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ESSAIS SUR LA CROISSANCE ET LES PERFORMANCES ÉCONOMIQUES DANS LES VILLES

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« Tout ce que vous faites, en paroles ou en actions, faites-le au nom du Seigneur Jésus, en remerciant par lui Dieu le Père.» (Colossiens 3 : 17, Bible)

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RÉSUMÉ

La dernière décennie a vu un renouveau de la littérature sur la croissance urbaine en raison des nouvelles méthodologies de mesure du phénomène basées sur les informations géoréférencées et du rôle de la densité urbaine dans la durabilité des villes. Les urbanistes et les spécialistes des sciences sociales s'intéressent à la relation étroite entre la croissance et l'efficacité des villes. Dans cette perspective, des travaux intéressants qui analysent les déterminants de la croissance urbaine ont vu le jour. Pourquoi la population et l'emploi augmentent-ils dans les villes ? Quelles sont les villes qui connaissent la croissance la plus rapide et pourquoi ? Comment cette croissance est-elle affectée par des chocs économiques ?

Pour répondre à ces questions, cette thèse est organisée en trois chapitres, et examine comment la désindustrialisation récente, la variété de personnes, d'industries, influencent la croissance des villes. Le premier chapitre examine l'effet des fermetures de grandes usines manufacturières sur les changements socio-démographiques dans les zones urbaines entre 2001 et 2016. Le deuxième chapitre examine la diversité culturelle et industrielle en tant que déterminants du niveau d'innovation locale, un moteur important de la croissance économique urbaine, entre 2006 et 2016. Enfin, le troisième chapitre analyse la diversité industrielle comme source de croissance de l'emploi et de résilience dans les villes, entre 2006 et 2016.

Le premier chapitre, intitulé *"Cultural and public services as factors of city resilience ?"*, combine les données du recensement canadien et les données d'établissements pour la période 2001–2016 afin d'étudier l'impact des fermetures de grandes usines manufacturières sur la taille et la composition de la population au niveau des villes. Nous constatons que les fermetures d'usines manufacturières et les licenciements massifs entraînent une baisse de la croissance démographique ultérieure, en particulier parmi les populations jeunes, en âge de travailler, migrantes et peu qualifiées. Nous constatons d'importantes retombées négatives des fermetures de grandes usines manufacturières sur l'emploi local dans d'autres industries, ce qui peut expliquer pourquoi de tels chocs négatifs de la demande de main-d'œuvre locale affectent la dynamique de la population. Les services publics (santé et éducation) et les installations culturelles et récréatives rendent les villes plus résilientes et les aident à conserver leur population après ces chocs négatifs.

Le deuxième chapitre intitulé *"Innovation in diversified cities"*, combine des données complètes sur les brevets, les établissements et le recensement au Canada pour analyser si la diversité affecte l'activité d'innovation locale de 2006 à 2016. Je distingue la diversité dans la population et dans le secteur manufacturier. Les résultats suggèrent que les villes dont la composition ethnique de la population et la composition sectorielle du manufacturier sont plus diversifiées connaissent un niveau d'activité d'innovation plus élevé. La diversité ethnique a des effets plus de 4 à 11% plus importants sur l'activité d'innovation que la diversité manufacturière. Je montre également que la diversité a des effets hétérogènes selon le domaine d'innovation. La diversité ethnique a des effets positifs sur les innovations chimiques, informatiques et électroniques, tandis que la diversité manufacturière a des effets positifs sur toutes les classes d'innovation.

Le troisième chapitre, intitulé *"Diversity, local labor market and resilience"*, combine des données d'établissements et des données du recensement canadien pour la période 2006–2016 afin d'étudier l'impact de la diversité manufacturière sur l'emploi au niveau de la ville. Je constate que la diversité manufacturière entraîne une plus forte croissance de l'emploi, en particulier de l'emploi chez les hommes, et des personnes peu qualifiées. Je trouve également des effets d'entraînement positifs significatifs de la diversité manufacturière sur l'emploi local dans d'autres industries telles que la construction, les arts et les loisirs, et les services professionnels. De plus, les villes qui innovent plus ont un effet plus important de la diversité manufacturière sur la croissance de leur emploi local. Enfin, la diversité manufacturière rend les villes plus résilientes et les aide à conserver l'emploi après des chocs négatifs sur la demande de main-d'œuvre locale.

Mots clés : Changement sociodémographique ; diversité culturelle ; diversité industrielle ; innovation ; manufacturier ; marché du travail local ; fermetures d'usines ; résilience économique ; villes canadiennes.

ABSTRACT

The last decade has seen a revival of the literature on urban growth due to new methodologies for measuring the phenomenon based on digital mapping and geo-referenced information and the role of urban density in the sustainability of cities. Urban planners and social scientists are interested in the close relationship between growth and the efficiency of cities. From this perspective, interesting work has emerged that analyzes the determinants of urban growth. Why do cities grow in population and employment? Which cities are growing fastest and why? How is this growth affected in the presence of economic shocks?

To answer these questions, this thesis is organized into three chapters, and examines how recent deindustrialization, the variety of people, industries, and technologies, influence growth in cities. The first chapter looks at the effect of large manufacturing plant closures on socio-demographic changes in urban areas between 2001 and 2016. The second chapter examines cultural and industrial diversity as determinants of the level of local innovation, an important driver of urban economic growth, between 2006 and 2016. Finally, the third chapter analyzes industrial diversity as a source of employment growth and resilience in cities between 2006 and 2016.

The first chapter entitled *"Cultural and public services as factors of city resilience?"*, combines Canadian census and establishment-level data for 2001–2016 to study the impact of big manufacturing plant closures and downsizing on the size and composition of city-level population. We find that manufacturing plant closures and mass layoffs lead to a decline in subsequent population growth, especially among the young, the working-age, the migrant, and the less skilled populations. We find significant negative spillovers of big manufacturing plant closures on the local employment in other industries, which can explain why such negative local labor demand shocks affect population dynamics. Public services (health and education) and cultural and recreational amenities make cities more resilient and help them retain population following negative local labor demand shocks.

The second chapter entitled *"Innovation in diversified cities"*, combines comprehensive patent, establishment and census data in Canada to analyze whether diversity affects local innovation activity from 2006 to 2016. I distinguish be-

tween diversity in the population and in manufacturing. The results suggest that cities with a more diverse ethnic composition of the population and more diverse sectoral composition in manufacturing experience a higher level of innovation activity. Ethnic diversity has more than 4-11% larger effects on innovation activity than manufacturing diversity. I also show that diversity has heterogeneous effects depending on the field of innovation. Ethnic diversity has positive effects on chemical, computer and electronic innovations, while manufacturing diversity has positive effects on all innovation classes.

The third chapter entitled *"Diversity, local labor market and resilience"*, combines combine establishment-level and Canadian census data for the period 2006–2016 to study the impact of manufacturing diversity on city-level employment. I find that manufacturing diversity leads to higher employment growth, especially male employment, and less skilled people. I also find significant positive spillover effects of manufacturing diversity on local employment in other industries such as construction, arts and recreation, and professional services. Moreover, cities that innovate more have a greater effect of manufacturing diversity on their local employment growth. Finally, manufacturing diversity makes cities more resilient and helps them retain employment after negative shocks to local labor demand.

Keywords: Canadian cities; cultural diversity; economic resilience; industrial diversity; innovation; local labor market; manufacturing; plant closures; socio-demographic change.

INTRODUCTION

Les villes constituent une plate-forme permettant d'organiser les ressources et les interactions nécessaires à l'activité économique. On estime que les villes génèrent 80% de la croissance économique totale. Au-delà des avantages naturels que sont la dotation en ressources, la proximité des marchés ou le climat, certaines villes possèdent une dynamique interne qui améliore leurs performances économiques (Rosenthal and Strange, 2003). Ces dynamiques internes impliquent une grande variété de personnes, d'entreprises et de technologies. Ainsi, plus le nombre d'acteurs capables de participer à des activités productives est élevé, plus la probabilité est grande qu'une ville soit en mesure de récolter les bénéfices qui en découlent et de poursuivre sa croissance. Par exemple, le niveau de productivité des villes (et donc leur production économique) dépend de la taille de leur population. Des études récentes de l'OCDE suggèrent que doubler la taille de la population, augmente le niveau de productivité d'une ville de 2 à 5%.[1] Cela est dû à plusieurs facteurs, comme une concurrence accrue ou des marchés du travail plus larges (et donc une meilleure adéquation entre les travailleurs et les emplois) dans les grandes villes, mais aussi à une diffusion plus rapide des idées et à un environnement intellectuel et entrepreneurial plus diversifié.

Si les villes ont tendance à croître au fil du temps, elles ne croissent pas uniformément au même rythme. En 2016, la taille moyenne de la population des 156 régions urbaines du Canada était de 188 000 habitants, avec une fourchette allant de 5,9 millions à un peu plus de 10 000 habitants. Entre 2001 et 2016, ces villes ont connu une croissance moyenne de 14,4%. Ailleurs, les zones ur-

1. L'étude de l'OCDE a été réalisée sur un échantillon d'une centaine de régions dans cinq pays : l'Allemagne, le Mexique, l'Espagne, le Royaume-Uni et les États-Unis, entre 1990 et 2010. Le phénomène consistant à augmenter la productivité en doublant la taille de la population a été observé au cours des dernières décennies dans les pays. OCDE (2015), The Metropolitan Century : Understanding Urbanisation and its Consequences, Éditions OCDE, Paris, https ://doi.org/10.1787/9789264228733-en.

baines ont connu un taux de croissance similaire entre 2000 et 2010, avec une croissance de 10,7% aux États-Unis, ainsi qu'en Europe, allant de 17,5% en Espagne à 4% en France. Cette tendance soulève des questions sur les raisons pour lesquelles les villes continuent de croître même lorsqu'elles sont déjà fortement urbanisées, et pourquoi certaines villes croissent plus rapidement que d'autres.

Le système urbain canadien est différent de celui des autres économies modernes. Le Canada est considéré comme une économie fondée sur les ressources, avec une grande proportion de petites villes (moins de 50 000 habitants) et de villes isolées (Bourne and Simmons, 2003). Il a été démontré qu'un modèle qui intègre quelques variables géographiques et de distance de base, ainsi que certaines caractéristiques locales mesurables, peut expliquer de manière cohérente une grande partie de la variation des taux de croissance (de la population et de l'emploi) au Canada (Shearmur and Polèse, 2007). Les petites régions du Canada, qui constituent la plupart des zones urbaines, dépendent fortement du secteur des ressources, notamment le pétrole, le gaz, les mines et la foresterie, soit directement en tant que principal employeur, soit indirectement en tant que centres de services et petites usines fournissant les secteurs des ressources (Polèse and Shearmur, 2006). Pour tenir compte de cette dynamique du système urbain canadien, on pourrait inclure un indicateur de la présence du secteur des ressources.

Un autre facteur clé affectant la croissance de l'emploi au Canada est la proximité de la frontière américaine (Shearmur and Polèse, 2007). À mesure que les frontières nationales s'ouvrent davantage au commerce, les entreprises auront tendance à être attirées par les endroits qui offrent le meilleur accès à des marchés importants ou nouveaux. [2]

Pourquoi est-il important de se concentrer sur la croissance dans les villes ?

2. À cette fin, nous avons construit une variable qui mesure la distance à la frontière américaine pour contrôler cette dynamique. Nos résultats ne changent pas. Cette variable est fortement corrélée à la distance aux grandes villes, car ces dernières sont proches de la frontière américaine. Nous avons choisi de ne conserver que cette dernière variable.

Il est important de se concentrer sur la croissance dans les villes pour au moins trois raisons. La première est que la croissance de la population urbaine est économiquement importante en soi. Des investissements massifs dans de nouveaux logements et de nouvelles infrastructures doivent être effectués pour répondre à la croissance de la population urbaine. Les ménages canadiens allouent environ un quart de leur revenu au logement, et grâce au plan « Investir dans le Canada » en 2016, le gouvernement du Canada investit plus de 180 milliards de dollars sur 12 ans dans des projets d'infrastructure. Comme la plupart de ces investissements sont hautement durables, il est important de les planifier correctement, et pour ce faire, nous devons comprendre pourquoi et comment les villes se développent.

Deuxièmement, le déclin démographique est associé à une diminution du capital humain (Glaeser and Gyourko, 2005; Notowidigdo, 2019), qui est un moteur important du développement économique des villes (Glaeser et al., 1995). Les personnes restantes sont confrontées à un niveau élevé de désutilité de la vie en raison de la diminution des ressources et des services disponibles, d'autant plus que ces villes en déclin ont du mal à se redresser à long terme. (Burda, 2006; Uhlig, 2006).

Enfin, l'économie urbaine a proposé un certain nombre de théories pour expliquer la croissance des villes. La littérature sur ce sujet est vaste et s'est concentrée sur l'analyse de ce qui suit : (i) la division du travail et/ou la spécialisation accrue des entreprises au sein des villes, (ii) les économies d'échelle (tous les marchés locaux sont plus grands ; les entreprises peuvent se développer grâce aux marchés locaux, devenir plus efficaces, et donc se développer davantage en attirant la main-d'œuvre d'ailleurs), (iii) les économies Marshall-Arrow-Romer - c'est-à-dire l'augmentation de la productivité qui résulte de l'échange d'idées et d'informations, facilité par la proximité physique entre les acteurs urbains (voir Duranton and Puga, 2014). Ces théories fournissent des indications utiles pour mener des travaux empiriques sur la croissance urbaine en nous fournissant des spécifications et en mettant en évidence un certain nombre de défis d'identification.

Comment explorer les moteurs de la croissance dans les villes ?

Cette thèse comprend trois chapitres qui se concentreront sur les déterminants de la croissance dans les villes et étudieront les facteurs de résilience qui permettent aux villes de conserver leur population et d'assurer une croissance continue face aux chocs économiques. Cet aspect n'est pas facile à explorer car la croissance dans les villes et ses déterminants sont souvent simultanément affectés, ou s'influencent mutuellement. Pour cela, je vais utiliser des stratégies d'analyse empirique récentes et rigoureuses, afin d'isoler un effet causal de certains moteurs de la croissance dans les villes.

Le premier chapitre porte sur l'impact des chocs économiques du marché du travail sur l'évolution démographique. Les changements démographiques sont un problème majeur pour les villes. Il est important de mesurer les effets des fermetures de grandes usines sur les économies locales pour comprendre si les coûts énormes des plans de sauvegarde gouvernementaux sont justifiés par rapport aux coûts à court et à long terme des fermetures. De plus, les besoins en termes d'équipements et de services sont différents selon l'âge ou la situation familiale. Il est donc important d'examiner l'effet des fermetures d'usines sur différents groupes de population. Ce chapitre estime l'effet des fermetures de grandes usines manufacturière sur la taille et la composition de la population des zones urbaines canadiennes entre 2001 et 2016. Nous analysons également si certaines caractéristiques locales aident à retenir la population en cas de chocs négatifs sur l'emploi.

Le chapitre fournit une description des fermetures d'usines et des changements démographiques dans les villes canadiennes au cours des 20 dernières années. Les grandes villes ont connu une croissance démographique, les petites et moyennes villes ont connu soit une croissance, soit un déclin de leur population. La faible croissance démographique est surtout observée en Colombie-Britannique, dans le nord de l'Ontario, au Québec et dans les provinces de l'Atlantique, tandis que l'Alberta a connu des niveaux de croissance élevés. L'Atlantique, le Québec et l'Ontario sont les provinces les plus durement touchées par la désindustrialisation. Les régions urbaines de l'Ouest canadien sont les moins touchées par la désindustrialisation.

Le chapitre trouve également un effet causal des fermetures de grandes usines sur les changements démographiques. Nous constatons que les fermetures de grandes usines manufacturière ont un effet négatif sur la croissance de la population dans les villes. La part de la population en âge de travailler diminue dans les villes qui subissent des chocs négatifs en matière d'emploi. La part des personnes qui ont un partenaire et la part de celles qui ont au moins un enfant augmentent après un choc négatif sur l'emploi. Nous constatons également que les immigrants sont plus susceptibles de quitter les villes après un choc négatif sur le marché du travail local. Nous constatons également que les villes qui sont initialement mieux dotées en services publics et en équipements artistiques et récréatifs décroissent relativement moins après la fermeture de grandes usines. Les résultats sont robustes aux caractéristiques observables qui pourraient influencer les changements de population au niveau de la ville, comme la température locale, la proximité de la côte et d'autres grands centres urbains, ainsi que les différences de politique régionale.

Le deuxième chapitre porte sur l'effet de la diversité sur l'innovation dans les villes. Je me suis intéressé à l'innovation parce qu'elle est un moteur important de la croissance dans les villes. Les villes innovantes connaissent une croissance plus rapide des salaires et de l'emploi dans les villes. L'innovation est également une activité locale importante qui favorise la création de start-ups qui soutiennent la croissance de la ville. Ainsi, pour comprendre un peu mieux pourquoi une ville est plus innovante qu'une autre, j'examine l'effet de la diversité sur l'innovation. Il est important de mesurer les effets de la diversité dans les villes. Les personnes nées à l'étranger représentent aujourd'hui environ 10% de la main-d'oeuvre dans les pays développés et il serait intéressant de savoir quel serait l'effet de la diversité ethnique sur les performances économiques. La diversité ethnique peut conduire à une diversité de compétences, d'expériences et d'idées, ce qui favoriserait la croissance des villes. La diversité industrielle peut conduire à des complémentarités dans la production et créer une résilience aux ralentissements économiques grâce à toutes ces activités de diversification.

Ce chapitre estime l'effet de la diversité, sur le nombre de brevet-inventeurs par personnes âgées de 15 à 64 ans dans les zones urbaines canadiennes entre 2006 et 2016. Pour ce faire, je mesure la diversité culturelle par la part des différents groupes ethniques. Je mesure la diversité industrielle par la part d'usines selon leur secteur. Le chapitre fournit une description de l'innovation et de la diversité dans les villes canadiennes au cours des 20 dernières années. Le Québec et la Saskatchewan présentent les niveaux de diversité ethnique les plus faibles, par rapport à l'Ontario et à la Colombie-Britannique qui présentent les niveaux de diversité ethnique les plus élevés. J'observe une description complètement différente en ce qui concerne la diversité manufacturière, où les niveaux les plus bas se trouvent dans les provinces de l'Ouest. Les plus grandes villes sont les plus innovantes par rapport aux plus petites.

Dans ce chapitre, je trouve également un effet causal de la diversité sur l'innovation. Je constate que la présence de plusieurs groupes ethniques différents augmente le niveau d'innovation dans les villes. Je constate également qu'un plus grand nombre d'usines manufacturière opérant dans différents secteurs augmente le niveau d'innovation dans les villes. Je constate que l'effet de la diversité culturelle sur l'innovation est plus fort que celui de la diversité industrielle.Passer d'une ville située dans le quartile le plus bas de la diversité ethnique à une ville située dans le quartile le plus élevé de la diversité ethnique augmenterait le niveau de l'activité d'innovation locale de 23 %, contre 13 % pour un changement similaire dans la diversité manufacturière. Ces résultats sont robustes à l'immigration récente, à la taille de la ville, à la productivité des inventeurs et à la qualité des brevets. De plus, leurs effets diffèrent également selon le type d'activité d'innovation. La diversité ethnique a des effets positifs sur les innovations chimiques, informatiques et électroniques. et électroniques, tandis que la diversité de la production a des effets positifs sur toutes les classes d'innovation.

Le troisième chapitre se concentre sur le rôle de la diversité manufacturière en tant que moteur de la croissance de l'emploi et facteur de résilience des villes. La résilience urbaine est une question importante pour le développement des villes face aux catastrophes et aux événements inattendus qui affectent les populations et les entreprises locales. Cette recherche examine donc l'effet de la diversité manufacturière, mesurée par la composition de l'emploi manufacturier par secteur, sur la croissance de l'emploi, en particulier en présence de fermetures de grandes usines manufacturières. Il est important de mesurer l'effet de la diversification industrielle sur la croissance économique pendant une récession afin de fournir des informations utiles pour les décisions politiques à plus long terme, telles que la détermination de la nécessité de mettre en place des politiques pour mieux résister aux chocs économiques comme celui généré par le COVID 19. Pour estimer l'effet de la diversité manufacturière sur la croissance de l'emploi dans les zones urbaines canadiennes, le chapitre combine des données au niveau des établissements et des données de recensement de la population de 2006 à 2016. Le chapitre examine également l'effet de la diversité manufacturière sur l'emploi selon le sexe, l'éducation et la profession, et aussi comment l'effet de la diversité manufacturière diffère selon le niveau initial d'innovation de la ville.

Ce chapitre décrit le niveau de diversité manufacturière dans les régions urbaines canadiennes en 2006. Les grandes villes affichent un niveau de diversité manufacturière plus élevé que la moyenne des régions urbaines canadiennes. Il y a une grande variation dans cette mesure relative de la diversité dans les petites et moyennes villes. Les régions urbaines de la Colombie-Britannique, du Canada atlantique et du Nord du Québec ont un niveau de diversité manufacturière inférieur à la moyenne des régions urbaines canadiennes. Celles de l'Alberta et de l'Ontario ont des niveaux de diversité manufacturière supérieurs à la moyenne. En ce qui concerne la description géographique du marché du travail local au Canada, les grandes villes ont toutes connu une croissance de l'emploi, avec des taux de croissance généralement supérieurs à la moyenne des régions urbaines. À l'opposé, les villes de petite et moyenne taille ont connu soit une croissance, soit un déclin de l'emploi.

