary conditions of diverse human capital and varied industrial structures are present. However, in contexts with more restrictive immigration regimes, lower absorptive capacity or limited sectoral diversity, the magnitude and interaction of these effects may be attenuated. This suggests that while the empirical estimates may vary, the underlying mechanisms are generalizable to urban systems where diversity and industrial complexity co-evolve.

To conclude, this study empirically validates and extends the theoretical frameworks of related variety, knowledge spillovers and immigrant innovation spillovers. It demonstrates the synergistic effects of cultural and industrial diversity while showing why they depend on the recency of immigrant diversity. By doing so, it contextualizes the nature and significance of diversity as a potential driver of urban innovation. Ultimately, it supports integrated, evidence-based urban policy to harness this potential.

# Appendix: Supplementary materials

This series of appendices is organized as follows: Appendix A describes the data used in the analysis, Appendix B details data processing and Appendix C presents additional regressions.

## Appendix A: Data for the regressions

Table A.1 presents descriptive statistics on the variables used in this study. The table shows a great deal of variation across urban areas in the initial characteristics, which will be helpful for the estimations.

**Appendix Table A.1**
**Descriptive statistics of regression variables**

| Variable | Number of observation | Mean | Standard deviation | Value | |
|---|---|---|---|---|---|
| | | | | Minimum | Maximum |
| **Innovation** | | | | | |
| Inventors per total population (log) | 608 | 0.5 | 0.3 | 0 | 1.78 |
| **Diversity index** | | | | | |
| Ethnic diversity | 608 | 2.09 | 0.6 | 0.14 | 3.39 |
| Immigration diversity | 504 | 1.29 | 0.83 | 0 | 2.92 |
| Sector diversity | 608 | 3.89 | 1.07 | 0 | 8.19 |
| **Initial level** | | | | | |
| Percentage share of largest ethnic or immigrant group | 608 | 0.11 | 0.04 | 0.05 | 0.36 |
| Percentage share of largest industry sector | 608 | 0.86 | 0.12 | 0.25 | 1 |
| Total population (log) | 608 | 10.84 | 1.28 | 8.96 | 15.59 |
| R&D spending per total population | 608 | 3.63 | 1.91 | 0 | 7.62 |
| Trade per total population | 568 | 6.36 | 3.9 | 0 | 12.18 |
| Percentage share of people with university degree | 608 | 0.14 | 0.06 | 0.05 | 0.4 |
| Distance to nearest university (km) (log) | 608 | 10.58 | 1.37 | 6.43 | 13.84 |

**Note:** R&D = research and development.

**Sources:** Statistics Canada, T2-Longitudinal Employment Analysis Program database, Canadian Employer–Employee Dynamics Database, Census of Population database; Canadian Intellectual Property Office, Canadian Patents Database; and Universities Canada.

Table A.2 shows the pairwise correlations between the main explanatory variables used in the regression models, allowing for the assessment of the strength and direction of the linear relationships between these variables and the identification of any potential multicollinearity issues. Overall, correlation is moderate between ethnic diversity, immigrant diversity and sectoral diversity, suggesting partially related dynamics. In contrast, population correlates strongly with immigrant diversity (0.78) and sectoral diversity (0.79), reflecting the concentration of diversity in urban areas. Negative correlations between distance to a university and several socioeconomic variables (population, graduates, and research and development spending) indicate that more remote regions are generally less developed. The weak correlation between the shares of majority groups and the other variables limits the risk of redundancy in the models. This matrix supports the robustness of the models by showing that, despite some correlations, most variables remain sufficiently independent to be used together in regressions.

**Appendix Table A.2**
**Pairwise correlation of regression variables**

| Variables | Ethnic diversity | Immigration diversity | Sector diversity | Percentage share of largest ethnic or immigrant group | Percentage share of largest sector | Population (log) | R&D spending per capita | Trade per capita | Percentage share of university graduates | Distance to university (log) |
|---|---|---|---|---|---|---|---|---|---|---|
| Ethnic diversity | 1 | 0.38 | 0.33 | 0.41 | -0.1 | 0.25 | -0.05 | 0.14 | 0.36 | -0.1 |
| Immigration diversity | 0.38 | 1 | 0.68 | 0.25 | -0.14 | 0.78 | 0.44 | 0.03 | 0.48 | -0.44 |
| Sector diversity | 0.33 | 0.68 | 1 | 0.27 | -0.01 | 0.79 | 0.55 | -0.08 | 0.5 | -0.43 |
| Percentage share of largest ethnic or immigrant group | 0.41 | 0.25 | 0.27 | 1 | -0.16 | 0.24 | 0.02 | 0.17 | 0.5 | -0.09 |
| Percentage share of largest sector | -0.1 | -0.14 | -0.01 | -0.16 | 1 | -0.15 | 0.06 | -0.08 | -0.14 | 0.07 |
| Population (log) | 0.25 | 0.78 | 0.79 | 0.24 | -0.15 | 1 | 0.57 | 0.15 | 0.59 | -0.57 |
| R&D spending per capita | -0.05 | 0.44 | 0.55 | 0.02 | 0.06 | 0.57 | 1 | 0.31 | 0.38 | -0.37 |
| Trade per capita | 0.14 | 0.03 | -0.08 | 0.17 | -0.08 | 0.15 | 0.31 | 1 | 0.26 | -0.1 |
| Percentage share of university graduates | 0.36 | 0.48 | 0.5 | 0.5 | -0.14 | 0.59 | 0.38 | 0.26 | 1 | -0.41 |
| Distance to university (log) | -0.1 | -0.44 | -0.43 | -0.09 | 0.07 | -0.57 | -0.37 | -0.1 | -0.41 | 1 |