Dans ce chapitre, je trouve également un effet causal de la diversité industrielle sur la croissance de l'emploi. Je constate que la diversité manufacturière entraîne une plus forte croissance de l'emploi, en particulier dans les services d'arts, de loisirs et de divertissement, les services de construction et les services professionnels, qui semblent être fortement liés à l'industrie manufacturière, notamment par des liens d'entrées-sorties. Je montre également que la diversité de l'industrie manufacturière est orientée vers l'emploi des hommes par rapport aux femmes, et vers une croissance plus élevée de la part des personnes sans diplôme universitaire, caractéristique des emplois dans la construction, la fabrication et les services récréatifs. Je montre également que l'innovation génère des effets supplémentaires de la diversité industrielle sur la croissance de l'emploi. Enfin, je montre que les villes qui sont initialement plus diversifiées sont plus résilientes aux grands chocs négatifs sur l'emploi. Les villes présentant un niveau élevé de diversité industrielle ont vu l'emploi rester relativement stable lorsque de grandes usines de fabrication ont fermé.

CHAPTER I

CULTURAL AND PUBLIC SERVICES AS FACTORS OF CITY RESILIENCE?

Abstract

We combine Canadian census and establishment-level data for 2001–2016 to study the impact of big manufacturing plant closures and downsizing on the size and composition of city-level population. We find that manufacturing plant closures and mass layoffs lead to a decline in subsequent population growth, especially among the young, the working-age, the migrant, and the less skilled populations. We find significant negative spillovers of big manufacturing plant closures on the local employment in other industries, which can explain why such negative local labor demand shocks affect population dynamics. Public services (health and education) and cultural and recreational amenities make cities more resilient and help them retain population following negative local labor demand shocks.

Keywords: Canadian cities; socio-demographic change; plant closures; manufacturing.
JEL Classification Codes: J10; R11; R12; R23.

1.1 Introduction

It appears from the rich literature evaluating the impact of various shocks on city growth that cities are much more vulnerable to political and economic dislocation than to physical destruction (Glaeser, 2021). How the demographic composition of cities changes in the wake of negative economic shocks and what city-level characteristics favor urban resilience are far less studied. We try to fill this gap here.

We evaluate the impact of the closures and massive downsizing of big manufacturing plants on the growth and the composition of the population of cities. We find that plant closures lead to lower subsequent population growth, affect younger residents, single residents and migrants more than older residents, families and non-migrants, and have larger effects on the less skilled workers. Cities that are initially better endowed in education and health services, as well as in arts and recreation amenities, are more resilient to large negative employment shocks. These mitigating effects are heterogeneous across socio-demographic population characteristics. Finally, we show that the closures and massive downsizing of big manufacturing plants negatively affect the employment growth of several other sectors in the local economy, especially in the construction, cultural and FIRE services. These negative spillover effects might partly explain why negative employment shocks in the manufacturing sector have such a significant depressing effect on the demographic dynamics of cities.

Our findings are important for several reasons. First, central and local governments make substantial investments to ward off big plant closures. For example, in 2008 and 2009, the U.S. administration paid $50 billion to General Motors and Chrysler to prevent the closure of their plants, whereas the Canadian federal government paid $9.5 billion to General Motors to secure its business and thousands of jobs in Oshawa.

Measuring the effects of big plant closures on local economies is thus important to understand whether the huge costs of those safeguard plans are justified compared to the short- and long-run costs of the closures. Second, the propensity to consume varies significantly across age groups, and the needs in terms of amenities and services also differ by age or family status. Assessing the heterogeneous impact of big plant closures across population categories is thus important to better understand the potential long-run consequences of these closures on the local economy. Finally, beyond safeguard plans, it is important to identify local factors that can explain why some cities succeed at retaining certain types of residents despite large labor demand shocks. What makes cities resilient is a recurring question in urban and regional economics and a first-order policy concern.

To estimate the effect of big manufacturing plant closures on the size and the composition of the population of Canadian urban areas, we combine establishment level data and population census data from 2001 to 2017. Identifying the impact of poor local economic performance on population changes is challenging due to possible reverse causality. A rich literature has shown that denser labor markets offer higher wages (e.g. Glaeser and Mare, 2001; Combes et al., 2008), while the regional concentration of particular industries could provide insurance against idiosyncratic employment shocks (see e.g. Ellison et al., 2010; Overman and Puga, 2010). Put differently, local economic conditions certainly influence population dynamics, i.e., *people follow jobs*. Yet, job opportunities are not the only factor that attracts population.

Several papers show that people move to cities with better amenities and higher quality-of-life (e.g. Glaeser et al., 2001; Rappaport, 2007; Albouy and Stuart, 2020). Then, firms might follow to reap the benefits from a denser labor markets and a larger pool of workers (e.g. Head and Mayer, 2004). In this case, population growth determines local economic conditions, i.e., *jobs follow people.* [1] This reverse causality would lead to overestimating the impact of big plant closures on local population. Another type of issue is that plant closures are partly

1. These bidirectional causal mechanisms are well explained by "New Economic Geography" models which suggest that agglomeration economies, where big markets attract firms, which in turn attract new workers and consumers, are conducive to self-reinforcing regional growth (Krugman, 1991b; Fujita et al., 1999).

compensated by plant openings. If, for some reason, the plant turnover varies across cities so that cities with a higher plant closure rate have also a higher plant creation rate, this would bias the estimated effect of big plant closures toward zero.

To deal with these endogeneity problems, we rely on an IV strategy. In our preferred specification, our treatment variable is the share of initial manufacturing jobs lost between 2003 and 2017 due to big manufacturing plant closures in each Canadian city. We instrument it with a Bartik which is the predicted growth rate of the number of manufacturing jobs computed as the interaction between the initial manufacturing composition of the city (NAICS 4-digit industries) and the observed growth rate of the number of jobs of these same industries in the U.S. Our instrument arguably captures global technology and trade shocks that affect manufacturing industries in both the US and Canada. Finally, we also control for observable characteristics that might influence city-level population changes such as local temperature, proximity to the coast and to other major urban centers, as well as regional policy differences.

Our work is related to three strands of the literature. First, research on job displacement has shown that workers who lose their jobs due to big plant closures or mass layoffs suffer from long-lasting income losses (e.g. Ruhm, 1991; Jacobson and LaLonde, 1993; Couch and Placzek, 2010), longer unemployment durations (e.g. Eliason and Storrie, 2006), and other adverse outcomes. [2] Building on the literature on multiplier effects [3], other studies analyze the spillover effects of plant closures and mass layoffs on neighboring plants and regional labor markets (see e.g. Gathmann et al., 2020; Jofre-Monseny et al., 2018). However, we are not aware of any study on the relationship between plant closures and

2. These include reduced fertility (e.g., Huttunen and Kellokumpu, 2016), higher mortality (e.g., Sullivan and Von Wachter, 2009), higher risk of divorce (e.g., Charles and Stephens Jr., 2004), and lower income for their kids when they become adults (e.g., Oreopoulos et al., 2008).

3. For example, Moretti (2010) finds using US data that one additional manufacturing job generates 1.6 jobs in the non-tradable sector due to increased demand for local goods and services. Faggio (2019) and Jofre-Monseny et al. (2020) find significant multiplier effects from public-sector jobs in Spain and in the UK.

demographic changes at the local level. Yet, plant closures and mass layoffs can reshape the demographic composition of cities by displacing more mobile populations, which might in turn affect the growth prospects of those cities. [4]

Second, several studies have shown that high-skilled workers and immigrants are highly responsive to local labor demand shocks in terms of labor supply (see, e.g., Topel, 1986; Bound and Holzer, 2000; Cadena and Kovak, 2016). This is confirmed by Albouy et al. (2019), who show that positive local labor demand shocks in the 1990s and 2000s increase the local share of residents holding a university degree in Canada, but not in the US. Beyond different mobility costs, the inelastic housing supply, the existence of social transfers, and the immigration selection criteria can explain this heterogeneous response of workers to local labor demand shocks (see, e.g., Glaeser and Gyourko, 2005; Notowidigdo, 2019). Based on negative employment shocks from the recent decades of deindustrialization, we provide here a different but complementary view on this issue and further analyze the heterogeneous response depending on age and family status. Younger residents and immigrants selected to Canada on the basis of economic criteria are much more sensitive to local economic conditions affecting employment opportunities. On the opposite, we find that family commitments (being in a couple, having at least one child) constitute a significant mobility cost for workers.

Last, we identify some city-level characteristics that explain resilience to big manufacturing plant closures, thereby contributing to the recent literature on the resilience of local economies. Martin et al. (2011) show that French exporting firms suffered more from the 2008 trade collapse when they were located close to other exporters or were targeted by cluster policies. Behrens et al. (2020) show that plants in Canadian textile clusters are not more likely survive or to adapt by changing their main sector of activity than those outside clusters. Finally, Delgado and Porter (2017), show that industries located near other

4. In the context of adverse trade shocks, Twinam (2020) and Autor et al. (2021) find some negative effects on local population dynamics, especially for foreign-born and younger residents, even though the magnitude of these effects seems to be context-specific and to depend on the size of the local units that are considered.

related industries experienced higher employment growth than unrelated industries during the great recession of 2007-2009. Whereas these studies focus on how firms adapt or survive, we adopt here a different angle by examining the performance of cities in retaining specific segments of their population following a negative shock to their local labor market. On the other hand, recent contributions investigate the role of cultural and recreational industries in local development. Polèse (2012) shows with Canadian data that if the presence of cultural industries fosters employment growth in other industries, this is true for specific industries and in the context of large cities only. Behrens et al. (2021a) show that the presence of some cultural and creative industries in poor neighborhoods is significantly associated with subsequent gentrification. We have a different view here and show that the presence of certain services, such as education, health, arts and culture, is contributing to the demographic resilience of cities.

The rest of the chapter is organized as follows. Section 1.2 describes the data used in the empirical analysis. Section 1.3 presents OLS and IV results on the impact of big manufacturing plant closures and downsizing on population composition. In section 1.4 we estimate the impact of big manufacturing plant closures and downsizing on local employment in non-manufacturing industries. Section 1.5 examines the heterogeneous effects along initial characteristics of cities, thus identifying factors of resilience. Section 1.6 concludes.

1.2 Data and descriptive statistics

In this section, we describe the establishment-level database we use to measure big manufacturing plant closures and downsizing, as well as the demographic, economic, and geographic variables we control for in the empirical analysis. We also provide descriptive statistics that motivate our subsequent analysis.

1.2.1 Establishment-level data and plant-closure rate

Our primary source of data are the *Scott's National All Business Directories* that contain exhaustive information on establishments operating in Canada, with an extensive coverage of the manufacturing sector (NAICS 31–33). We have these data every two years from 2003 to 2017.[5] Each plant in that database reports: a unique identifier, information on its primary 6-digit NAICS code, its opening year, its number of employees, whether it is an exporter or a headquarter, and complete address information. The latter allows us to geocode the plants and to assign them to cities.[6] Table 1.1 provides an overview of the geographic structure of manufacturing in Canada in 2003 and 2017, respectively. Most manufacturing plants are located in Quebec and Ontario within the 'manufacturing belt' that runs from Quebec City, QC, to Windsor, ON. Table 1.1 shows that the total number of manufacturing establishments in our sample has declined from 52,784 in 2003 to 34,135 in 2017. This is in line with the deindustrialization process observed in most developed countries over the past decades. Observe also that while the number of plants has sharply declined between 2003 and 2017, their average size has slightly increased, from 31 employees in 2003 to 35 employees in 2017. This suggests positive selection among survivors: more productive and larger plants are more likely to survive strong negative shocks (see Bernard and Jensen, 2007).

While the Scott's database is very exhaustive, it is not a census of manufacturing plants. Yet, it is probably the best alternative to restricted-access datasets such as Statistics Canada's Annual Survey of Manufacturers or the Business Register.[7] In contrast to the first dataset, it provides more information on smaller plants. In contrast to the second dataset, it allows us to track plants and basic information about them over 15 years. Correlations of sectoral or provincial establishment counts and employment in the Scott's Data and Statistics Canada datasets are very high (about 0.95 on average), which suggests that our data provide a fairly accurate picture of the overall manufacturing struc-

5. Data from the 2015 version are missing in our database, thus leaving us with seven cross-sections from 2003 to 2017. We only need the first and the last one for the analysis here.

6. More information on the geocoding procedure is provided in Appendix 1.7.2.

7. See Tables 1.14, 1.15, and 1.16 in the Appendix for a comparison between the Scott's National All Business database and other Statistics Canada databases listing establishments.

Table 1.1: Geographic breakdown of manufacturing plants in Canada.

Region	Province	2003 # of plants	2003 Avg. jobs	2017 # of plants	2017 Avg. jobs
Western	Alberta	3,650	32.9	2,891	36.9
	British Columbia	5,923	27.7	3,966	30.6
	Manitoba	1,556	33.6	1,061	37.3
	Saskatchewan	1,291	23.5	895	25.8
		12,420	***29.5***	***8,813***	***33.0***
Atlantic	New Brunswick	1,376	32.0	740	37.2
	Newfoundland and Labrador	578	39.6	320	41.2
	Nova Scotia	1,576	26.0	816	30.7
	Prince Edward Island	303	24.0	154	34.9
		3,833	***30.0***	***2,030***	***35.1***
Ontario	Ontario	***21,758***	***35.3***	***14,277***	***36.1***
Quebec	Quebec	***14,773***	***34.5***	***8,980***	***39.4***
Canada		**52,784**	**30.9**	**34,135**	**35.0**

Notes: Data from the Scott's National All Business Directories. The table is based on manufacturing plants (NAICS 31–33). The three territories (Northwest Territories, Nunavut, and Yukon) are not reported in the table but are included in the total.

ture with respect to industrial composition, the number of plants, and employment.

We construct measures of the manufacturing job-loss rate and plant-closure rate in city c. Our measures are based on the literature on the effects of mass layoffs that focuses on 'significant closures':[8] (i) large plants—with at least 50 employees—present in 2003 that are not present anymore in 2017; and (ii) large plants—with at least 50 employees—present in 2003 and that disappeared or lost at least 30% of their employees by 2017. Formally, our measures for city c are defined as:

$$\text{Job loss rate}_c = \frac{\text{\# Employees in large plants present in 2003 but not in 2017 in } c}{\text{\# Employees in all plants present in 2003 in } c} \quad (1.1)$$

$$\text{Closure rate}_c = \frac{\text{\# Large plants present in 2003 but not in 2017 in } c}{\text{\# Plants present in 2003 in } c}, \quad (1.2)$$

8. See Jacobson and LaLonde (1993); Sullivan and Von Wachter (2009); Couch and Placzek (2010); Huttunen and Kellokumpu (2016) among others.

where the former (a weighted measure) is based on the employment of big closing/downsizing plants, whereas the latter (an unweighted measure) relies on plant counts.

In what follows, we use job loss rate measured following both definition (i) and definition (ii) for our benchmark analyses. We show in a robustness check that our results hold when using the closure rate.

We can construct measures (1.1) and (1.2) across all industries for each city c but also for the whole of Canada by industry. Table 1.2 reports descriptive statistics on big manufacturing plant closures by industry in Canada. [9]

Table 1.2: Descriptive statistics of big manufacturing plants closed by NAICS 3-digit sectors.

NAICS3	Manufacturing sector	(1) Closure rate closed in initial plants	(2) Job loss rate losses in initial jobs	(3) Avg. # jobs of closed big plants	(4) Relative share of exporters closed/non closed	(5) Relative share of headquaters closed/non closed
311	Food	9.7%	32.5%	152.9	1.00	0.71
312	Beverage and tobacco product	6.4%	23.3%	168.2	0.85	0.92
313	Chemical	16.2%	54.8%	164.3	0.91	0.91
313	Textile mills	7.5%	40.6%	123.7	0.78	0.62
314	Textile product mills	12.5%	47.1%	127.9	0.87	0.57
315	Clothing	5.8%	24.7%	129.3	0.95	0.10
316	Leather and allied product	9.5%	36.7%	141.5	1.03	0.91
321	Wood product	20.6%	49.2%	209.4	1.01	0.71
322	Paper	4.3%	29.6%	125.4	0.91	0.76
323	Printing and related support actv.	7.2%	26.7%	238.6	1.06	0.90
324	Petroleum and coal product	8.9%	30.3%	134.7	0.99	0.95
326	Plastics and rubber products	10.0%	32.1%	130.4	1.02	0.98
327	Non-metallic mineral product	5.4%	26.6%	127.8	1.08	0.81
331	Primary metal	13.6%	38.0%	184.3	1.00	1.22
332	Fabricated metal product	5.1%	24.2%	127.2	1.05	0.78
333	Machinery	6.4%	26.2%	119.3	0.97	0.98
334	Computer and electronic product	8.6%	34.7%	167.3	1.00	0.92
335	Electrical equipment, appliance	8.5%	31.9%	156.8	0.99	0.95
336	Transportation equipment	12.5%	39.8%	195.7	0.92	0.78
337	Furniture and related product	4.6%	25.2%	127.2	0.89	0.95
339	Miscellaneous	2.9%	28.2%	138.6	1.05	0.77
	All sectors	**7.5%**	**32.7%**	**144.9**	**0.98**	**0.82**

Notes: "Big plants" refer to 50+ establishments from 2003 that disappeared in 2017. The data are from Scott's National All Business Directories.

Column 1 reports the share of big plants that closed as a proportion of the total number of plants in 2003 (whatever their size). The (weighted) average clo-

9. Table 1.2 uses definition (i) for what constitutes a closing plant. See Table 1.17 for the same type of descriptive statistics with definition (ii) when we account for mass layoffs (downsizing of plant-level employment by at least 30% between 2003 and 2017) on top of closures.

sure rate equals 7.5%, with substantial heterogeneity across sectors.[10] There is little implication that plant closures are concentrated in small plants in terms of manufacturing job losses. Between 2003 and 2017, 13 percent of plant closures were at large plants, accounting for 42 percent of the total job loss. Large layoffs move many employees into unemployment at the same time, reducing employment opportunities, in addition to affecting businesses that depend on the large plant's output. The closure of small plants, unless there are enough of them, does not produce a significant negative demand shock in the local labor market.

Column 2 presents the share of jobs that are lost due to the closure of big plants. By construction, this share is much higher on average (32.7%) than the plant-closure rate in column 1. The sectors with the highest job loss rates are the chemical, metal, wood product, transportation equipment, and textile and clothing sectors. These sectors also have a high closure rate, which is not surprising since the correlation between the figures in the first two columns of Table 1.2 equals 0.84. Column 3 shows that the average size of closing establishments equals 145 employees. Column 4 shows the ratio between the share of exporters among big plants that closed and the share of exporters among big plants that did not close. On average, there are as many exporters among the big plants that closed as among those that did not close, even though this relative share varies substantially across sectors.

Finally, column 5 shows that there are fewer headquarters among the big plants that closed compared to the big plants that did not close, in line with the fact that when a firm has several establishments, it starts by closing production establishments rather than headquarters.

Turning to the geographic aspects of plant closures, Table 1.3 shows that there is substantial heterogeneity across Canadian provinces. The two big manufac-

10. Out of the 52,784 plants that were active in 2003, 8,941 were big plants with 50+ employees, and out of these, 3,969, i.e. 7.5% of the total number of plants, had closed by 2017 (5,188 when we add downsized plants).

turing provinces, Quebec and Ontario, are the most severely hit. [11] The Western provinces were less severely hit by deindustrialization. This is especially striking when we compare the local job loss rate to the one observed in Canada at the level of Canadian urban areas, as shown on Figure 1.1. Urban areas in Western Canada have a lower manufacturing job loss rate than urban areas in Eastern Canada, especially in the manufacturing belt.

Table 1.3: Big manufacturing plant closure and job loss rates in Canada.

Region	Province	Closure rate as a % of initial plants	Job loss rate as a % of initial jobs	Avg. Jobs of large closed plants
Western	Alberta	6.5%	26.3%	133.4
	British Columbia	5.9%	29.5%	139.3
	Manitoba	7.5%	26.6%	119.9
	Saskatchewan	4.6%	29.2%	147.4
		6.1%	***28.0%***	***135.2***
Atlantic	New Brunswick	6.4%	33.0%	165.1
	Newfoundland and Labrador	8.5%	37.1%	173.1
	Nova Scotia	5.3%	29.0%	143.3
	Prince Edward Island	6.9%	39.6%	137.5
		6.3%	***32.8%***	***156.8***
Ontario	Ontario	***8.0%***	***34.2%***	***150.9***
Quebec	Quebec	***8.3%***	***33.7%***	***140.1***
Canada		**7.5%**	**32.7%**	**144.9**

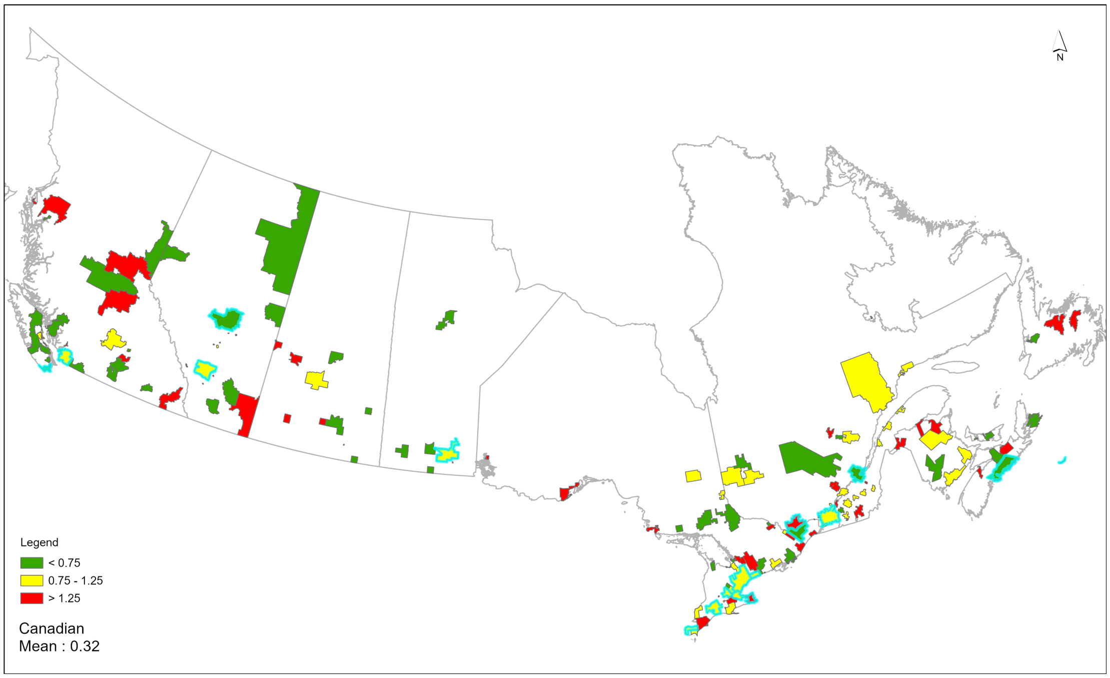
Notes : "Big plants" refer to 50+ establishments as measured in 2003. The data are from Scott's National All Business Directories.

1.2.2 Socio-economic data

We use data from the Canadian census released by the Computing in the Humanities and Social Sciences (CHASS) data center at the University of Toronto. These data are available for *dissemination areas*, the smallest geographic units at which census data are publicly released. We aggregate the information to the level of urban areas. We have information on socio-demographic characteristics such as the total population and the demographic composition of urban areas (in particular gender, age, education, and occupation) for the years 2001,

11. See table 1.18 for a similar description when mass layoffs are also accounted for.

Figure 1.1: Relative job loss rates due to big plant closures in Canadian urban areas



Notes: Distribution of manufacturing job loss rates due to large (50+) plant closures in Canadian Urban Areas. Canadian Urban Areas' job loss rates are measured relatively to the Canadian average. The Canadian mean refers to the rate of job loss in Canada. Green zones are urban areas with a job loss rate lower than the Canadian average. Yellow areas are urban areas with a job loss rate that is approximately equal to the Canadian average. Red areas are urban areas with a job loss rate higher than the Canadian average.Cyan contours outline cities with population of at least 300,000.

2006, 2011, and 2016. [12]

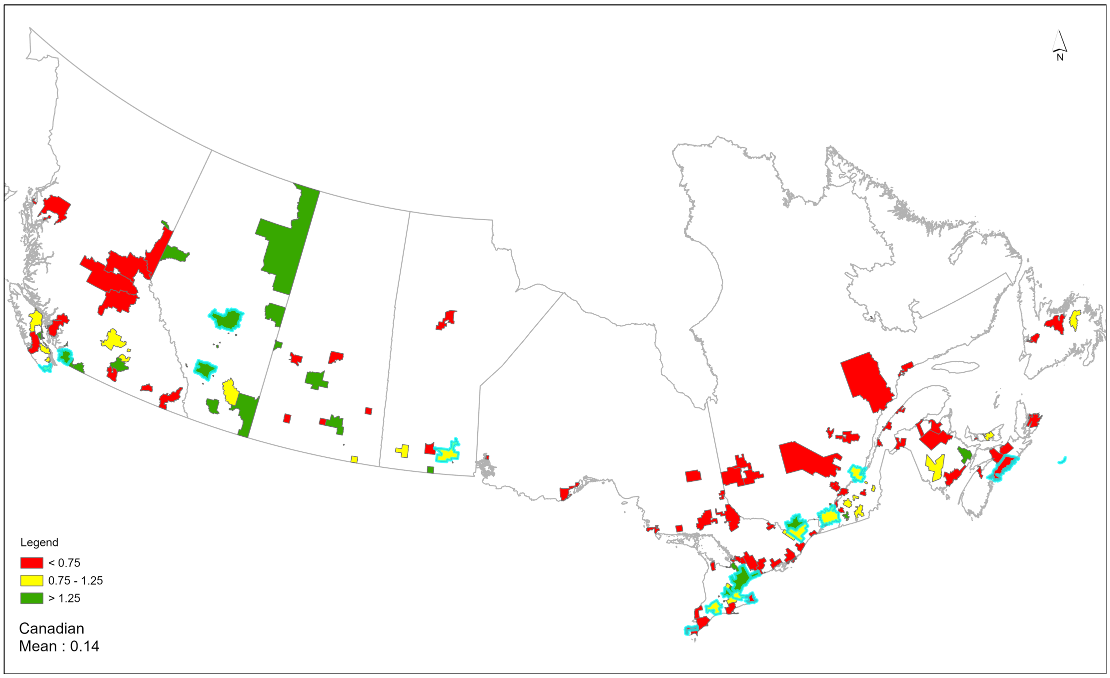
Urban areas—defined as census metropolitan areas (CMA) and census agglomerations (CA)—consist of one or more neighboring municipalities located around a core area and strongly interconnected in terms of commuting flows. [13] Statistics Canada defines a CMA as an area with a total population of at least 100,000, of which 50,000 at least live in the core; whereas a CA is an area with a core population of at least 10,000. By construction, most people living in an urban area also work there. Thus, urban areas are the right spatial unit to investigate the links between plant closures and demographic changes. Our analysis is based

12. Additional details are provided in Appendix A.

13. A description of the distribution of urban areas by province is provided in Table 1.19.

on 154 Canadian urban areas whose boundaries are stable between 2001 and 2016. [14]

Figure 1.2: Relative population growth rates in Canadian Urban Areas



Notes: Growth rates are measured relatively to the Canadian average.The Canadian mean refers to the rate of job loss in Canada. Green zones are urban areas with a job loss rate lower than the Canadian average. Yellow areas are urban areas with a job loss rate that is approximately equal to the Canadian average. Red areas are urban areas with a job loss rate higher than the Canadian average. Cyan contours outline cities with population of at least 300,000.

Figure 1.2 shows there is wide variation in population growth rates across Canadian urban areas. The population of Campbellton's in New Brunswick shrank the most (-18.2% from an initial population of 16,980 in 2001), while the population of Wood Buffalo in Alberta grew the fastest (+72.4% from an initial population of 42,475 in 2001). Large cities (with 300,000+ inhabitants, outlined in cyan on the figure) all experienced population growth, with growth

14. Statistics Canada uses population thresholds to define urban areas. Hence, their number has changed from 145 in 2001 to 156 in 2017. We keep all the areas that appear as an urban area for at least one of the census years under study. After eliminating some outliers, this leaves us with 154 urban areas. Statistics Canada also adjusts the boundaries of urban areas over time. In order to have a stable geography for our 154 urban areas, we take for each of them the envelope of the boundaries observed over the four census periods. More details are provided in Appendix 1.7.2.

rates usually in excess of the Canadian average. On the opposite, small- and medium-sized cities experienced either population growth or population decline. The majority of urban areas in Eastern Canada experienced lower population growth than the Canadian average, particularly in the Atlantic provinces and in the peripheral parts of Ontario and Quebec.[15] In Western Canada, below-average population growth is mostly observed in British Columbia, whereas Alberta had growth levels above the Canadian average.[16] As panel (a) of Figure 1.3 shows, the situation is even more pronounced when looking at the growth of the working-age population.

On the opposite, when looking at the growth of the highly skilled population—defined as those with at least a bachelor degree—it appears that larger urban areas grew at a pace closer to the Canadian agerage (see panel (b) of Figure 1.3).

1.2.3 Additional data

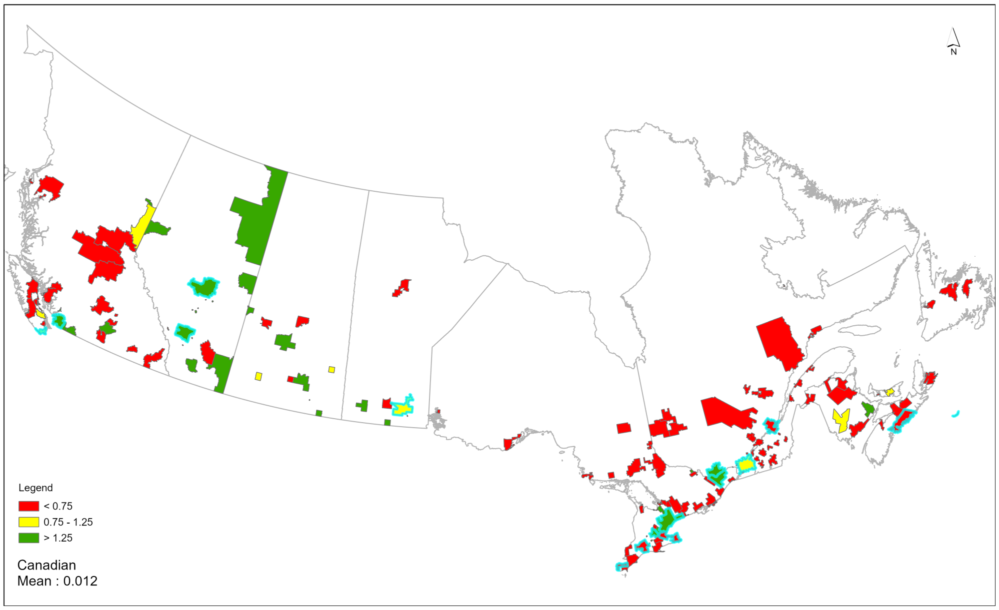
Clearly, some cities are doing better than others in terms of demographic changes as measured by population growth, workforce growth, and growth of the highly skilled. Our goal in the subsequent analysis is to better understand if and how big manufacturing plant closures explain the contrasted demographic changes documented above. To do so, we need to control for many potential confounders, especially initial city characteristics such as human capital, geographic characteristics (climate, access to the coast) and differences in regional public policies. We also need data that allow us to better understand the mechanisms that may drive the heterogeneity in outcomes: which factors may help make cities more resilient? To this end, we use data on the initial share of the labor

15. See, e.g., Johnson (2002) and Polèse and Shearmur (2002) for a more detailed description of the decline of the workforce and the young population in Atlantic Canada.

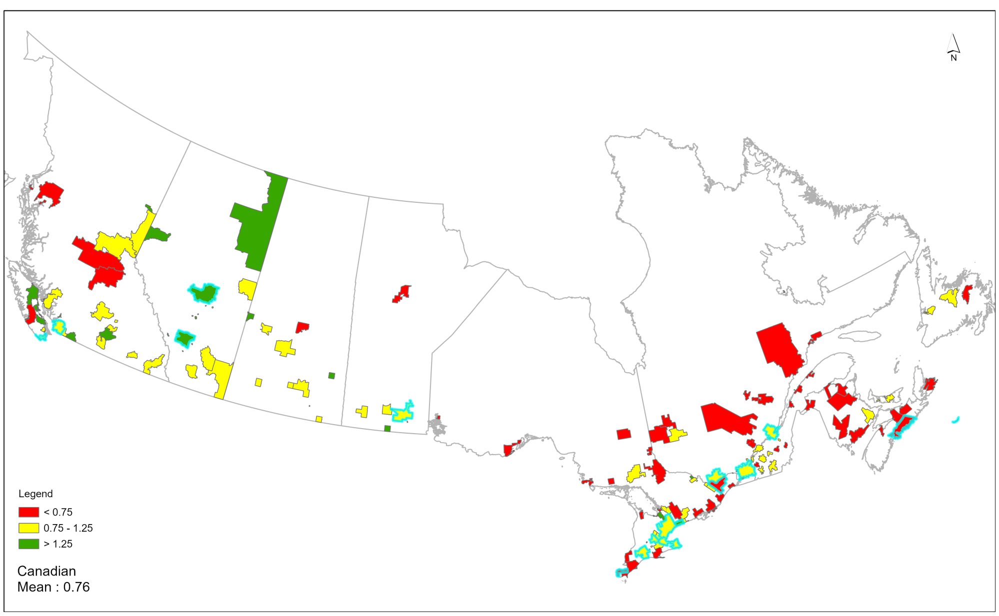
16. The population dynamics in Alberta are probably related to oil development. The industry was particularly buoyant in the early 2000s but has experienced a significant slump since 2014. While this does not control for Alberta specificity, we add region fixed effects to control for prairie regional specificities such as the attractiveness of the resource industry relative to other regions.

Figure 1.3: Relative working-age and high-skilled population growth rates in Canadian Urban Areas

(a) Relative working-age population growth rates



(b) Relative high-skilled population growth rates



Notes: Working age population are people aged 20 to 54. The high-skilled are residents of age 15+ with at least a bachelor degree. The urban areas' growth rates are measured relatively to the Canadian growth rate. The Canadian mean refers to the rate of job loss in Canada. Green zones are urban areas with a job loss rate lower than the Canadian average. Yellow areas are urban areas with a job loss rate that is approximately equal to the Canadian average. Red areas are urban areas with a job loss rate higher than the Canadian average. Cyan contours outline cities with population of at least 300,000.

force working in arts and recreational employment (a measure of consumption amenities), as well as the share of the labor force in educational and health services. Additional details on the data sources used for these various covariates are provided in Appendix A and Table 1.11 presents descriptive statistics for these variables.

1.3 Plant closures and socio-demographic changes: Regression analysis

We present in this section our empirical specification and our baseline results.

1.3.1 Empirical specification

In our first exercise, we are interested in the effect of big manufacturing plant closures and downsizing on city-level growth rates of population-group y. Population-group y are the population groups that will be analyzed such as working age population, elderly population, migrants, couples, parents, skilled people, jobs by industries, etc. Our baseline specification is the following:

$$\text{growth rate of } y_{c,r}^{2001-2016} = \alpha \times \text{job loss rate}_c^{2003-2017} + \beta \times \mathrm{X}_c^{2001} + \theta_r + \varepsilon_c, \quad (1.3)$$

where X_c^{2001} is a vector of initial city characteristics, θ_r are regional fixed effect (Western provinces, Ontario, Quebec, and the Atlantic provinces), and ε_i is an error term. Our vector of initial city characteristics contains: (i) the log initial population in 2001; (ii) dummy variables indicating whether city c is in the top quartile in terms of its share of residents aged 20-54 and its share of residents with a university degree ; (iii) dummy variables indicating whether city c is in the top quartile in terms of its share of employment in manufacturing; (iv) the January and July maximum temperatures; (v) the log distance to the closest coast; and (vi) the log distance to the closest urban center with at least 300,000 inhabitants.

We use dummy shares, because the population variable is highly correlated with the measure of the share of 20–54-year-old and skilled people, in our data. We therefore preferred to transform them into dummy to reduce the strong correlation that influences the results. We keep share of manufacturing in dummy to be consistent with the other dummy variables. However, considering only the manufacturing employment variable instead of the dummy does not qualitatively change the results.

Our variable of interest is the job loss rate between 2003 and 2017 measured, following definition (i), by the share of manufacturing jobs present in 2003 that disappeared by 2017 due to big (50+ employees) plant closures. To check the robustness of our results, we will also consider the share of jobs lost due to big plant closures and mass layoffs (at least 30% of the number of employees) as in definition (ii). We will also check that the results hold when using the closure rate instead of the job loss rate. Regarding the dependent variable, we will consider the growth rate of the total population and of specific subgroups of the population based on age, education, gender, and family characteristics.

We chose an analysis window of about 15 years because population censuses are conducted every five years. Choosing a short window would not allow us to see the effect of closures on the dynamics of population groups. In addition, choosing a window of analysis that ends around the year 2008 could affect our analysis through the effect of the economic crisis on population dynamics and closures. It is difficult to know how long the effect of closures on populations will last. This may depend on the mobility of the group studied. For example, migrants are more sensitive to economic opportunities and will be more likely to move quickly in the face of negative economic demand shocks than other groups such as couples or the elderly. The 15-year window allows for all these differences in mobility between groups, as well as data availability.

Estimating the impact of plant closures on city-level demographic changes using OLS is likely to yield a biased estimate of α. Indeed, it is plausible that plant closures and population changes are simultaneously determined by changes in other dimensions of the local environment (changes in the quality of infrastructure or the crime rate, for example). Even more, as explained in the introduction, it is likely that equation (1.3) suffers from reverse causality: people may leave a city because firms close, but firms may also close because people leave the city. Finally, a higher closure rate might hide a higher turnover of establishments, so that differences in closure rates across cities might not reflect differences in net job creation.

To address these concerns, we instrument the city-level job loss rate by a predicted change in local manufacturing employment. To build our Bartik instrument, we interact the initial sectoral composition of manufacturing employment at the city-level with the growth rate of employment in the U.S. for these same sectors. [17] We thus construct the following IV for each city c:

$$\text{IV}_c = \sum_s \frac{\text{Emp}_{c,s}^{2003}}{\text{Emp}_c^{2003}} \frac{\Delta\text{Emp}_{US,s}^{2003-2017}}{\text{Emp}_{US,s}^{2003}} \tag{1.4}$$

where s denotes 4-digit NAICS industries. For each city, our IV is the weighted average of the growth rates of the number of jobs at the 4-digit level in the U.S. between 2003 and 2017, weighted by the initial share of each sector in the manufacturing employment of the city.

We think this instrument is relevant since it captures global shocks that affect manufacturing industries both in Canada and the U.S. Offshoring and import competition from low-wage countries, for example, have severely hit the textile, clothing, and computer and electronic industries in many developed economies around the world, including Canada and the U.S. However, Canada being small compared to the U.S., it is unlikely that sectoral growth rates in the U.S. are directly affected by sectoral growth rates in Canada (which could themselves be affected by factors that directly affect city-level demographic evolutions in Canada).

It is possible to design a similar IV strategy for the United States. For example, (see Albouy et al., 2019) design "Bartik" employment instruments with U.S. and

17. We use the County Business Patterns database of the U.S. Census Bureau that provides information on the total number of employees in the U.S. by 4-digit NAICS industry in 2003 and 2017. This information allows us to compute the employment growth rate between these two dates for each sector. As in Canada, the vast majority of U.S. manufacturing sectors experienced a decline in employment between 2003 and 2017, particularly in the clothing, textile and computer equipment sectors (see Table 1.20 in the Appendix 1.7.3).

Canadian data to examine labor market dynamics in the two economies. While the two countries have experienced similar structural transformations-such as the decline of their manufacturing sectors-they differ moderately in terms of institutions, transfer policies, and immigration. There are also more pronounced patterns of urban sorting in Canada among its larger, better-educated foreign-born population. Another specificity of the Canadian data is the information on employment by industry in urban areas.

Identification based on Bartik instruments implicitly assumes the exogeneity of the shocks and/or of the shares used to build the instrument (see Borusyak et al., 2020; Goldsmith-Pinkham et al., 2020). We think that we can safely consider that the shares are exogenous in our context: it is highly unlikely that demographic or amenity changes in some specific Canadian cities are directly related to the initial share in their manufacturing employment of the industries that shrunk the most in the U.S., especially at the 4-digit level of the industrial nomenclature and controlling for the various covariates we include in the regression. Still, we will provide some checks that make our IV strategy credible. We cluster all standard errors at the level of Canadian macro-regions as defined above.

1.3.2 Results

Columns (1)–(6) of Table 1.4 show results of the OLS estimation of equation (1.3) across age groups. Three outcome variables are considered: the growth rate of the total population, the growth rate of the working-age population (ages 20-54) and the growth rate of the older population (ages 55+). The treatment variables are the two definitions of job loss rates we mentioned (based on big plant closures alone, and on big plant closures plus substantial downsizing). Whatever the outcome and the treatment variables, the OLS results show that manufacturing job losses are negatively correlated with population growth at the city-level, with semi-elasticities that are very similar across age groups and range from -0.16 to -0.10 approximately. The IV regressions in columns (7)–(12) of Table 1.4 provide a different picture. For total population growth, the coefficient on the manufacturing job loss rate remains negative, but its size (and standard error) increases in absolute value compared to the OLS estimate.