**Note:** R&D = research and development.

**Sources:** Statistics Canada, T2-Longitudinal Employment Analysis Program database, Canadian Employer–Employee Dynamics Database, Census of Population database; Canadian Intellectual Property Office, Canadian Patents Database; and Universities Canada.

## Appendix B: Data processing

Census metropolitan areas (CMAs) and census agglomerations (CAs) are the ideal spatial units in Canada for the analysis of local labour markets, as their boundaries are delineated based on the commuting patterns of residents. While provinces are too coarse a spatial scale, dissemination areas (census blocks) are too fine to analyze population dynamics following local labour market shocks, because a worker could easily work in one dissemination area and reside in another. Because each dissemination area belongs to a given urban area (CMA or CA), available census data are aggregated at the level of dissemination areas at the urban area level.

Census data at the urban area (CMA or CA) level were obtained for 137 urban areas in 1996, 145 in 2001, 148 in 2006, 151 in 2011, 156 in 2016 and 156 in 2021. The differences between years are explained by the fact that from a statistical point of view, an urban area can lose its CA status and disappear, or gain or regain it and appear or reappear. For example, if the population of a CA's core falls below 10,000, the CA is removed. However, once an urban area becomes a CMA, it remains a CMA even if its total population falls below 100,000 or if its core population falls below 50,000. From 1996 to 2021, there were 164 unique urban areas (CMAs and CAs).

Each urban area was overlaid for every year it appears, and the envelope of the overlaid boundaries was taken. Finally, to ensure time stability, Magog in 2001 became Sherbrooke in 2006, and Saint-Jean-sur-Richelieu in 2001, 2006 and 2011 became Montréal in 2016. The CAs of Carleton Place and Arnprior were dissolved as they were added to the Ottawa–Gatineau CMA in 2021, and the Leamington CA was dissolved, as it was added to the Windsor CMA in 2021. This study captures demographic changes that are related to labour market shocks, not to changes in geographical boundaries. The sample includes only those agglomerations with an average population of at least 10,000 inhabitants from 1996 to 2021 and for which all the necessary information for the econometric analysis was available, resulting in a total of 152 stable urban areas. A population ratio, which is the ratio between the total population of the urban area in a given census year as measured by Statistics Canada and the measured total population of the "stabilized" urban area, was calculated. On average, as shown in Table B.1, this ratio is equal to 0.95 from 1996 to 2021. This means that the demographics of stabilized urban areas are quite similar to those of the original urban areas.

**Appendix Table B.1**
**Population ratio between current and stabilized urban areas**

| | Year | | | | | |
|---|---|---|---|---|---|---|
| **Statistics** | **1996** | **2001** | **2006** | **2011** | **2016** | **2021** |
| | ratio | | | | | |
| Minimum (value) | 0.254 | 0.535 | 0.32 | 0.407 | 0.323 | 0.41 |
| Mean | 0.929 | 0.943 | 0.958 | 0.958 | 0.964 | 0.973 |
| Maximum (value) | 1 | 1 | 1 | 1 | 1 | 1 |
| Standard error | 0.121 | 0.091 | 0.089 | 0.095 | 0.098 | 0.092 |

**Source:** Statistics Canada, Census of Population database.

Table B.2 shows CMA and CA information from Statistics Canada that was used to identify urban areas from 1996 to 2021.