The last four columns show that the increase in the size of the coefficient and in the standard errors masks a highly heterogeneous impact of big manufacturing plant closures on population dynamics across age groups. In columns IV(3) and IV(4), we see that the growth rate of the working age population is negatively affected by big plant closures with a semi-elasticity of about -0.7 to -0.8. On the contrary, manufacturing job losses have no impact on the growth rate of the number of older residents, with a coefficient that is statistically insignificant and close to zero. The fact that the coefficient on the job loss rate becomes more negative with the IV for total population and working age population growth suggests that beyond the circular relationship between population growth and economic growth we highlighted (which should bias downward our OLS estimates), cities that are demographically more dynamic have also both higher job destruction and job creation rates. This could explain why the OLS estimates are biased toward zero for these two outcome variables. Overall, our results show that the closures of big manufacturing plants have led to population declines in Canadian urban areas, this demographic decline being concentrated among the working-age population. The effect is quantitatively sizable. A one percentage point increase in the manufacturing job loss rate causes a 0.71% decrease of the population aged 20-54. Based on the descriptive statistics provided in Table 1.11, a one-standard deviation in the job loss rate due to big plant closures induces a decrease in the working-age population growth rate by 0.72 standard deviations.[18] Big plant closures have thus been an economically significant driver of the city-level dynamics of the working age population in Canada over the past twenty years.[19]

18. The calculation is as follows: $\frac{0.214\times0.71}{0.212} \simeq 0.72$. This effect equals 0.6 of a standard deviation for total population.

19. There are Canadian specificities that can interfere with this instrument, notably regional industrial effects. In the Prairie provinces, manufacturing is driven by the (localized) resource and agricultural industries, so our IV will underestimate their growth since the IV is based on US averages which do capture global trends, but not this type of localized effect. A more elaborate version of the chapter, could add controls on the share of resource industries and agriculture to verify if the IV results still hold.

Regarding the effects of the controls, the results are intuitive. Proximity to large urban centers is attractive for working age residents who certainly favor large markets with better employment opportunities, whereas climatic amenities matter for the older population only. Cities that are initially younger are more attractive to all categories of population in terms of age. Furthermore, we provide additional results in Appendix 1.7.4 where we show that the picture remains qualitatively the same if we consider manufacturing plant closure rates instead of job losses (Table 1.21).

Table 1.4: Job losses and population changes in Canadian cities

Dependent variable *y*: Growth of	Total Population		People aged 20-54		People aged over 55		Total Population		People aged 20-54		People aged over 55	
	OLS(1)	OLS(2)	OLS(3)	OLS(4)	OLS(5)	OLS(6)	IV(1)	IV(2)	IV(3)	IV(4)	IV(5)	IV(6)
Job loss rate (Big plant closures)	-0.165**		-0.156**		-0.177		-0.519**		-0.711***		0.075	
	(0.042)		(0.035)		(0.082)		(0.259)		(0.243)		(0.190)	
Job loss rate (Big plant closures + Downsizing)		-0.111***		-0.107**		-0.092**		-0.553		-0.757**		0.080
		(0.011)		(0.019)		(0.024)		(0.346)		(0.351)		(0.190)
Ln Initial population	-0.030**	-0.030**	-0.020*	-0.020*	-0.050*	-0.051*	-0.023**	-0.019	-0.008	-0.004	-0.055***	-0.056***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.021)	(0.020)	(0.010)	(0.017)	(0.009)	(0.017)	(0.019)	(0.019)
High initial share of people aged 20-54	0.116**	0.115**	0.128**	0.127**	0.279*	0.278*	0.120***	0.121***	0.135***	0.136***	0.276***	0.276***
	(0.027)	(0.025)	(0.032)	(0.031)	(0.097)	(0.094)	(0.029)	(0.032)	(0.036)	(0.040)	(0.078)	(0.078)
High initial share of skilled people	0.048	0.050	0.054	0.056	0.021	0.024	0.040*	0.042	0.042	0.044	0.027	0.027
	(0.023)	(0.025)	(0.031)	(0.033)	(0.050)	(0.050)	(0.023)	(0.036)	(0.026)	(0.042)	(0.042)	(0.040)
High initial share of empl. in manufacturing	-0.012	-0.009	-0.019	-0.017	-0.021	-0.022	0.011	0.042	0.017	0.059	-0.037	-0.042
	(0.017)	(0.017)	(0.020)	(0.021)	(0.018)	(0.019)	(0.019)	(0.047)	(0.018)	(0.045)	(0.026)	(0.035)
January maximum temperature	0.012*	0.012*	0.008	0.008	0.027**	0.028**	0.011***	0.011***	0.006	0.007	0.028***	0.028***
	(0.004)	(0.004)	(0.007)	(0.007)	(0.006)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
July maximum temperature	0.008	0.008	0.006	0.006	0.007**	0.008**	0.004	0.003	-0.000	-0.002	0.010***	0.010***
	(0.006)	(0.005)	(0.008)	(0.008)	(0.002)	(0.002)	(0.008)	(0.011)	(0.010)	(0.014)	(0.003)	(0.003)
Log distance to nearest big city	-0.007	-0.007	-0.007	-0.008	-0.001	-0.002	-0.005***	-0.005***	-0.005***	-0.004***	-0.002	-0.002
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)
Log distance to nearest coastline	0.003	0.004	0.011	0.012	-0.001	0.000	0.001	0.004	0.009	0.013	0.001	0.000
	(0.011)	(0.011)	(0.013)	(0.013)	(0.009)	(0.010)	(0.008)	(0.009)	(0.010)	(0.011)	(0.008)	(0.008)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate							-0.844	-0.792	-0.844	-0.792	-0.844	-0.792
IV P value							0.001	0.000	0.001	0.000	0.001	0.000
IV Partial R2							0.09	0.09	0.09	0.09	0.09	0.09
First stage F statistic							12	35	12	35	12	35
Adjusted R2	0.32	0.30	0.38	0.37	0.29	0.28						
Urban Areas	154	154	154	154	154	154	154	154	154	154	154	154

Notes: "Big plants" refer to 50+ establishments and "downsized plants" to 50+ establishments in 2003 that lose at least 30% of their workforce in 2017. "High initial share" means to be in the top quartile of the cities in our sample. The "skilled" are the 15+ residents with at least a bachelor degree. A big city is a city with at least 300,000 residents. Temperatures are in Celsius and distances in meters. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Scott's National All databases, Statistic Canada's Census 2001-2016 and boundaries files, Environment Canada's weather data.

In Table 1.5, we look at the effect of manufacturing job losses on the evolution of the share of different age groups in the overall population. Compared to the previous results, it allows us to assess whether population growth for a given age group is affected by big plant closures differently from that of the overall population. The first four columns of Table 1.5 show that younger residents are definitely those within the overall population that are more likely to leave a city following big plant closures. Indeed, all else equal, the evolution of their share is negatively impacted by big plant closures. On the opposite, big plant closures cause an increase in the share of the elderly in the overall population. This is coherent with demographic changes at the city-level induced by job-related migrations of the residents: by forcing those of working age to leave, big manufacturing plant closures and downsizing have also reduced the share of the residents aged 0-19 since they are generally the children of working-age parents, leaving behind an older population.

Table 1.5: Job losses and population changes across age groups in Canadian cities

Dependent variable y: Growth of	People aged 0-19		People aged 20-54		People aged over 55	
	IV(1)	IV(2)	IV(3)	IV(4)	IV(5)	IV(6)
Job loss rate (Big plant closures)	-0.077***		-0.107***		0.185***	
	(0.024)		(0.010)		(0.032)	
Job loss rate (Big plant closures + Downsizing)		-0.083**		-0.114***		0.197***
		(0.034)		(0.019)		(0.052)
Ln Initial population	0.002	0.002	0.004**	0.005**	-0.006	-0.008
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)
High initial share of people aged 20-54	0.001	0.002	0.006	0.006	-0.007*	-0.008
	(0.001)	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)
High initial share of skilled people	0.006**	0.007**	0.002	0.003	-0.009	-0.010
	(0.003)	(0.003)	(0.005)	(0.006)	(0.008)	(0.009)
High initial share of empl. in manufacturing	0.007***	0.012***	0.001	0.007**	-0.008	-0.019***
	(0.001)	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)
January maximum temperature	-0.001	-0.001	-0.001	-0.001	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
July maximum temperature	-0.001	-0.001	-0.001	-0.001	0.002	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Log distance to nearest big city	-0.001**	-0.001**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Log distance to nearest coastline	0.001	0.002**	0.002	0.003	-0.003	-0.005*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	-0.844	-0.792	-0.844	-0.792	-0.844	-0.792
IV P value	0.001	0.000	0.001	0.000	0.001	0.000
IV Partial R2	0.09	0.09	0.09	0.09	0.09	0.09
First stage F statistic	12	35	12	35	12	35
Urban Areas	154	154	154	154	154	154

Notes: "Big plants" refer to 50+ establishments and "downsized plants" to 50+ establishments in 2003 that lose at least 30% of their workforce in 2017. "High initial share" means to be in the top quartile of the cities in our sample. The "skilled" are the 15+ residents with at least a bachelor degree. A big city is a city with at least 300,000 residents. Temperatures are in Celsius and distances in meters. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Scott's National All databases, Statistic Canada's Census 2001-2016 and boundaries files, Environment Canada's weather data.

Table 1.6 provides a similar analysis for different population groups in terms of gender, family status, and birthplace. Our IV results show that manufacturing job losses due to big plant closures and downsizing have gender-neutral effects in terms of population since the male-to-female ratio is unaffected. On the opposite, having a partner (married or in a common law union) and/or at least one child reduces the probability of leaving the city following a negative local labor-demand shock. This is consistent with the fact that people with family commitments have higher mobility costs than others (due to joint location decisions and school enrolement, in particular). Our results also show that immigrants are more likely to leave cities that face negative local labor demand shocks: their share in the population decreases following manufacturing job losses. This is coherent with previous studies showing that immigrants are more sensitive to local economic opportunities (Cadena and Kovak, 2016; Albouy et al., 2019) and often work in manufacturing jobs.

Table 1.6: Job losses and population changes across family groups in Canadian cities

Dependent variable *y*: Growth of	Male to female ratio		Couples share		Parents share		Migrants share	
	IV(1)	IV(2)	IV(3)	IV(4)	IV(5)	IV(6)	IV(7)	IV(8)
Job loss rate (Big plant closures)	-0.015		0.039***		0.302***		-0.122***	
	(0.013)		(0.014)		(0.020)		(0.035)	
Job loss rate (Big plant closures + Downsizing)		-0.016		0.041**		0.322***		-0.131**
		(0.015)		(0.019)		(0.074)		(0.055)
Ln Initial population	0.005***	0.005***	-0.001	-0.002	-0.026**	-0.028**	0.003	0.004
	(0.001)	(0.001)	(0.002)	(0.002)	(0.011)	(0.012)	(0.002)	(0.003)
High initial share of people aged 20-54	-0.002	-0.002	0.011***	0.011***	-0.080**	-0.081**	0.017	0.018
	(0.004)	(0.004)	(0.003)	(0.003)	(0.034)	(0.035)	(0.011)	(0.012)
High initial share of skilled people	0.004	0.004	0.009***	0.009***	-0.003	-0.004	0.013***	0.013**
	(0.006)	(0.006)	(0.002)	(0.003)	(0.008)	(0.012)	(0.005)	(0.005)
High initial share of empl. in manufacturing	0.004**	0.005***	-0.005	-0.007*	-0.029	-0.047*	0.014***	0.021***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.020)	(0.025)	(0.003)	(0.008)
January maximum temperature	-0.002***	-0.002***	0.000	0.000	0.004	0.004	-0.003**	-0.003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.001)	(0.001)
July maximum temperature	0.001*	0.001	-0.001	-0.001	0.014***	0.015***	-0.001	-0.002
	(0.000)	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)	(0.002)	(0.002)
Log distance to nearest big city	0.001***	0.001***	0.001**	0.001**	0.003***	0.003**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Log distance to nearest coastline	0.001	0.001	0.001	0.001	-0.015***	-0.017***	0.002	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	-0.844	-0.792	-0.844	-0.792	-0.844	-0.792	-0.814	-0.756
IV P value	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000
IV Partial R2	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.08
First stage F statistic	12	35	12	35	12	35	12	37
Urban Areas	154	154	154	154	154	154	153	153

Notes : "Big plants" refer to 50+ establishments and "downsized plants" to 50+ establishments in 2003 that lose at least 30% of their workforce in 2017. "High initial share" means to be in the top quartile of the cities in our sample. The "skilled" are the 15+ residents with at least a bachelor degree. A big city is a city with at least 300,000 residents. Temperatures are in Celsius and distances in meters. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Scott's National All databases, Statistic Canada's Census 2001-2016 and boundaries files, Environment Canada's weather data.

Finally, in Table 1.7, we look at the effect of job losses in the manufacturing sector on the growth of two different education groups, more skilled residents (those with at least a bachelor degree) and less skilled residents (the rest). Columns (3) and (4) show that there is no significant effect of manufacturing job losses on the growth of skilled residents, whereas columns (5) and (6) show that job losses due to the closure of large plants lead to a significant decline in the number of unskilled residents in the city. This indicates that skilled residents are less likely to leave a city as a result of big manufacturing plant closures. Indeed, other things being equal, columns (7) and (8) show that the evolution of the share of skilled residents is positively influenced by large plant closures. The literature on the polarization of labor markets shows that medium-skilled jobs have declined over the past 30 years, whereas the share of high- and low-skilled jobs has increased. This partly stems from deindustrialization since medium-skilled jobs are more prominent in the manufacturing sector than in the economy as a whole (Goos et al., 2009; Autor and Dorn, 2013). Since we examine the closure of big manufacturing plants—which mainly employ low- and medium- skilled workers—this certainly explains why we do not see a decline in the number and share of high-skilled residents, even though the latter are generally more responsive to local labor demand shocks in terms of labor supply than less educated workers (see e.g. Topel, 1986; Bound and Holzer, 2000; Albouy et al., 2019).

1.3.3 Robustness checks

Several recent contributions discuss the conditions under which Bartik instruments are valid and propose procedures to ensure they can be used safely. Following the suggestions made by Borusyak et al. (2020), we do three things.

First, we check that the Bartik IV exhibits enough variation to be relevant. With a mean and a median values of -0.16, a standard deviation of 0.08, and a difference between the first and the fourth quintiles of 18 p.p., we believe it does. Another way to assess the relevance of the instrument is to measure the inverse of the Herfindahl index of the sectoral shares at the national level. In case a few specific industries represent the lion share of national manufacturing employ-

Table 1.7: Job losses and population changes across education groups in Canadian cities

Dependent variable y: Growth of	Total Population		Skilled Population		Non-Skilled Population		Skilled Share	
	IV(1)	IV(2)	IV(3)	IV(4)	IV(5)	IV(6)	IV(7)	IV(8)
Job loss rate (Big plant closures)	-0.519**		-0.243		-0.565**		0.033***	
	(0.259)		(0.404)		(0.272)		(0.008)	
Job loss rate (Big plant closures + Downsizing)		-0.553		-0.259		-0.602		0.035***
		(0.346)		(0.464)		(0.372)		(0.013)
Ln Initial population	-0.023**	-0.019	-0.083**	-0.081**	-0.023	-0.019	-0.001	-0.001
	(0.010)	(0.017)	(0.039)	(0.039)	(0.016)	(0.024)	(0.003)	(0.004)
High initial share of people aged 20-54	0.120***	0.121***	0.288***	0.288***	0.099***	0.101***	0.011***	0.011***
	(0.029)	(0.032)	(0.087)	(0.087)	(0.028)	(0.032)	(0.003)	(0.003)
High initial share of skilled people	0.040*	0.042	0.007	0.008	0.003	0.005	0.018***	0.018***
	(0.023)	(0.036)	(0.059)	(0.064)	(0.036)	(0.050)	(0.004)	(0.005)
High initial share of empl. in manufacturing	0.011	0.042	-0.089	-0.075	0.021	0.054	-0.008**	-0.010*
	(0.019)	(0.047)	(0.063)	(0.077)	(0.025)	(0.057)	(0.004)	(0.005)
January maximum temperature	0.011***	0.011***	0.023***	0.024***	0.012***	0.012***	0.001**	0.001**
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.000)	(0.000)
July maximum temperature	0.004	0.003	0.029***	0.029***	-0.001	-0.002	0.002**	0.002**
	(0.008)	(0.011)	(0.009)	(0.011)	(0.010)	(0.014)	(0.001)	(0.001)
Log distance to nearest big city	-0.005***	-0.005***	-0.012	-0.011	-0.004***	-0.004**	-0.001	-0.001
	(0.001)	(0.001)	(0.008)	(0.008)	(0.001)	(0.002)	(0.000)	(0.001)
Log distance to nearest coastline	0.001	0.004	-0.024	-0.022	0.006	0.009	-0.002**	-0.002**
	(0.008)	(0.009)	(0.015)	(0.017)	(0.009)	(0.011)	(0.001)	(0.001)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	-0.844	-0.792	-0.844	-0.792	-0.844	-0.792	-0.844	-0.792
IV P value	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000
IV Partial R2	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
First stage F statistic	12	35	12	35	12	35	12	35
Urban Areas	154	154	154	154	154	154	154	154

Notes: "Big plants" refer to 50+ establishments and "downsized plants" to 50+ establishments in 2003 that lose at least 30% of their workforce in 2017. "High initial share" means to be in the top quartile of the cities in our sample. The "skilled" are the 15+ residents with at least a bachelor degree and the "non-skilled" are residents over 15 years of age without a bachelor's degree. A big city is a city with at least 300,000 residents. Temperatures are in Celsius and distances in meters. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Scott's National All databases, Statistic Canada's Census 2001-2016 and boundaries files, Environment Canada's weather data.

ment, it is unlikely that sectoral shares vary enough across locations to provide a good IV. Here, this statistic is equal to 42.8 (the highest industry share at the national level being no larger than 0.06), which suggests there is a reasonable degree of variation in industry shares. All in all, these statistics confirm the above-10 Kleinbergen-Paap tests of the regressions: the Bartik IV can be considered as a relevant IV in our case.

Regarding the validity of the instrument, we report in Table 1.22 a placebo test where the dependent variable is the population growth rate between 1991 and 2001 instead of 2001 and 2016. This placebo amounts to a test for the parallel trend assumption. All the coefficients we obtain in the IV regressions are close to 0 and statistically insignificant. Another concern with the benchmark IV regressions is that if some industries are highly concentrated in urban areas with specific unobserved trends, there could be a correlation between the instrument and the error term in the IV regressions. To take care of this issue, we build an alternative Bartik instrument from which we remove the industries that are the most highly geographically concentrated.[20] As can be seen in Table 1.23, the results are very stable. Overall, these checks confirm the validity of the Bartik instrument in the context of our study.

1.4 The multiplier effect of big plant closures

In this section we estimate the impact of big manufacturing plant closures and mass layoffs on the employment of other industries. Indeed, Moretti (2010) shows that jobs in the tradable sector create additional jobs in the non-tradable one, mainly through an increase in the demand for local goods and services. He estimates separate elasticities for each industry within the non-tradable sector and finds that job changes in the tradable sector have the largest effect on construction, wholesale trade and personal services jobs. Gathmann et al. (2020) and Jofre-Monseny et al. (2018) investigate multiplier effects in the case of big plant closures and/or mass layoffs and find that these effects are small.

Here, we examine the effect of big manufacturing plant closures and mass layoffs on employment growth in the non-manufacturing sector. Thanks to the information on local employment at the NAICS 2-digit level available in the Census data, we are able to consider (i) construction services, (ii) arts, entertainment and recreation services, (iii) professional services composed of the information, finance, real estate, scientific and technical, management and administrative support services, (iv) trade and transport services composed of the retail trade, wholesale trade, transport and warehousing sectors, (v) education and health services, and (vi) accomodation and food services.[21] The results are

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20. We define them as the industries for which the inverse of the Herfindahl index of the CMA-level shares in the overall industry-level employment is below 5 (i.e. Herfindahl index of geographic concentration above 0.2).

21. Construction services correspond to NAICS 23, Arts, entertainment and recreation services to NAICS 71, Professional services to NAICS 51 to 56, Trade and transport services to

reported in Table 1.8.

Among the non-manufacturing industries most negatively affected by the closure of big manufacturing plants we find construction, arts, entertainment and recreation, and professional services. Trade and transport services are also affected, but to a lesser extent in terms of marginal impact. These negative spillovers of big manufacturing plant closures and downsizing on the employment in other industries reflect both propagation of the shock to the local economy through input-output linkages (manufacturing plants consume a lot of professional and trade services for example) and through lower local demand from consumers since the manufacturing jobs destroyed by deindustrialization were on average quite high-paying jobs (which could explain the negative effect on arts, entertainment and recreation services for example).

Education and health services are not significantly affected by big manufacturing plant closures and downsizing which certainly reflects the fact that in Canada, these services are public services that, in case of negative shocks, are maintained by public authorities longer than if they were provided privately. While we could have expected a significant negative impact on accomodation and food services, this does not seem to be the case. However, the data we have do not allow us to investigate whether behind this apparent absence of impact there is a significant increase in turnover where high-end full service restaurants and hotels are replaced by lower-end limited services restaurants and motels for example.

All in all, the significant negative spillovers from big plant closures we observe in several industries show that the job losses experienced at the city-level go well beyond the immediate loss related to the plant closures or downsizing. This provides a possible explanation as to why these shocks affect so significantly the demographic dynamics of the cities that are the most severely hit.

NAICS 41, 44, 48 and 49, Education and health services to NAICS 61 and 62, and finally Accomodation and food services to NAICS 72.

Table 1.8: Job losses and employment changes by sector

Dependent variable y: Growth of	Construction services		Arts, entertainment and recreation services		Professional services		Trade and transport services		Education and health services		Accomodation and food services	
	IV(1)	IV(2)	IV(3)	IV(4)	IV(5)	IV(6)	IV(7)	IV(8)	IV(9)	IV(10)	IV(11)	IV(12)
Job loss rate (Big plant closures)	-0.765***		-0.697**		-0.572**		-0.450**		-0.318		-0.278	
	(0.214)		(0.335)		(0.262)		(0.224)		(0.370)		(0.319)	
Job loss rate (Big plant closures + Downsizing)		-0.814**		-0.741***		-0.610*		-0.480*		-0.339		-0.297
		(0.348)		(0.256)		(0.350)		(0.289)		(0.430)		(0.375)
Ln of sectors employment in 2001	-0.009	-0.004	-0.198***	-0.197***	-0.038**	-0.033	-0.003	0.001	-0.047***	-0.046***	-0.010	-0.008
	(0.051)	(0.063)	(0.057)	(0.056)	(0.017)	(0.021)	(0.013)	(0.020)	(0.012)	(0.014)	(0.029)	(0.035)
High initial share of people aged 20-54	-0.004	-0.003	0.093	0.095	0.145***	0.145***	0.063***	0.063***	0.156***	0.157***	0.100***	0.101***
	(0.041)	(0.043)	(0.058)	(0.062)	(0.038)	(0.036)	(0.013)	(0.016)	(0.025)	(0.029)	(0.028)	(0.026)
High initial share of skilled people	0.025	0.028	0.259***	0.263***	0.051	0.051	-0.007	-0.006	0.047***	0.048**	0.017	0.018
	(0.032)	(0.024)	(0.087)	(0.096)	(0.049)	(0.065)	(0.028)	(0.040)	(0.015)	(0.021)	(0.042)	(0.050)
High initial share of empl. in manufacturing	0.137***	0.183**	0.004	0.044	0.077**	0.112**	0.083***	0.110***	-0.021	-0.002	0.005	0.021
	(0.044)	(0.082)	(0.063)	(0.061)	(0.033)	(0.047)	(0.018)	(0.042)	(0.045)	(0.067)	(0.040)	(0.065)
January maximum temperature	-0.000	0.001	0.048***	0.050***	0.014***	0.015***	0.010***	0.010***	0.016***	0.017***	0.004	0.005
	(0.009)	(0.009)	(0.004)	(0.004)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)	(0.009)
July maximum temperature	-0.021	-0.024	0.007	0.005	0.004	0.002	0.004	0.002	0.016**	0.016	0.015	0.014
	(0.022)	(0.026)	(0.012)	(0.013)	(0.010)	(0.013)	(0.008)	(0.010)	(0.007)	(0.010)	(0.009)	(0.011)
Log distance to nearest big city	-0.010	-0.010	-0.032**	-0.033**	-0.003	-0.003	-0.004***	-0.004**	-0.011**	-0.012***	-0.010***	-0.010***
	(0.010)	(0.011)	(0.013)	(0.013)	(0.004)	(0.004)	(0.001)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Log distance to nearest coastline	-0.009	-0.005	-0.004	-0.000	-0.012*	-0.008	-0.004	-0.001	-0.002	-0.000	-0.011*	-0.009
	(0.010)	(0.011)	(0.010)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.006)	(0.008)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	-0.848	-0.797	-0.842	-0.792	-0.846	-0.793	-0.839	-0.787	-0.843	-0.792	-0.838	-0.786
IV P value	0.001	0.000	0.002	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000
IV Partial R2	0.09	0.09	0.09	0.08	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.08
First stage F statistic	11	32	10	27	11	34	12	37	12	36	12	33
Urban Areas	154	154	154	154	154	154	154	154	154	154	154	154

Notes : "Big plants" refer to 50+ establishments. "High initial share" means to be in the top quartile of the cities in our sample. The "skilled" are the 15+ residents with at least a bachelor degree. A big city is a city with at least 300,000 residents. Temperatures are in Celsius and distances in meters. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Scott's National All databases, Statistic Canada's Census 2001-2016 and boundaries files, Environment Canada's weather data.

1.5 City-level resilience to big plant closures and mass layoffs

We now examine whether certain initial city characteristics can mitigate the negative effects of big manufacturing plant closures on demographic changes. We investigate successively two dimensions: (i) the provision of educational and health services; and (ii) the provision of cultural and recreational amenities. [22] Note that these two dimensions are very weakly correlated in our data. Hence, we capture different mechanisms when studying each of them.

The provision of local public services to the population could mitigate the negative effect of big plant closures on demographic changes by absorbing part of the consequences of the shock for those who lose their job. They might also represent an amenity that is valued and therefore can retain residents. The census

22. The dimensions of resilience explored were chosen because we want to see how certain amenities help retain people. Education, social services, and cultural services are amenities, unlike, for example, government services or military bases.

data report information on the number of residents employed in educational services (NAICS 61) and in health care and social assistance services (NAICS 62). The sum of these two industries subsumes employment in schools, hospitals, and home and social assistance. We compute for each city the initial share of employment in these two industries. We then construct a dummy identifying those cities in the top quartile observed of the distribution, and we interact it with our measure of manufacturing job losses. The results in Table 1.9 are striking: cities with the highest initial population share working in public services are almost insensitive to big plant closures or mass layoffs in terms of population growth. Migrants are more sensitive to the initial presence of public services than the rest of the population, whereas no significant heterogeneity is detected along this dimensions for working age and for high-skilled residents.[23]

Turning to cultural amenities, we proxy them using data on employment in cultural (art and entertainment) and recreational services (NAICS 71). We conjecture that the impact of big manufacturing plant closures and mass layoffs on population changes is heterogeneous depending on the initial employment share of these industries. The results in Table 1.10 show that the presence of cultural and recreational services is a factor of resilience for cities; those cities with an initial share of employment in cultural and recreational industries in the top quartile are rather insensitive to big manufacturing plant closures. This result is mainly driven by the working-age population and the high-skilled workers. However, contrary to educational and health services, it seems that cultural and recreational services do not disproportionately act as a mitigating factor for immigrants.

To summarize, the depressing effect of big manufacturing plant closures on the demographic evolution of cities can be mitigated by the presence of public services in education and health and of specific consumption amenities such as

23. These results hold when we remove provincial capitals or very big cities (above 1 million inhabitants), i.e., they are not driven by those cities. They are available upon request.

Table 1.9: Job losses, population changes, and public services in Canadian cities

Dependent variable y: Growth of	Total Population		Population 20-54 share		High-skilled share		Migrants share	
	IV(1)	IV(2)	IV(3)	IV(4)	IV(5)	IV(6)	IV(7)	IV(8)
Job loss rate (Big plant closures)	-1.043***		-0.145***		0.053***		-0.214***	
	(0.214)		(0.046)		(0.019)		(0.055)	
Big Job losses 1 x High initial share in education and health services	0.886***		0.065		-0.034		0.163**	
	(0.204)		(0.058)		(0.027)		(0.071)	
Job loss rate (Big plant closures + Downsizing)		-1.142***		-0.160***		0.058***		-0.235***
		(0.443)		(0.041)		(0.020)		(0.053)
Big Job losses 2 x High initial share in education and health services		0.990**		0.077		-0.039		0.184***
		(0.411)		(0.063)		(0.025)		(0.067)
Ln Initial population	-0.023***	-0.019	0.004**	0.005*	-0.001	-0.001	0.003	0.004
	(0.004)	(0.014)	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.004)
High initial share of people aged 20-54	0.107***	0.105***	0.006	0.005	0.012***	0.012***	0.016	0.016
	(0.035)	(0.040)	(0.005)	(0.006)	(0.004)	(0.004)	(0.011)	(0.012)
High initial share of skilled people	0.067***	0.070***	0.004	0.004	0.017***	0.016***	0.015***	0.016***
	(0.005)	(0.017)	(0.006)	(0.007)	(0.003)	(0.004)	(0.006)	(0.005)
High initial share of empl. in manufacturing	0.025***	0.087**	0.002	0.011*	-0.009***	-0.012***	0.017***	0.030***
	(0.009)	(0.043)	(0.007)	(0.006)	(0.003)	(0.004)	(0.006)	(0.008)
High initial share in education and health services	-0.316***	-0.397***	-0.020	-0.028	0.013*	0.017*	-0.048**	-0.064**
	(0.055)	(0.148)	(0.018)	(0.022)	(0.008)	(0.009)	(0.024)	(0.026)
January maximum temperature	0.009	0.010*	-0.001	-0.001	0.001*	0.001*	-0.002	-0.002
	(0.007)	(0.006)	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)
July maximum temperature	-0.001	-0.004	-0.001	-0.002	0.002***	0.003**	-0.002	-0.003
	(0.009)	(0.015)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
Log distance to nearest big city	-0.004***	-0.005*	0.000	0.000	-0.001	-0.001	-0.001***	-0.001*
	(0.001)	(0.003)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Log distance to nearest coastline	0.001	0.005	0.002	0.003	-0.002*	-0.002**	0.002	0.003*
	(0.007)	(0.009)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	-0.612	-0.553	-0.612	-0.553	-0.612	-0.553	-0.606	-0.546
IV P value	0.226	0.122	0.226	0.122	0.226	0.122	0.224	0.119
IV Partial R2	0.11	0.10	0.11	0.10	0.11	0.10	0.10	0.09
First stage F statistic	17	43	17	43	17	43	16	40
Urban Areas	154	154	154	154	154	154	153	153

Notes: "Big plants" refer to 50+ establishments and "downsized plants" to 50+ establishments in 2003 that lose at least 30% of their workforce in 2017. "High initial share" means to be in the top quartile of the cities in our sample. The "skilled" are the 15+ residents with at least a bachelor degree. A big city is a city with at least 300,000 residents. Temperatures are in Celsius and distances in meters. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Scott's National All databases, Statistic Canada's Census 2001-2016 and boundaries files, Environment Canada's weather data.

recreational services. [24] However, the intensity and the significance of the mitigating effect varies across population groups, reflecting probably the variety of tastes and needs across age, education, and cultural groups. [25]

24. The analysis presented in Section 1.5 addresses the issue of spatial sorting. We show that the provision of local public services helps retain workers following a negative shock. In our analysis we include the variable measuring the presence of local public services and its interaction with large plant job losses. We believe that the first variable controls for the fact that public services could attract a specific type of worker.

25. To provide additional understanding of the dimensions of resilience enabled by consumer amenities and care and education services, one could explore the effects of closures on changes in unemployment and inactivity rates. One would expect that in cities that retain comparatively more job losers, the level of unemployment or inactivity would increase, if

Table 1.10: Job losses, population changes, and cultural services in Canadian Urban Areas

Dependent variable *y*: Growth of	Total Population		Population 20-54 share		High-skilled share		Migrants share	
	IV(1)	IV(2)	IV(3)	IV(4)	IV(5)	IV(6)	IV(7)	IV(8)
Job loss rate (Big plant closures)	-0.650**		-0.116***		0.021*		-0.096***	
	(0.322)		(0.017)		(0.013)		(0.030)	
Big Job losses 1 x High initial share in arts and recreation ind.	0.642***		0.039*		0.031***		-0.135**	
	(0.247)		(0.020)		(0.012)		(0.065)	
Job loss rate (Big plant closures + Downsizing)		-0.753		-0.136***		0.025		-0.116**
		(0.474)		(0.032)		(0.018)		(0.058)
Big Job losses 2 x High initial share in arts and recreation ind.		0.776**		0.079***		0.015*		-0.063
		(0.354)		(0.029)		(0.009)		(0.046)
Ln Initial population	-0.027**	-0.020	0.004**	0.005*	-0.001	-0.001	0.004**	0.004
	(0.011)	(0.015)	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)
High initial share of people aged 20-54	0.101***	0.100***	0.005	0.004	0.012***	0.012***	0.022**	0.020*
	(0.023)	(0.020)	(0.004)	(0.004)	(0.003)	(0.003)	(0.011)	(0.012)
High initial share of skilled people	0.065***	0.057***	0.003	0.004	0.017***	0.016***	0.007	0.011**
	(0.008)	(0.011)	(0.005)	(0.006)	(0.004)	(0.004)	(0.006)	(0.006)
High initial share of empl. in manufacturing	0.020	0.051	0.002	0.008*	-0.006	-0.008	0.012***	0.021***
	(0.020)	(0.051)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.008)
High initial share in arts and recreation ind.	-0.189***	-0.272**	-0.009	-0.026***	0.003	0.008	0.046*	0.026
	(0.064)	(0.114)	(0.006)	(0.009)	(0.007)	(0.006)	(0.024)	(0.019)
January maximum temperature	0.012***	0.014***	-0.001	-0.001	0.001***	0.000***	-0.003***	-0.003**
	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
July maximum temperature	0.003	0.000	-0.001	-0.002	0.002**	0.002**	-0.001	-0.002
	(0.010)	(0.014)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Log distance to nearest big city	-0.005**	-0.005**	0.000	0.000	-0.001	-0.001	-0.001***	-0.001**
	(0.002)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Log distance to nearest coastline	0.002	0.006	0.002	0.003	-0.002**	-0.002**	0.002	0.003*
	(0.008)	(0.010)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	-0.903	-0.738	-0.903	-0.738	-0.903	-0.738	-0.869	-0.694
IV P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IV Partial R2	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.08
First stage F statistic	12	15	12	15	12	15	12	15
Urban Areas	154	154	154	154	154	154	153	153

Notes: "Big plants" refer to 50+ establishments and "downsized plants" to 50+ establishments in 2003 that lose at least 30% of their workforce in 2017. "High initial share" means to be in the top quartile of the cities in our sample. The "skilled" are the 15+ residents with at least a bachelor degree. A big city is a city with at least 300,000 residents. Temperatures are in Celsius and distances in meters. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Scott's National All databases, Statistic Canada's Census 2001-2016 and boundaries files, Environment Canada's weather data.

The resilience of cities which have strong public health and administrative sectors is a classic result, especially in Canada. This is partly true in all countries, but especially in Canada given its geography - one of rather isolated cities, some of which dominate a low-density resource intensive hinterland. Even when manufacturing (or resources) decline in these areas, public administration carries on - at least for quite long periods (e.g. Bradford, 2005, 2007). This is both for political reasons, and because these regions still need to be adminis-

these people are not employed. The educated are predominantly inactive, and the unemployed benefit from important public services in Canada, including health care and government assistance.

tered even if the economy is in decline. Furthermore, the federal government has actively sought to locate some of its agencies in isolated or declining regions.

1.6 Conclusion

In this chapter, we have analyzed the effect of big manufacturing plant closures and mass layoffs on subsequent demographic changes in Canadian cities. We have shown that job losses due to big plant closures and mass layoffs negatively affect population growth in urban areas in Canada between 2001 and 2016. This effect is concentrated among younger (working age) residents. The share of families and couples in the local population increases in cities where job losses are the highest, which shows they are less mobile than single people. On the opposite, the share of immigrants decreases, in line with the well-documented fact that immigrants are more mobile and their location decisions are more driven by job opportunities. Some initial city-level characteristics such as the provision of public services (education, health and social services), as well as consumption amenities (arts and recreational services) help to mitigate the negative effect of plant closures on subsequent demographic changes for certain categories of population. One implication of our results is that investments in education, health and social services, or in cultural and recreational services might have long-run effects by fostering the ability of cities to retain their most mobile residents in case of bad shocks. These insights might be particularly relevant to think of of the possible demographic consequences of the COVID-19 crisis for cities.

1.7 Appendix to Chapter 1

This set of appendixes is organised as follows. Appendix A describes the data used in our analysis. Appendix B provides definitions of the variables and details the process we followed to geocode our database. Appendix C provides additional descriptive statistics and Appendix D displays additional results.

1.7.1 Data

Census data The Census data released by the Computing in the Humanities and Social Sciences (CHASS) data center at the University of Toronto contain a great deal of information on the socio-demographic characteristics of the residents as well as on the jobs thy occupy. We use them to construct several of our controls on top of our dependent variables.

The literature has shown that certain initial socio-economic characteristics of the population affect city-level population growth. Among them, the level of schooling—of human capital—of the population is strongly correlated with subsequent city growth (see, e.g., Glaeser et al., 1995; Moretti, 2004a). Our proxy for the initial human capital is the share of residents holding at least a bachelor degree in 2001. We are also interested in which factors make cities more resilient. We focus more specifically on the presence of cultural and recreational activities, and on the presence of education and health services. In this purpose, census data allow us to compute the share of residents employed in these specific industries in 2001. [26]

Table 1.11 presents descriptive statistics on the variables used in this study. The average population growth rate observed across Canadian urban areas is equal to 14.3%. In 2001, in Canadian urban areas, half of the population was part of the working age population defined as 20-54 year-old residents, 12% had a university degree on average, and 14.1% of employment was in manufacturing on average. In addition, 18% of the residents worked in educational, health and social assistance services, and 2% in cultural and recreational services. However, as the table illustrates, there is a great deal of variation across urban areas for all of these initial characteristics that are helpful for our estimations.

Geographic Data We control in our regression analysis for several relevant geographic characteristics that may influence city-level population growth.

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26. See more details here: https://www23.statcan.gc.ca/imdb/p3VD.pl?Function=getVD&TVD=307532

Table 1.11: Descriptive statistics, urban area variables.

Variable	Obs	Sample Mean	Std. Dev.	Minimum	Maximum	Population Mean
Growth rate						
Total Population	154	0.143	0.181	-0.184	0.953	0.172
People aged between 20-54 years	154	0.012	0.212	-0.333	0.902	0.063
People aged over 55 years	154	0.633	0.257	0.153	1.934	0.606
People with university degree at bachelor or above	154	0.765	0.436	0.010	2.721	0.813
People with non-university degree at bachelor or above	154	0.222	0.184	-0.094	1.179	0.213
Changes in shares						
Male to female ratio	154	0.005	0.021	-0.067	0.059	0.004
Couple families (married and common-law couples)	154	0.040	0.027	-0.016	0.108	0.038
People with one or more children	154	0.007	0.112	-0.262	0.463	-0.078
Immigrant people	153	0.019	0.035	-0.037	0.156	0.044
Closures rate						
% big plants closed	154	0.070	0.050	0	0.263	0.075
% big and downsized plants closed	154	0.091	0.062	0	0.333	0.098
Job losses rates						
% job losses of big plants closed	154	0.304	0.214	0	0.921	0.327
% job losses of big and downzised plants	154	0.358	0.212	0	0.921	0.389
Initial level						
Initial population (2001)	154	158,226	510,705	7,720	4,677,175	30,000,000
% Initial working age population	154	0.498	0.038	0.343	0.608	0.516
% Initial people with university degree	154	0.118	0.044	0.054	0.309	0.169
Labor force (industry)						
% Initial share of employment in manufacturing	154	0.141	0.080	0.016	0.342	0.140
% Arts and recreational employment	154	0.019	0.011	0.005	0.097	0.019
% Public services (educational and health) employment	154	0.178	0.032	0.104	0.292	0.163
Geographic variables						
Maximum January temperature (C)	154	7	3	-2	14	7
Maximum July temperature (C)	154	31	2	21	38	31
Distance to nearest coast (m)	154	206,044	199,927	0	858,863	206,044
Distance to nearest big urban area (m)	154	202,455	285,300	0	990,837	202,455

Notes: A big city is a city with at least 300,000 residents.

Distance Data: Proximity to the coast, which contributes to moderating extreme temperatures, is strongly positively correlated with population growth in the U.S. (see Rappaport and Sachs, 2003). We thus measure the distance between the centroid of each city and the nearest maritime coast. It has also been shown that cities that are close to the top metropolises in the urban hierarchy are more attractive to firms and workers (see Partridge et al., 2009). We thus calculate the distance separating each urban area from the largest urban area of at least 300,000 inhabitants.

Weather Data: Climatic conditions, as proxied by temperatures, are also among the amenities identified in the literature as a determinant of the residential attractiveness of cities (see Glaeser et al., 2001; Rappaport, 2007). We use the monthly climate summaries from the Canadian Centre for Climate Services of

Environment and Climate Change to measure, for each city, the average daily warmest temperatures attained in January and July from 2001 to 2016. [27]

Regions: Regional Development Agencies support manufacturers across Canada. [28] Specific regional public policies might also influence city-level population growth; we can think of Quebec, which has its own immigration policy, partly determined by its needs in terms of workforce. We thus build specific dummy variables for the Atlantic regions (New Brunswick, Newfoundland and Labrador, Nova Scotia, Prince Edward Island), the West (Alberta, British Columbia, Manitoba, Saskatchewan), Quebec and Ontario. [29]

1.7.2 Data processing and variable description

Variable definitions

Arts, entertainment and recreation: This industry comprises establishments that produce, promote or participate in public performances, exhibitions or other events; provide artistic products and performances; preserve and exhibit objects and sites of historical, cultural; and operate facilities or provide services that enable their clients to participate in sports or recreational activities or to engage in hobbies and entertainment. It corresponds to the NAICS code 71 (Statistics Canada definition).