**Appendix Table B.2**
**Descriptive statistics of urban areas by province or territory**

| Province or territory | Total urban areas | Census metropolitan areas | Census agglomerations | Average population | Minimum average population | Maximum average population |
|---|---|---|---|---|---|---|
| | number | | | | | |
| Alberta | 18 | 3 | 15 | 275,132.70 | 42,670.67 | 4,627,053.00 |
| British Columbia | 26 | 4 | 22 | 100,460.00 | 56,846.67 | 8,886,959.00 |
| Manitoba | 5 | 1 | 4 | 99,042.00 | 50,620.00 | 2,922,189.00 |
| New Brunswick | 7 | 2 | 5 | 378,840.70 | 60,902.67 | 535,304.00 |
| Newfoundland and Labrador | 4 | 1 | 3 | 77,317.34 | 49,215.33 | 761,773.30 |
| Northwest Territories | 1 | 0 | 1 | 74,374.66 | 74,374.66 | 74,374.66 |
| Nova Scotia | 5 | 1 | 4 | 103,824.00 | 103,824.00 | 1,549,153.00 |
| Ontario | 43 | 16 | 27 | 271,498.00 | 42,656.80 | 21,100,000.00 |
| Prince Edward Island | 2 | 0 | 2 | 265,203.30 | 66,516.00 | 265,203.30 |
| Quebec | 30 | 6 | 24 | 74,787.34 | 48,946.00 | 15,300,000.00 |
| Saskatchewan | 10 | *2* | 8 | 73,138.00 | 41,526.00 | 1,038,084.00 |
| Yukon | 1 | 0 | 1 | 101,347.30 | 101,347.30 | 101,347.30 |
| All provinces and territories | 152 | 36 | 116 | 157,913.78 | 61,620.51 | 4,763,453.38 |

**Source:** Statistics Canada, Census of Population database.

# Appendix C: Additional table

**Apendix Table C.1**
**Regression results for innovation activity, 2001 to 2021**

| | Inventors per capita (OLS, all patents) (log) | | | Inventors per capita (IV, all patents) (log) | | | Inventors per capita (alternative IV, all patents) (log) | | | Inventors per capita (IV, granted patents) (log) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | coefficient | | standard deviation | coefficient | | standard deviation | coefficient | | standard deviation | coefficient | | standard deviation |
| Ethnic diversity index | 0.137 | † | (0.077) | 0.125 | † | (0.070) | 0.909) | † | (0.469) | 0.069 | | (0.055) |
| Sector diversity index | 0.068 | | (0.047) | 0.092 | † | (0.050) | 0.418 | † | (0.236) | 0.040 | | (0.035) |
| Ethnic–sector interaction | 0.031 | † | (0.018) | 0.029 | † | (0.017) | 0.146 | | (0.103) | 0.005 | | (0.013) |
| Share of largest industry | 0.623 | | (0.565) | 0.450 | | (0.584) | -0.025 | | (0.901) | 0.216 | | (0.459) |
| Share of largest ethnic group | -0.047 | | (0.107) | -0.051 | | (0.104) | -0.011 | | (0.311) | -0.010 | | (0.069) |
| Total population (log) | 0.009 | | (0.020) | -0.005 | | (0.027) | -0.057 | | (0.064) | -0.011 | | (0.022) |
| R&D expenditures per capita (log) | 0.069 | ** | (0.013) | 0.065 | ** | (0.012) | 0.055 | ** | (0.015) | 0.037 | ** | (0.009) |
| Trade per capita (log) | -0.012 | | (0.012) | -0.014 | | (0.012) | -0.007 | | (0.015) | -0.014 | † | (0.008) |
| Share of graduates | 1.473 | ** | (0.523) | 1.510 | ** | (0.499) | 1.411 | * | (0.583) | 0.541 | | (0.378) |
| Distance to university (log) | -0.004 | | (0.011) | -0.003 | | (0.010) | -0.007 | | (0.013) | 0.013 | | (0.008) |
| Province fixed effect | Yes | | Yes | Yes | | Yes | Yes | | Yes | Yes | | Yes |
| Year fixed effect | Yes | | Yes | Yes | | Yes | Yes | | Yes | Yes | | Yes |
| Observations | 282 | | 282 | 282 | | 282 | 252 | | 252 | 252 | | 252 |
| Adjusted R-squared | 0.53 | | 0.53 | … | | … | … | | … | … | | … |
| **IV first-stage results** | | | | | | | | | | | | |
| Historical ethnic diversity | … | | … | 0.96 | ** | … | 0.30 | ** | … | 0.91 | ** | … |
| Kleinbergen-Paap F-statistic | … | | … | 432 | | … | 4 | | … | 432 | | … |
| Historical sector diversity | … | | … | 0.95 | ** | … | 1.86 | ** | … | 0.95 | ** | … |
| Kleinbergen-Paap F-statistic | … | | … | 63 | | … | 17 | | … | 63 | | … |

… not applicable

* significantly different from reference category (p < 0.05)

** significantly different from reference category (p < 0.01)

† significantly different from reference category (p < 0.10)

**Notes:** OLS = ordinary least squares. IV = instrumental variable. R&D = research and development.

**Sources:** Statistics Canada, T2-Longitudinal Employment Analysis Program database, Canadian Employer–Employee Dynamics Database and Census of Population database; Canadian Intellectual Property Office, Canadian Patents Database; and Universities Canada.

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