Big downsizing plant: This refers to an establishment with 50+ employees in 2003 that has lost at least 30% of its workforce by 2017.

Closure rate: This variable is calculated using data from Scott's National All

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27. These data are available from stations that produce daily data from 2001 to 2016.

28. These agencies are Atlantic Canada Opportunities Agency for Atlantic regions, Federal Economic Development Initiative and Federal Economic Development Agency for Ontario, Canada Economic Development for Quebec, and Western Economic Diversification Canada for Western region.

29. We do not use provincial dummies in our regressions because in some provinces, there are too few cities, such as in Atlantic Canada or in Manitoba and Saskatchewan, to allow for statistical inference based on within-province variations (see Table 1.19 in the Appendix).

databases. It refers to the number of 50+ manufacturing plants present in 2003 that no longer exist in 2017 divided by the initial number of manufacturing plants in 2003 in the urban area.

Distance to big urban area: It refers to the distance in meters to the nearest urban area with at least 300,000 inhabitants. We compute it thanks to a GIS software. We calculate the distance between the centroids of the two different urban areas.

Distance to coast: It refers to the distance in meters to the nearest coastline. We compute it thanks to a GIS software. We have 76904 water layer polygons, representing Canadian coasts, provided by Statistics Canada. This allows us to calculate the distance between an urban area's centroid and the nearest Canadian coast.

Educational services industry: This sector comprises establishments primarily engaged in providing education and training in a wide variety of fields by specialized establishments, such as schools, colleges, universities and training centres. It corresponds to the NAICS code 61. (Statistics Canada definition)

Health care and social assistance: This sector comprises establishments primarily engaged in providing health care, providing residential care for medical and social reasons, and providing social assistance, such as counselling, social welfare, child welfare, community housing and food services, vocational rehabilitation and child care. It corresponds to the NAICS code 62. (Statistics Canada definition)

Immigrants: People that have immigrant or non-permanent status in private households. The term "immigrant" refers to a person who is or has been a landed immigrant/permanent resident. "Non-permanent resident" refers to a person from another country who has a work or study permit or is a refugee claimant, and any family members born abroad and living in Canada with them.

Job loss rate: This variable is calculated using data from Scott's National All databases. It refers to the number of jobs in the 50+ manufacturing plants that were active in 2003 but that no longer exist in 2017 divided by the number of jobs in the manufacturing plants that were active in 2003 in the urban area.

January and July temperatures (maximum): This is the average of the warmest temperature attained on each day of January and July from 2001 to 2016. We compute them using GIS software and historical weather data.

Manufacturing industry: This sector comprises establishments primarily engaged in the chemical, mechanical or physical transformation of materials or substances into new products that may be ready for use or consumption, or a raw material that an establishment can use in further manufacturing. It corresponds to NAICS codes 31, 32 and 33. (Statistics Canada definition)

Parent people: People that are couples or lone-parent in private households with at least one child.

Population (Total): It refers to the number of persons living within a dissemination area, aggregated at the CMA/CA level.

Residents in couples: People that are couple families i.e married couples or common-law couples in private households.

Skilled people: Residents aged 15+ in private households with a university certificate, diploma or degree at bachelor level or above such as bachelor's degree, university certificate or diploma above bachelor level, degree in medicine, dentistry, veterinary medicine or optometry, master's degree or earned doctorate.

Urban area: An urban area is a census metropolitan area (CMA) or a census agglomeration (CA), defined by Statistics Canada as a group of one or more adjacent municipalities centred on a population centre. A CMA must have a total population of at least 100,000 of which 50,000 or more must live in the core. A CA must have a core population of at least 10,000. To be included in the CMA or CA, other adjacent municipalities must have a high degree of integration with the core, as measured by commuting flows derived from previous census place of work data.

Working age population: Population aged 20-54.

Data processing

Geographical structure. Census Metropolitan Areas (CMA) and Census Agglomerations (CA) are the ideal spatial units in Canada for the analysis of local labor markets since their boundaries are delineated based on the commuting patterns of residents. Provinces are too coarse a spatial scale, whereas dissemination areas (census blocks) are too fine to analyze population dynamics following local labor market shocks, because a worker could easily work in one dissemination area and reside in another. Since each dissemination area belongs to a given urban area (CMA/CA), we aggregate the Census data available at the level of dissemination areas at the urban area level.

We obtain census data at the urban area (CMA/CA) level for 145 urban areas in 2001, 148 in 2006, 151 in 2011 and 157 in 2016. The differences between years are explained by the fact that from a statistical point of view, an urban area can lose its census agglomeration status and disappear, or (re)gain it and (re)appear. Note for example that if the population of the core of a CA declines below 10,000, the CA is removed. However, once an urban area becomes a CMA, it remains a CMA even if its total population declines below 100,000 or if the population of its core falls below 50,000.

There are 164 unique urban areas in total (CMA/CA) between 2001 and 2016, of which 136 are present in the 4 census years, 10 in 3 census years, 8 in 2 census years, and 10 in a single census year. We overlay each urban area for every year it appears, and we take the envelope of the overlaid boundaries. Magog (present in 2001) has been added to Sherbrooke in 2006, so we merge them. Saint-Jean-sur-Richelieu (present in 2001, 2006, 2011) has been added to Montreal in 2016, so we merge them. We get 162 urban areas whose boundaries in terms of municipalities are stable over time. Indeed, in this study, we want to capture demographic changes that are related to labor market shocks, not to changes in geographical boundaries.

We keep in the sample only those agglomerations that have at least 10,000 inhabitants on average over the whole 2001-2016 period and for which we have all the necessary information for the econometric analysis. We end up with 154 stable urban areas. We calculate 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 total population of the "stabilized" urban area as we measure it. On average, we can see in Table 1.12 that this ratio is equal to 0.96 over the period 2001-2016, which means that the demographics of stabilized urban areas are quite similar to the demographics of the original urban areas.

Table 1.12: Population ratio between the actual and the stabilized urban areas

	Year			
	2001	2006	2011	2016
Minimum	0.535	0.393	0.407	0.404
Mean	0.953	0.967	0.972	0.972
Maximum	1	1	1	1
Std. error	0.086	0.074	0.082	0.085

The boundaries of "actual" urban areas are those defined by Statistics Canada in a given census year. The boundaries of "stabilized" urban areas are defined by the envelope of the boundaries observed across the various census years.

Geocoding process. The raw Scotts data provide some geographical coordinates for the establishments but after several checks, they do not seem extremely reliable. We thus geocode the dataset again.

The geocoding is a process through which an algorithm transforms an address into a pair of coordinates that can be positioned on a map of the surface of the earth. Throughout the process, in addition to the coordinates (longitude, latitude), the geocoder provides the actual addresses related to the coordinates of the points that it returns.

We first start by geolocating the Scotts Database on a postal code basis. To geolocate plants based on postal codes of the Scotts Database, we use latitude and longitude data of postal code centroids obtained from Statistics Canada's Postal Code Conversion Files (PCCF). The problem with zip code geolocation is that a zip code is relatively accurate for large cities, and more imperfect for small cities since the surface area of postal codes is larger in low-density places. We consider the geocoding of the Scott's database based on the postal codes to be "approximate". We thus also run geocoding processes based on the address of the establishments.

The Scott's database provides information on the company name and its full address (street number, street name, postal code, city and province). We use this information to geocode again the database in three ways. First, we use a commercial API on the Google Map server and we provide as input to the geocoder the full address line of each plant. Second, we used th same API of the Google Map server but we combine the company name with the full address line of the plant to generate the input for the geocoder. In this case, the geocoder is supposed to collect the exact location of the plant even if the plant has changed its location after the date on which the Scotts dataset was compiled. Third, we use an alternative API and the DMTI dataset which is an extensive database containing more than 15 million of feature points representing addresses in Canada. This private dataset records the location of addresses in Canada with their related geographic coordinates with a rooftop precision. From the DMTI, we construct an Address-Locator using ArcGIS tools and we geocode all the Scotts addresses via this alternative process.

We find that the geocoding of Google Maps is "rooftop", meaning that the plant is geocoded accurately down to the street address. The geocoding of DMTI is either "range interpolated", meaning that the plant is geocoded by interpolation of two precise points, or "rooftop".

In the end, we assign to each establishment the geographical coordinates that are the most precise among those that are available. First, when both the Google geocoding and the DMTI geocoding report the same coordinates, we retain these coordinates. If the returned coordinates differ, we first select the one based on the company name and the complete address line (Google 2) if available, otherwise we select the geocoding based on the complete address line only (Google 1), otherwise we select the DMTI geocoding, otherwise we maintain the postal code geocoding.

Following this procedure, nearly 88% of our data has a very precise location (rooftop accuracy). The rest is range interpolated or approximate accuracy (postal code geocoding). Table 1.13 shows the distribution of Canadian manufacturing plants according to the geocoding chosen between 2001 and 2017.

Table 1.13: Manufacturing plants data geocoding.

	Scott's 2001	Scott's 2003	Scott's 2005	Scott's 2007	Scott's 2009	Scott's 2011	Scott's 2013	Scott's 2017
Geocoding process								
Google 2 (Plant name & address)	33,744	33,080	32,198	31,240	30,521	29,529	25,972	23,746
Google 1 (Address)	11,350	11,115	10,661	10,033	9,466	8,904	7,242	6,204
DMTI (Address)	2,750	2,699	2,552	2,333	2,188	2,072	1,544	1,458
SCOTTS (PCCF)	6,500	5,890	5,153	4,682	4,474	4,119	3,343	2,727
Total Manufacturing plants	**54,344**	**52,784**	**50,564**	**48,288**	**46,649**	**44,624**	**38,101**	**34,135**
Geocoding Accuracy								
Rooftop	45,235	44,607	43,421	41,977	40,724	39,296	33,900	30,744
Range Interpolated	2,609	2,287	1,990	1,629	1,451	1,209	858	664
Postal Code	6,500	5,890	5,153	4,682	4,474	4,119	3,343	2,727
Total Manufacturing plants	**54,344**	**52,784**	**50,564**	**48,288**	**46,649**	**44,624**	**38,101**	**34,135**

The geocoding process was done by Postal Code Conversion Files (PCCF), Google's commercial API and DMTI spatial.

1.7.3 Additional tables and figures

Tables on data

Table 1.14: Comparing the Scott's National All database to the Annual Survey of Manufacturing (ASM).

	2001		2003		2005		2007		2009		2011	
Province	ASM	Scott's	ASM	Scott's	ASM	Scott's	ASM	Scott's	ASM	Scott's	ASM	Scott's
Alberta	4,843	3,935	4,882	3,650	7,750	3,482	8,091	3,723	7,852	3,597	7,003	3,477
British Columbia	7,085	6,212	6,933	5,923	11,942	5,400	12,179	5,267	11,605	5,031	11,552	4,946
Manitoba	1,465	1,654	1,481	1,556	2,307	1,489	2,351	1,405	2,323	1,280	1,918	1,302
New Brunswick	986	1,392	963	1,376	1,533	1,262	1,496	1,167	1,412	1,181	1,381	1,030
Newfoundland	525	576	522	578	706	544	738	517	657	482	660	432
Nova Scotia	1,097	1,677	1,106	1,576	1,944	1,506	1,904	1,354	1,817	1,312	1,760	1,184
Ontario	21,514	21,289	21,470	21,758	34,184	20,996	33,634	20,301	31,991	19,670	29,046	18,721
Prince Edward Island	233	328	211	303	299	327	369	309	358	282	342	260
Quebec	15,191	15,933	15,251	14,773	23,042	14,200	22,324	12,992	21,149	12,660	19,272	12,091
Saskatchewan	1,044	1,348	1,008	1,291	1,664	1,318	1,845	1,203	1,861	1,109	1,410	1,140
Territories		0		0		40		50		45		41
Canada	53,983	54,344	53,827	52,784	85,371	50,564	84,931	48,288	81,025	46,649	74,344	44,624
Cross-industry correlation	***0.973***		***0.972***		***0.945***		***0.935***		***0.932***		***0.881***	

Notes: Data are from the Scott's databases and Statistics Canada Annual Survey of Manufacturing (and Logging Industries) Table 16-10-0054-01 and Table 16-10-0038-01. The 2001 and 2003 ASMs report only employer plants with sales exceeding C$30,000 whereas the 2005 to 2009 ASMs report information for manufacturing plants (including logging industries, which is absent in the 2001 and 2003 ASMs) for all plants. The descriptive statistics reported as "cross-industry" in the bottom panel of the table are computed across all 3 digits manufacturing industries (NAICS 311–339).

Table 1.15: Comparing the Scott's National All database to the Canadian business counts (CBC).

	2001		2005		2009		2013		2017	
Province	CBC	Scott's	CBC	Scott's	CBC	Scott's	CBC	Scott's	CBC	Scott's
Alberta	5,843	3,935	5,416	3,482	5,351	3,597	4,882	3,144	4,095	2,891
British Columbia	8,797	6,212	8,261	5,400	7,697	5,031	6,933	4,148	5,984	3,966
Manitoba	1,883	1,654	1,741	1,489	1,605	1,280	1,481	1,108	1,049	1,061
New Brunswick	1,446	1,392	1,195	1,262	1,018	1,181	963	873	431	740
Newfoundland	757	576	629	544	508	482	522	364	244	320
Nova Scotia	1,832	1,677	1,483	1,506	1,225	1,312	1,106	970	666	816
Ontario	25,006	21,289	23,220	20,996	21,673	19,670	21,470	15,933	16,722	14,277
Prince Edward Island	354	328	292	327	256	282	211	199	114	154
Quebec	18,349	15,933	17,026	14,200	15,238	12,660	15,251	10,378	9,939	8,980
Saskatchewan	1,378	1,348	1,259	1,318	1,151	1,109	1,008	948	877	895
Territories		0		40		45		36		35
Canada	65,645	54,344	60,522	50,564	55,722	46,649	53,827	38,101	40,121	34,135
Cross-industry correlation	***0.908***		***0.939***		***0.937***		***0.931***		***0.773***	

Notes: Data are from Scott's National All databases and CBP (Table 33-10-0028-01 ,Table 33-10-0035-01). The descriptive statistics reported as "cross-industry" in the bottom panel of the table are computed across all 3 manufacturing digits industries (NAICS 311–339).

Table 1.16: Comparing the Scott's National All databases to the Labor Force Survey (LFS) by Cities (>100K).

	2001		2003		2005		2007		2009		2011		2013		2017	
Census Metropolitan Area	LFS	Scott's	LFS	Scott's	LFS	Scott's	LFS	Scott's	LFS	Scott's	LFS	Scott's	LFS	Scott's	LFS	Scott's
Abbotsford - Mission	10.6	6.7	9.9	6.7	9.9	7	10.4	6.7	8.5	6.3	7.5	5.8	8.2	4.9	9.7	5.1
Barrie	13.1	6.5	14.8	6.5	17.4	7.3	15.4	7.9	10.4	6.9	14.4	5.7	14.8	5.7	15.5	5.3
Brantford	15.8	9.6	17.4	10.2	17.7	15.2	15.8	14.1	14.5	13.4	13.6	10.8	13.8	10.5	14.4	9.5
Calgary	51.2	47.9	53.4	46.9	42.6	46.5	47.3	52	42.5	50	46.1	46.3	46.2	40.2	39	36.1
Edmonton	48.4	40.9	50.2	43.4	48.8	47.8	53.5	55.2	44.2	52.6	51.4	51.1	58.7	47.2	41.5	45.6
Gatineau	6.8	3.8	6.7	4.6	8	5	7.5	4.4	6.7	3.6	7	3.4	6.3	3	7	3.2
Greater Sudbury	3.6	3.6	4.3	4	4.4	4	3.7	3.7	3.5	3.6	3.9	3.5	3.3	3.4	3.1	3
Guelph	19.7	18	19.8	19.5	20.2	18.7	19.2	16.2	15.3	16.6	15.6	15.7	14.7	15.2	16.8	16.8
Halifax	11.5	11.1	10.8	12.1	9.9	10.9	12.5	12.2	11.8	12.9	11.4	12.7	10	10.6	10.5	8.7
Hamilton	73.7	37.4	76.2	38.5	69.2	39	58.1	37.5	51.1	35.3	49.3	34.4	46.6	31.8	49.8	29.3
Kelowna	6.5	5	7.8	5.4	6.4	6	8.3	5.9	6.6	5.4	6.3	5	4.4	5.9	5	4.7
Kingston	6.6	4.2	6	3.7	6.1	3.2	5.2	2.9	4.1	3	4.4	2.9	4	2.4	3.9	3.4
London	36	21.5	41.7	24	39.4	25.4	35.1	25.8	29.9	24.7	29.2	19.9	27.4	19.2	29.8	15.6
Moncton	6	5.2	5	6	4.4	6.1	4.3	5.6	5.9	6	5.4	5	4.6	5.2	4.2	4.1
Montreal	314.4	271.5	291.4	253.7	286.9	242	246.2	219.6	242.8	218.9	224.2	205.7	225.7	171.6	226	156.2
Oshawa	32.1	9.7	33.6	11	32.5	10.8	26.8	9.8	20.5	8.6	19.4	7.4	20.5	6.2	17.1	6.2
Ottawa	35.8	18.7	28.2	18.5	30.3	18.1	36	19.7	29.2	20.5	20.3	21.9	17	17.8	17.7	16.7
Peterborough	7.1	5	7.6	4.7	7.2	4.4	8.2	4.8	6	4.8	5.9	4.4	4.8	4.7	3.8	5.3
Quebec	32.4	29.5	33	29.6	40.7	34.9	39.3	34.4	32.3	34.8	32.2	32.4	28.4	32.1	32.1	28.4
Regina	5	6.5	5.5	5.9	6.4	6.1	6.5	6.8	7.5	6.3	6.8	7	7	5.4	8.3	5.5
Saguenay	11.2	7.5	10.2	7.5	10.6	8.3	11	8.6	9.1	8.8	8.6	9.2	9.3	6.8	7.8	6
Saint John	5.1	5.9	5.1	5.6	4.1	5.5	6	5.2	5.4	5.6	5.5	3.4	4.4	3.7	5.9	3.3
Saskatoon	10.1	11.8	9.2	12.5	11.8	11.2	11.3	10	11.1	9.7	9.1	10	11.4	8.8	8.8	8.4
Sherbrooke	19.7	16.7	23.1	15.7	17.6	14.8	14	11.6	12.4	11.9	13.3	11.8	11.9	10.9	14.8	11.1
St John's	3.5	6.8	3.4	5.9	3.9	5.4	5.2	6	4.4	6	3.8	5.7	5.1	6	3.7	4.5
St. Catharines - Niagara	32.4	22.1	30.5	21.8	26.9	20.7	25.6	18.7	20.6	16.6	21	15	21.8	12.8	21.6	12.6
Thunder Bay	7	3.6	6.7	3.7	5	3.7	4.4	3.4	2.9	2.8	2.9	3.5	4.2	2.5	3.2	2.1
Toronto	452.3	359.8	466.6	382.8	457.1	372	397.6	353.8	328.4	340.6	331.9	308.1	334.1	278.2	336.8	251.7
Trois-Rivieres	11.7	7.5	11	8.2	11.4	7.8	10.5	7.8	9.7	8.3	8.3	7.7	8.3	6.5	9.6	5.9
Vancouver	104.2	97.6	112.7	96.5	101.2	93	105.6	96.9	86.1	94.3	85.1	91.4	84.7	75.8	99.9	75.3
Victoria	6.3	5.3	8.5	6.1	7.7	5.7	6.7	5.7	6.2	5.9	5.9	5.7	5.8	5.4	7.2	4.8
Waterloo	63.2	42.6	63	46.1	63.7	46.8	59	43.6	49.8	40.9	49.3	35.9	52.3	30.3	51.3	30.5
Windsor	46.3	25.1	48.2	27.3	48	26.5	35.5	27.7	29.6	25.5	30.7	21.5	31.4	19	38.4	18.6
Winnipeg	50.5	37.9	47	38.2	45.7	38.4	48	35.6	40.5	33.1	37.5	33.6	41.3	29.7	42.8	25.2
Cross-employment correlation	***0.995***		***0.996***		***0.996***		***0.997***		***0.995***		***0.997***		***0.996***		***0.995***	

Notes: Distribution of Census Metropolitan Areas' employment (x1000) of manufacturing plants (NAICS 311–339). Data are from Scott's National All databases and Labor Force Survey Statistic Canada (Table 14-10-0098-01). The descriptive statistics reported as "cross-industry" in the bottom panel of the table are computed across all 3 digits industries.

Table 1.17: Descriptive statistics of big (and downsized) manufacturing plants closed by NAICS 3-digit sectors.

NAICS3	Manufacturing sector	(1) Closure rate closed in initial plants	(2) Job loss rate losses in initial jobs	(3) Avg. # jobs of closed big plants	(4) Relative share of exporters closed/non closed	(5) Relative share of headquaters closed/non closed
311	Food	12.0%	37.6%	143.7	1.01	0.18
312	Beverage and tobacco product	9.1%	29.1%	146.8	0.98	0.26
313	Chemical	20.0%	64.8%	156.7	0.83	0.34
313	Textile mills	9.8%	48.8%	113.6	0.85	0.18
314	Textile product mills	15.7%	55.6%	120.6	0.89	0.15
315	Clothing	10.5%	44.7%	130.1	1.05	0.33
316	Leather and allied product	11.8%	42.8%	132.5	1.04	0.19
321	Wood product	25.4%	54.4%	187.6	1.02	0.21
322	Paper	5.5%	34.3%	113.8	0.94	0.23
323	Printing and related support actv.	11.1%	31.3%	181.6	1.08	0.27
324	Petroleum and coal product	12.2%	38.1%	124.2	0.93	0.38
326	Plastics and rubber products	12.9%	38.0%	119.8	1.00	0.23
327	Non-metallic mineral product	7.0%	31.5%	116.8	1.07	0.31
331	Primary metal	17.1%	44.9%	173.4	0.96	0.29
332	Fabricated metal product	7.0%	29.2%	110.0	1.03	0.25
333	Machinery	8.5%	30.9%	106.3	0.98	0.33
334	Computer and electronic product	12.4%	42.6%	142.9	1.09	0.36
335	Electrical equipment, appliance	12.1%	40.5%	140.2	1.04	0.26
336	Transportation equipment	16.1%	48.7%	185.5	0.94	0.29
337	Furniture and related product	6.2%	32.3%	120.4	0.90	0.31
339	Miscellaneous	4.1%	34.8%	122.3	1.09	0.27
	All sectors	**9.8%**	**38.9%**	**132.0**	**0.76**	**0.65**

Notes: "Big plants" refer to 50+ establishments from 2003 that disappeared in 2017 and "big downsized plants" to 50+ establishments that lose at least 30% of their workforce between 2003 and 2017. The data are from Scott's National All Business Directories.

Table 1.18: Big (and downsized) manufacturing plants closure and job loss rates in Canada.

Region	Province	% Big plants closed in initial plants	% Big job losses in initial jobs	Avg. Jobs of big plants closed
Western	Alberta	8.5%	33.5%	129.7
	British Columbia	7.4%	34.9%	130.0
	Manitoba	9.6%	33.1%	115.3
	Saskatchewan	6.2%	34.4%	130.6
		7.9%	***34.1%***	***127.7***
Atlantic	New Brunswick	8.1%	38.5%	151.5
	Newfoundland and Labrador	10.2%	43.1%	166.9
	Nova Scotia	6.7%	33.3%	129.8
	Prince Edward Island	8.3%	44.9%	130.7
		7.9%	***38.0%***	***145.2***
Ontario	Ontario	***10.5%***	***40.4%***	***135.5***
Quebec	Quebec	***11.0%***	***40.5%***	***127.3***
Canada		**9.8%**	**38.9%**	**132.0**

Notes : "Big plants" refer to 50+ establishments from 2003 that disappeared in 2017 and "big downsized plants" to 50+ establishments that lose at least 30% of their workforce between 2003 and 2017. The three territories (Northwest Territories, Nunavut and Yukon) are removed from the table but not from total. The data are from Scott's National All Business Directories.

Table 1.19: Geographical breakdown of urban areas in Canada.

Region	Province	Total urban areas	Census metropolitan areas (CMA)	Census agglomeration CA	Minimum average population	Maximum average population
Western	Alberta	17	3	14	10,893	1,170,165
	British Columbia	26	4	22	14,038	2,222,570
	Manitoba	6	1	5	12,490	726,738
	Saskatchewan	10	2	8	10,215	261,208
		59	***10***	***49***	***10,215***	***2,222,570***
Atlantic	New Brunswick	7	2	5	15,435	131,695
	Newfoundland and Labrador	5	1	4	10,270	189,048
	Nova Scotia	5	1	4	25,733	379,475
	Prince Edward Island	2	0	2	16,423	64,940
		19	***4***	***15***	***10,270***	***379,475***
Ontario	Ontario	***46***	***16***	***30***	***10,245***	***5,296,808***
Quebec	Quebec	***30***	***6***	***24***	***12,243***	***3,815,543***
Canada		**154**	**36**	**118**	**10,215**	**5,296,808**

Notes : The table is based on manufacturing plants (NAICS 31-33) of 50+ employees, from 2003 that disappeared in 2017. The average population is that over our period of analysis (2001-2016). The data are from Scott's National All Business Directories.

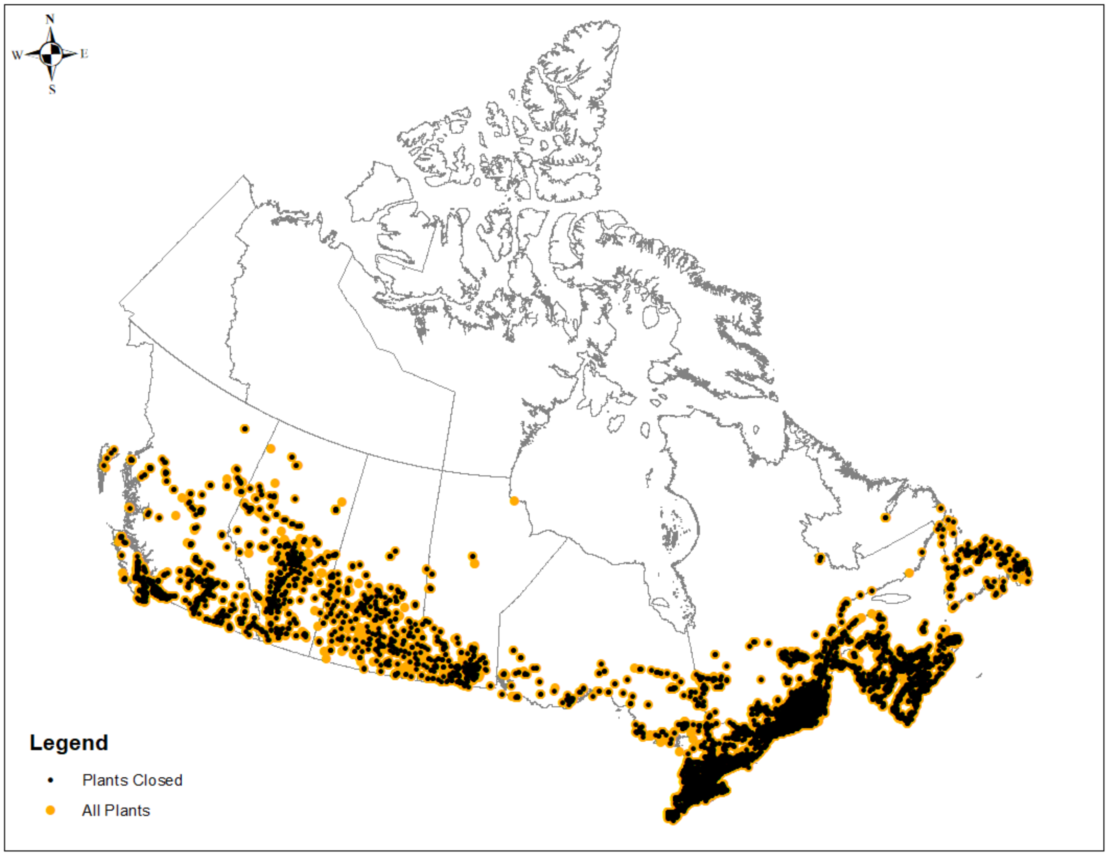
Table 1.20: Growth rates of U.S employment by NAICS 4-digits industries.

NAICS4	U.S manufacturing sector	Growth rate	NAICS4	U.S manufacturing sector	Growth rate
3346	Reproducing magnetic and optical media	-78.24%	3359	Other electrical equipment and component	-17.99%
3341	Computer and peripheral equipment	-77.27%	3274	Lime and gypsum product	-17.73%
3151	Clothing knitting mills	-75.06%	3272	Glass and glass product	-16.78%
3159	Clothing accessories and other clothing	-68.91%	3273	Cement and concrete product	-16.35%
3152	Cut and sew clothing	-68.60%	3334	Ventilation, heating, air-conditioning and refrigeration	-15.86%
3132	Fabric mills	-66.03%	3363	Motor vehicle parts	-15.13%
3343	Audio and video equipment	-64.12%	3261	Plastic product	-14.32%
3131	Fibre, yarn and thread mills	-60.91%	3321	Forging and stamping	-14.05%
3161	Leather and hide tanning and finishing	-57.56%	3313	Alumina and aluminum production and processing	-13.33%
3133	Textile and fabric finishing and fabric coating	-53.88%	3312	Steel product from purchased steel	-11.82%
3141	Textile furnishings mills	-51.77%	3314	Non-ferrous metal production and processing	-9.41%
3325	Hardware manufacturing	-49.57%	3391	Medical equipment and supplies	-9.03%
3342	Communications equipment	-48.63%	3251	Basic chemical	-8.33%
3352	Household appliance	-43.28%	3118	Bakeries and tortilla	-8.21%
3322	Cutlery and hand tool	-43.13%	3329	Other fabricated metal product	-8.17%
3271	Clay product and refractory	-43.01%	3256	Soap, cleaning compound and toilet preparation	-7.72%
3122	Tobacco manufacturing	-41.88%	3255	Paint, coating and adhesive	-7.25%
3371	Household and institutional furniture	-39.73%	3328	Coating, engraving, cold and heat treating	-5.70%
3231	Printing and related support activities	-36.56%	3324	Boiler, tank and shipping container	-4.00%
3326	Spring and wire product	-35.08%	3345	Navigational, measuring, medical and control instruments	-2.90%
3221	Pulp, paper and paperboard mills	-34.74%	3114	Fruit and vegetable preserving and specialty food	-2.19%
3169	Other leather and allied product	-34.47%	3323	Architectural and structural metals	-2.02%
3399	Other miscellaneous	-33.46%	3361	Motor vehicle	-1.46%
3344	Semiconductor and other electronic component	-33.15%	3253	Pesticide, fertilizer and other agricultural chemical	-1.08%
3162	Footwear manufacturing	-32.71%	3254	Pharmaceutical and medicine	-0.76%
3315	Foundries	-32.50%	3252	Resin, synthetic rubber, and artificial and synthetic fibres	-0.46%
3333	Commercial and service industry machinery	-31.97%	3113	Sugar and confectionery product	2.02%
3149	Other textile product mills	-29.95%	3112	Grain and oilseed milling	2.84%
3351	Electric lighting equipment	-29.02%	3366	Ship and boat building	2.93%
3379	Other furniture-related product	-27.51%	3116	Meat product	3.05%
3212	Veneer, plywood and engineered wood product	-27.45%	3327	Machine shops, turned product, and screw, nut and bolt	3.57%
3332	Industrial machinery	-25.99%	3339	Other general-purpose machinery	4.42%
3372	Office furniture (including fixtures)	-25.78%	3364	Aerospace product and parts	4.60%
3311	Iron and steel mills and ferro-alloy	-25.68%	3111	Animal food	6.17%
3222	Converted paper product	-25.32%	3331	Agricultural, construction and mining machinery	6.24%
3262	Rubber product	-24.39%	3336	Engine, turbine and power transmission equipment	7.46%
3259	Other chemical product	-24.00%	3241	Petroleum and coal product	7.52%
3353	Electrical equipment	-22.71%	3279	Other non-metallic mineral product	8.36%
3211	Sawmills and wood preservation	-21.81%	3115	Dairy product	10.77%
3219	Other wood product	-20.57%	3362	Motor vehicle body and trailer	14.02%
3117	Seafood product preparation and packaging	-19.65%	3365	Railroad rolling stock	19.29%
3369	Other transportation equipment	-19.65%	3119	Other food manufacturing	31.30%
3335	Metalworking machinery	-18.46%	3121	Beverage manufacturing	57.40%

Notes: Growth rates are between 2003 and 2017 for 4-digit sectors employment. Data are from U.S Bureau County Business Patterns.

Figures on data

Figure 1.4: Manufacturing plants in Canada in 2003.



1.7.4 Additional results

Table 1.21: Closures and population changes across age groups in Canadian Urban Areas

	Dependent Variables : Growth of											
Dependent variable *y*: Growth of	Total Population		People aged 20-54		People aged over 55		Total Population		People aged 20-54		People aged over 55	
	OLS(1)	OLS(2)	OLS(3)	OLS(4)	OLS(5)	OLS(6)	IV(1)	IV(2)	IV(3)	IV(4)	IV(5)	IV(6)
Closure rate (Big plant closures)	-0.719		-0.596		-1.000		-4.984***		-6.102***		-0.723	
	(0.351)		(0.282)		(0.621)		(1.260)		(1.818)		(1.262)	
Closure rate (Big plant closures + Downsizing)		-0.162		-0.066		-0.304		-5.097**		-6.240***		-0.739
		(0.120)		(0.109)		(0.157)		(1.980)		(2.290)		(1.497)
Ln Initial population	-0.032**	-0.033**	-0.021**	-0.023	-0.051*	-0.054*	-0.023	-0.038*	-0.010	-0.028	-0.052***	-0.054***
	(0.006)	(0.008)	(0.007)	(0.010)	(0.021)	(0.019)	(0.019)	(0.023)	(0.023)	(0.030)	(0.014)	(0.017)
High initial share of people aged 20-54	0.115**	0.113**	0.127**	0.126**	0.279*	0.275*	0.124***	0.087***	0.139***	0.092***	0.278***	0.273***
	(0.023)	(0.025)	(0.029)	(0.031)	(0.092)	(0.092)	(0.032)	(0.027)	(0.042)	(0.034)	(0.075)	(0.078)
High initial share of skilled people	0.046	0.052	0.053	0.057	0.018	0.025	0.013	0.040	0.010	0.043	0.020	0.024
	(0.025)	(0.024)	(0.035)	(0.033)	(0.045)	(0.046)	(0.030)	(0.058)	(0.042)	(0.077)	(0.029)	(0.035)
High initial share of empl. in manufacturing	0.010	-0.011	-0.002	-0.025	0.013	-0.011	0.202***	0.333*	0.245***	0.407*	0.000	0.019
	(0.027)	(0.011)	(0.024)	(0.017)	(0.051)	(0.023)	(0.057)	(0.195)	(0.054)	(0.213)	(0.068)	(0.117)
January maximum temperature	0.012*	0.013*	0.008	0.009	0.028**	0.028***	0.012	0.020***	0.007	0.017**	0.028***	0.029***
	(0.005)	(0.005)	(0.008)	(0.007)	(0.005)	(0.005)	(0.008)	(0.005)	(0.012)	(0.008)	(0.004)	(0.002)
July maximum temperature	0.008	0.009	0.006	0.007	0.007*	0.008**	0.000	-0.002	-0.004	-0.007	0.008***	0.007*
	(0.006)	(0.005)	(0.008)	(0.007)	(0.003)	(0.002)	(0.012)	(0.018)	(0.016)	(0.022)	(0.003)	(0.004)
Log distance to nearest big city	-0.008	-0.008	-0.008	-0.008	-0.002	-0.002	-0.006***	-0.012**	-0.006***	-0.013**	-0.002	-0.003
	(0.005)	(0.005)	(0.006)	(0.007)	(0.006)	(0.005)	(0.001)	(0.005)	(0.001)	(0.006)	(0.004)	(0.005)
Log distance to nearest coastline	0.003	0.004	0.011	0.012	-0.001	0.001	-0.002	0.010	0.004	0.019	-0.001	0.001
	(0.011)	(0.011)	(0.013)	(0.013)	(0.009)	(0.010)	(0.014)	(0.018)	(0.018)	(0.023)	(0.009)	(0.007)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate							-0.090	-0.088	-0.090	-0.088	-0.090	-0.088
IV P value							0.001	0.000	0.001	0.000	0.001	0.000
IV Partial R2							0.03	0.02	0.03	0.02	0.03	0.02
First stage F statistic							11	19	11	19	11	19
Adjusted R2	0.31	0.28	0.37	0.35	0.30	0.28						
Urban Areas	154	154	154	154	154	154	154	154	154	154	154	154

Notes : Table reports OLS and 2SLS estimates. "Big plants" refer to 50+ establishments and "downsized plants" to 50+ establishments in 2003 that lose at least 30% of their workforce in 2017. "High initial share" means to be in the top quartile of the cities in our sample. The "skilled" are the 15+ residents with at least a bachelor degree. A big city is a city with at least 300,000 residents. Temperatures are in Celsius and distances in meters. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Scott's National All databases, Statistic Canada's Census 2001-2016 and boundaries files, Environment Canada's weather data.

Table 1.22: Placebo Test : Job losses and population changes in Canadian cities

Dependent variable *y*: (2001 - 1996) Growth of	Total Population		Population 20-54 share		High-skilled share		Migrants share	
	IV(1)	IV(2)	IV(3)	IV(4)	IV(5)	IV(6)	IV(7)	IV(8)
Job loss rate (Big plant closures)	0.004		-0.016		0.005		0.021	
	(0.215)		(0.010)		(0.014)		(0.029)	
Job loss rate (Big plant closures + Downsizing)		0.004		-0.017		0.005		0.022
		(0.228)		(0.013)		(0.016)		(0.027)
Ln Initial population	-0.081***	-0.081***	-0.001	-0.001	0.005**	0.005*	-0.000	-0.000
	(0.016)	(0.016)	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)
High initial share of people aged 20-54	0.084***	0.084***	0.002	0.002	0.013**	0.013*	0.006	0.006
	(0.017)	(0.017)	(0.007)	(0.007)	(0.006)	(0.007)	(0.004)	(0.004)
High initial share of skilled people	0.053***	0.053***	0.007***	0.007***	0.042***	0.042***	-0.002	-0.003
	(0.012)	(0.012)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
High initial share of empl. in manufacturing	-0.093***	-0.093***	0.006*	0.007**	-0.005	-0.005	-0.002	-0.003
	(0.011)	(0.021)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.005)
January maximum temperature	0.026***	0.026***	0.001***	0.001***	0.001	0.001	-0.000	-0.000
	(0.003)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
July maximum temperature	0.009	0.009	0.000	0.000	-0.000	-0.000	0.001	0.001
	(0.009)	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log distance to nearest big city	-0.008**	-0.008**	0.000	0.000*	-0.002*	-0.002*	-0.001***	-0.001***
	(0.003)	(0.003)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Log distance to nearest coastline	-0.021*	-0.021	0.002***	0.002***	0.001	0.001	-0.003*	-0.003*
	(0.013)	(0.013)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	-0.844	-0.792	-0.844	-0.792	-0.844	-0.792	-0.844	-0.792
IV P value	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000
IV Partial R2	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
First stage F statistic	12	35	12	35	12	35	12	35
Urban Areas	154	154	154	154	154	154	154	154

Notes: "Big plants" refer to 50+ establishments and "downsized plants" to 50+ establishments in 2003 that lose at least 30% of their workforce in 2017. "High initial share" means to be in the top quartile of the cities in our sample. The "skilled" are the 15+ residents with at least a bachelor degree. A big city is a city with at least 300,000 residents. Temperatures are in Celsius and distances in meters. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Scott's National All databases, Statistic Canada's Census 1991-2016 and boundaries files, Environment Canada's weather data.

Table 1.23: Alternative IV: Job losses and population changes in Canadian cities

Dependent variable y: Growth of	Total Population		Population 20-54 share		High-skilled share		Migrants share	
	IV(1)	IV(2)	IV(3)	IV(4)	IV(5)	IV(6)	IV(7)	IV(8)
Job loss rate (Big plant closures)	-0.542**		-0.104***		0.040***		-0.136***	
	(0.269)		(0.014)		(0.008)		(0.040)	
Job loss rate (Big plant closures + Downsizing)		-0.569		-0.109***		0.042***		-0.144**
		(0.365)		(0.025)		(0.013)		(0.061)
Ln Initial population	-0.022**	-0.019	0.004**	0.005**	-0.001	-0.001	0.003	0.004
	(0.011)	(0.017)	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.004)
High initial share of people aged 20-54	0.121***	0.122***	0.006	0.006	0.011***	0.011***	0.018	0.018
	(0.030)	(0.032)	(0.004)	(0.004)	(0.003)	(0.003)	(0.012)	(0.013)
High initial share of skilled people	0.040*	0.042	0.003	0.003	0.018***	0.018***	0.012**	0.013**
	(0.023)	(0.037)	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)
High initial share of empl. in manufacturing	0.013	0.044	0.001	0.007	-0.009**	-0.011*	0.015***	0.023**
	(0.019)	(0.049)	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.009)
January maximum temperature	0.010***	0.011***	-0.001	-0.001	0.001***	0.001***	-0.003**	-0.003**
	(0.004)	(0.004)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
July maximum temperature	0.004	0.002	-0.001	-0.001	0.002**	0.002**	-0.001	-0.002
	(0.008)	(0.011)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Log distance to nearest big city	-0.005***	-0.005***	0.000	0.000	-0.001	-0.001	-0.001*	-0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Log distance to nearest coastline	0.001	0.004	0.002	0.003	-0.002**	-0.002**	0.002	0.003
	(0.008)	(0.009)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	-0.770	-0.733	-0.770	-0.733	-0.770	-0.733	-0.741	-0.698
IV P value	0.003	0.000	0.003	0.000	0.003	0.000	0.002	0.000
IV Partial R2	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.06
First stage F statistic	9	22	9	22	9	22	10	21
Urban Areas	154	154	154	154	154	154	153	153

Notes: Instruments used in regressions removes industries that are highly concentrated geographically. "Big plants" refer to 50+ establishments and "downsized plants" to 50+ establishments in 2003 that lose at least 30% of their workforce in 2017. "High initial share" means to be in the top quartile of the cities in our sample. The "skilled" are the 15+ residents with at least a bachelor degree. A big city is a city with at least 300,000 residents. Temperatures are in Celsius and distances in meters. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Scott's National All databases, Statistic Canada's Census 2001-2016 and boundaries files, Environment Canada's weather data.

CHAPTER II

INNOVATION IN DIVERSIFIED CITIES.

Abstract

I combine comprehensive patent, establishment and census data in Canada to analyze whether diversity affects local innovation activity from 2006 to 2016. I distinguish between diversity in the population and in manufacturing. The results suggest that cities with a more diverse ethnic composition of the population and more diverse sectoral composition in manufacturing experience a higher level of innovation activity. Ethnic diversity has more than 4-11% larger effects on innovation activity than manufacturing diversity. I also show that diversity has heterogeneous effects depending on the field of innovation. Ethnic diversity has positive effects on chemical, computer and electronic innovations, while manufacturing diversity has positive effects on all innovation classes.

Keywords: Canadian cities; innovation, cultural diversity, industrial diversity.
JEL Classification Codes: R11, R12, R23.

2.1 Introduction

The economic effects of "diversity" have recently received considerable attention in the economics literature, as modern societies have become markedly more heterogeneous in dimensions such as population ethnicity and firm output [1]. The literature on diversity has focused on its effect on local innovation as a measure of economic performance in cities. Indeed, innovation is considered as an important driver of growth in cities, particularly in terms of employment (see Acs, 2002). While the literature has so far addressed the impacts of cultural and industrial diversity separately, I consider them jointly in this chapter in order to investigate which level is more important. [2]

The chapter examines how innovation activity at the city level is affected by ethnic and manufacturing diversity. Innovation activity is defined as the number of patents per working-age population- assigned to urban areas based on the residential address of all inventors named on the patent. Diversity is measured by a fractionalization index in terms of the abundance of ethnicity-based population groups or manufacturing plants based on their sectors. I allow the diversity measure to include the bilateral distance between population groups (cultural, geographic, and genetic distances) and between manufacturing plants (distance based on input-output links, patent citations, and labor movement).

I find that a higher level of innovation activity is associated with a higher degree of fractionalization of the population by ethnic origins only when bilateral distances between groups (cultural, geographic, and genetic distances) are included in the diversity measure. Distinct ethnic groups provide a mix of ideas and skills favorable to innovation. A one standard deviation increase in ethnic

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1. The foreign-born account for about 10 percent of the labor force in OECD countries, three times as much as in 1960 and twice as much as in 1990 (Alesina et al., 2016). See Özden et al. (2011) for a description of the evolution of international migration over the past 50 years, and Brown and Greenbaum (2017) for a 35-year empirical examination of the role of industrial diversity.

2. Alesina and La Ferrara (2005) present an investigation of the impact of ethnic diversity on economic outcomes at different levels of aggregation and Iammarino (2011) presents a review of the literature on the effect of industrial diversity on economic growth.

diversity increases the level of innovation activity by 17 to 23%, depending on the measure of group distance. I also find that a greater fractionalization of manufacturing plants by sector is associated with a higher level of innovation activity, regardless of whether I include bilateral distances between groups. A one standard deviation increase in manufacturing diversity increases local innovation activity by 11 to 13%. Thus, the effect of ethnic diversity on innovation activity is larger than that of manufacturing diversity, and almost twice as important depending on the distance chosen between the groups. These results are robust to recent immigration, city size, inventor productivity, and patent quality. Moreover, their effects also differ by type of innovation. Ethnic diversity has a stronger effect on innovation activity than manufacturing diversity, but only on innovations in the chemical, computer-communications, and electrical-electronic fields.

These findings are important for several reasons. First, local governments are increasingly relying on economic immigration to address labor shortages in cities and regions. For example, Canada will increase permanent residency to foreign-born people to an historic level in 2021, a decision currently being considered by several developed countries, including the United Kingdom and the United States.[3] Canada is also announcing a $20 million investment in 2021 to diversify industries in the western Canadian economy. Measuring the economic effects of diversity is then important to understand how these policies affect local economies. Second, the technological progress generated by innovation is seen as a key factor in stimulating economic growth. Innovative cities and regions tend to grow faster, as they foster start-ups that support the city's growth through thick labor markets or localized knowledge transfer (see e.g. Acs, 2004). Governments are investing heavily in research and development to ensure sustained growth in their economies.[4]. It is therefore important to iden-

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3. Canada has announced in its 2021-2023 immigration levels plan that it will aim for the highest level of immigration in its history by welcoming almost 30% more immigrants per year than previously.

4. In 2017, the Canadian government considered in the budget actions related to its "innovation and skills plan" which includes accelerating innovation through a provision of $950

tify the determinants of local innovation, in particular how diversity affects innovation and at what level - firm or individual - diversity is most important. This distinction between cultural diversity and industrial diversity is very important in the data: some cities have both a heterogeneous ethnic composition and a fairly homogeneous manufacturing industry, and vice versa.

To estimate the effect of diversity on innovation activity of Canadian urban areas, the chapter combines patent-based data, establishment-level data and population census data from 2006 to 2016. Identifying the impact of diversity on local economic performance is challenging due to possible reverse causality. Diversity can lead to higher levels of innovation. A more diverse population and firms provide a diversity of skills, experiences, production and dissemination of ideas within and outside of firms, which promotes innovation in cities (see e.g. Alesina and La Ferrara, 2005). However, some studies have shown that innovative cities offer greater employment opportunities through higher wages and employment levels, as well as thicker local labor markets (see e.g. Hausman, 2021). Individuals and firms could therefore move to these cities to reap the benefits of innovation and thus influence the level of diversity in the city. To deal with endogeneity, the chapter uses an IV strategy. The treatment variables are the ethnic and manufacturing diversity indexes. I instrument them with the predicted ethnic and manufacturing diversity indexes calculated with the predicted shares of the ethnic or manufacturing plant groups. Predicted values are calculated as the interaction between the 1996 historical values of ethnic groups (from 149 countries) and manufacturing plant groups (from 85 4-digit NAICS industries), and the observed growth rate of each group in Canada. Finally, I also control for observable characteristics that may influence innovation at the city level, such as the share of foreign population, the share of manufacturing employment, the share of skilled people, proximity to universities, university R&D spending, and regional policy differences.

This chapter is related to three strands of the literature. First, research on the determinants of regional innovation has shown that local innovation is positively

million over five years to support a small number of business-led innovations.

correlated with higher levels of R&D spending (e.g. Bottazzi and Peri, 2003), number of universities (e.g. Feldman and Kogler, 2010), population density (e.g. Carlino et al., 2007), immigrants (e.g. Hunt and Gauthier-Loiselle, 2010) and is strongly related to competition (e.g. Aghion et al., 2005; Agrawal et al., 2014). Here, I propose a different but complementary perspective by analyzing the effect of ethnic and manufacturing diversity. I thus show that the local composition of cities in terms of population and firms can influence their economic performance through innovation.

Second, research on the regional diversity has shown that cultural diversity increases wages and rents (e.g. Ottaviano and Peri, 2006), employment (e.g. Lee, 2011), but has mixed effects on productivity (e.g. Parrotta et al., 2014; Trax et al., 2015). Other studies have considered diversity in terms of industrial composition and have shown that this industrial diversity has positive effects on innovation (e.g. Feldman and Audretsch, 1999; Duranton and Puga, 2001) and growth in cities (e.g. Glaeser et al., 1992). This literature focuses mainly on (a) case studies of firms that often focus on diversity in team composition, (b) or studies linking labor force heterogeneity - typically birthplace diversity and migration- to innovation using aggregated regional or industrial data. Firm level studies rarely test for geographical context and regional level studies don't test if links between diversity and innovation are driven by the presence of more diverse firms and people simultaneously. Cultural and industrial diversity could be an important aspect of urban variety, influencing local consumption and production respectively. To my knowledge, this chapter is the first to examine the relationship between two types of diversity and innovation simultaneously.

The chapter also contributes to the literature on regional knowledge spillovers. It builds on the theory that the geographic concentration of people and firms in cities facilitates the diffusion of tacit knowledge. While endogenous growth theory emphasizes the importance of research and development, Feldman (1994) has studied the importance of the spatial dimension in patterns of innovation and technological change. It turns out that geography provides a platform where knowledge can flow. Some studies examine whether knowledge transfers are localized through patent citations, by testing whether patent citations in an area come strongly from other inventors located there (e.g. Jaffe and Trajtenberg, 1993; Jaffe et al., 2000; Thompson, 2006). This chapter contributes to this large literature that examines knowledge diffusion in cities. The chapter shows how the economic performance of cities is affected by the transmission of knowledge by assuming that it occurs through very close spatial connections and a variety of skills and ideas between firms and individuals.

The rest of the chapter is organized as follows. Section 2.2 describes the data used in the chapter and explains the construction of the diversity indexes. Section 2.3 describes the OLS results on the impact of ethnic and manufacturing diversity on innovation activity. I also discuss endogeneity issues and their effect on the results. Section 2.4 briefly discusses some robustness checks and extensions. Section 2.5 examines how diversity affects different technological innovation classes and section 2.6 concludes.

2.2 Data and descriptive statistics

This section describes the patent database used to measure 'innovative activity' in urban areas, as well as the demographic, economic and geographic variables used throughout our empirical analysis to build both the independent and several control variables. It also presents descriptive statistics which motivate the subsequent analysis.

2.2.1 Patent data and measurement of innovative activity

Innovation can be classified into two categories: product innovation, which refers to a new or improved product, and process innovation, which refers to an improvement in the production technology of a firm. While several measures of the first type are documented in the literature, the second type is poorly documented because it concerns a process that is difficult to quantify and compare, such as the improvement of work techniques in firms. Most studies measure product innovation through (i) innovation inputs such as R&D expenditures or venture capital (VC) investments; (ii) final innovation output measures, such as the number of new product announcements (see for a survey Carlino and

Kerr, 2015); or (iii) intermediate outputs of the innovation effort, such as the number of patents.

Data on R&D are particularly difficult to collect at the local level (except through confidential surveys), and venture capital investments are concentrated in specific technology fields (e.g., computers, biotechnology) and types of firms (e.g., start-ups). Data on new product announcements are only available over long periods of time and may have selection biases, as editors of trade publications may select innovations that they believe to be of most relevance.

Patent data are the most widely used because they are easily accessible, more detailed, and available over long periods of time, which allows for better empirical analysis. Compared to R&D expenditures, patent data are a direct result of the inventive process. However, this measure also has some caveats. First, it does not measure the purpose of the innovation, but the process of its implementation (e.g. Jaffe and Lerner, 2004). This raises questions about the successful commercialization of the patented innovation. Studies have shown, however, that there is a strong correlation between patents and the location of new products in the market (e.g. Feldman, 1994). Second, the value of patents is very highly skewed, as most patents are not worth much, while a few are very valuable (e.g. Serrano, 2010). However, researchers can adjust the quality of patents in their innovation measures by weighting patents by the number of citations they receive (e.g. Jaffe and Trajtenberg, 1993; Murata et al., 2014). These data are not available at the local level in Canada. Finally, not all innovations are necessarily patented and there are large differences in the propensity to patent across industries and urban areas (e.g. Cohen et al., 2000; Shearmur, 2017).

I use the Canadian patent database digitized by the CD Howe Institute to construct measures of innovation activity. This database provides detailed information on the patent as well as the postal code of the place of residence of the inventors associated with the patent. Patents are then assigned to urban areas based on the residential address of all inventors named on the patent. It allows the construction of patent-inventor pairs by working age population in each

Canadian urban area. The inventor's residential address remains a good indicator of where the innovation activity occurs because the scale of analysis is the urban area. An urban area consists of one or more adjacent municipalities located around a population center. Statistics Canada's urban areas are constructed by definition such that a significant proportion of the residents of the municipalities forming the urban areas work in the center of the urban area. It allows to explore the link between people and firms. [5]

Patents are linked to the inventors' residence address. It is assumed that the inventor's place of work would be a better representation of the innovation activity performed. Therefore, a spatial scale that encompasses the inventor's place of residence and work would be necessary. For this purpose, the urban area is the best scale for such an analysis. The scale of diffusion areas would be too small to encompass the place of residence and work, and the provincial scale would be too large to conduct a meaningful analysis. Urban areas are constructed by Statistics Canada so that the municipalities within them are highly connected in terms of commuting. It is therefore very likely that inventors residing in these areas also work there. However, it must be emphasized that the city seems to be important in terms of "spillover" as a geographic unit. Exchanges of ideas and knowledge spillovers occur mostly at small distances.

However, this measure has also its shortcomings. First duplicating patents to all inventors, could distort the real representation of the innovation activity. This is not a major problem because in the database 83% of the patents have only one associated inventor and 92% have at most two associated inventors. Moreover, in Appendix 2.8, I associate the patents to the first inventor only (e.g. Carlino et al., 2007), or assign equally weighted fractions of the patent to each of its inventors, if a patent has multiple inventors (e.g. Moretti, 2021). The estimation results remain robust to the different assumptions. Second, some

5. The boundaries of the urban area have been stabilized and an explanation of this stabilization is detailed in 2.7.2. A detailed description of the distribution of urban areas by province is also provided in the table 2.10

innovations are not patented and patents differ in their economic impact, but the innovation literature has shown that technologies with a greater impact on social welfare and economic growth are more likely to be patented (Griliches, 1990). Feldman (1994) also found a positive and high correlation of 0.8 between patents and the locations where new products are introduced to the market. Patents therefore remain a useful measure, as they are a direct result of the inventive process. The analysis presented here is based on 155 Canadian urban areas from 2006 to 2016. The panel dataset, which includes two 5-year periods (2006-2011, 2011-2016), contains 310 urban area-period observations.

There are 89,468 geolocated patent-inventor pairs over the period 2006 to 2015 in Canada.[6] Table 2.1 shows an overview of their geographical structure in Canada from 2006 to 2015. Most patents are located in the most populated provinces of Quebec and Ontario.The number of patent-inventors decreased slightly by 3% between the two analysis periods. The largest increase are observed in the province of Alberta, which on average observed an increase of 32%. The provinces of Ontario and Quebec, which have the largest number of patent-inventors in Canada, experienced a decrease of 9% and 13% respectively.

I construct measures of the innovation activity in urban area c as follows :

$$\text{Innovation activity}_c = \frac{\#\text{ patent-inventors}}{\text{Working age population}} \times 10{,}000 \qquad (2.1)$$

This measure is based on the literature on the determinants of regional innovation which controls the level of innovation output with the size of the population, because it is likely that larger urban areas have a greater number of patents (see Carlino et al., 2007; Kerr and Lincoln, 2010; Niebuhr, 2010). Formally, the innovation activity measure for urban area c is defined as the number of patents per people aged between 15 and 64 years, averaged over each period to mini-

6. Data from 2016 are left out due to missing and truncated data. The data from 2006 to 2015, give a very good and sufficient coverage of the study period.

Table 2.1: Geographic breakdown of patents in Canada.

Region	Province	2006-2010 Total patent inventors	2006-2010 Average patents per working-age population	2011-2015 Total patent inventors	2011-2015 Average patents per working-age population
Western	Alberta	5,343	4.5	7,054	5.3
	British Columbia	4,423	3.1	4,424	2.9
	Manitoba	1,030	2.7	852	2.1
	Saskatchewan	1,171	3.6	1,234	3.6
		11,967	**3.5**	**13,564**	**3.5**
Atlantic	New Brunswick	347	1.4	409	1.6
	Newfoundland and Labrador	155	0.9	147	0.8
	Nova Scotia	614	2.0	588	1.9
	Prince Edward Island	59	1.3	70	1.5
		1,175	**1.4**	**1,214**	**1.5**
Ontario	Ontario	**22,171**	**5.2**	**20,221**	**4.6**
Quebec	Quebec	**10,236**	**3.9**	**8,894**	**3.3**
Canada		**45,565**	**2.3**	**43,903**	**2.2**

Notes: Distribution of patents by province from 2006 to 2015. The three territories (Northwest Territories, Nunavut and Yukon) are removed from the table but not from the total. Source: Authors' computations using Canadian patent data digitized by the CD Howe Institute.

mize the effects of annual fluctuations in patent intensity mainly in small urban areas. The innovation activity is heterogeneous across provinces, ranging from 0 to 26 (with a Canadian average of 2.3). While most provinces show a constant level of innovation activity between the two periods, Alberta and British Columbia experience an increase, while Quebec experiences a decrease.

2.2.2 Measurement of diversity

There are two key independent variables. One that measures the diversity of the population according to their ethnic origins and the other that measures the diversity of firms according to their manufacturing sectors.

Ethnic diversity

Cultural diversity can generate benefits and costs to innovation. The results can therefore be seen as a net positive effect of diversity on innovation or employment. On the one hand, it favors innovation by : (i) being conducive to the birth and fertilization of innovative ideas, through different ways of thinking and problem solving (see Florida, 2003) as well as complementary productive capacities, (ii) strengthening regional inclusion and attracting more creative talent, (iv) promoting the acquisition of complementary productive capacities and helping companies to acquire the external knowledge necessary for innovation in business (see Ottaviano and Peri, 2006). However, on the other hand, regional cultural diversity can also inhibit innovation capacity by: (i) leading to conflicts and communication difficulties between different cultures hindering the diffusion of knowledge and technology (see Alesina and La Ferrara, 2005), (ii) increasing differences between people and reducing the effectiveness of collective action, which reduces the provision of public goods such as health and education services (see Algan et al., 2017), (iii) increasing polarization, which has negative consequences at the macro level such as employment or income (see Colussi et al., 2021).

Using the Canadian census data released by the Computing in the Humanities and Social Sciences (CHASS) data center at the University of Toronto, it is possible to access the self-reported ethnicity of the respondent. Ethnic origins are then aggregated to the country level by using the Geo Referencing of Ethnic Groups, GREG database (see Weidmann et al., 2010).[7] An ethnicity is directly associated with a country, when the country name is used to describe it. When this is not the case, the ethnicity is distributed among the countries with which it is associated, using weights that calculate the ethnicity's share in that country.

Using ethnicity is more likely to capture how people perceive themselves based on their cultural-ethnic background. Each respondent can report one or more ethnicities that allow for a fine-grained expression of how the person perceives him or herself. Unlike citizenship, this allows for a richer measure, as people of the same citizenship may have a different ethnic background. However reporting of ethnicity may be approximated by individuals who do not know what exactly their origins refer to. This would generate a random measurement error

7. This will help to keep the same groups over time and also allow for similarities between country pairs for which data are only available at the country level.

in the measurement of ethnic diversity, thus leading to attenuation bias.

This article focuses on diversity among foreigners. Foreigners exclude Canadian, British and French origins which are the founding nations of Canada. Canada is unique in being a country with three very different founding nations, as well as many non-foreigners with recent international roots. Symbolically, questions on ethnic origin in the census have served primarily to enshrine the status and importance of ethno-cultural communities, other than the English and French, as full members of Canadian society (see Bourhis, 2003). The French and the British have been together in Canada for over 400 years. It is not claimed that they have homogenized, but they are closer to the original Canadians than other ethnic groups. The measure of ethnic diversity looks at other ethnic groups.

I measure ethnic diversity in two ways. In Appendix 2.7.3, I show how I get the two diversity measures from the same general expression. First, I consider the number of different groups of foreigners in the urban area by a simple fractionalization index. The index is expressed as follows:

$$\text{EthnicDiv1}_c^t = 1 - \sum_{i=1}^{N} {\text{s}_{ic}^t}^2 \tag{2.2}$$

where s_{ic}^t are the share of foreign people from the ethnicity i among the foreign residents of urban area c in period t.

Second, I use another measure of ethnic diversity that differs from the first by considering population groups as heterogeneous. The second index is calculated as follows:

$$\text{EthnicDiv2}_c^t = \sum_{i=1}^{N} \sum_{j=1}^{N} \text{s}_{ic}^t \text{s}_{jc}^t d_{ij} \tag{2.3}$$

where s_{ic}^t and s_{jc}^t are the share of people from the countries i and j among the foreign residents of urban area c in period t, N is the total number of countries, and d_{ij} refers to the dissimilarity between the two countries.[8] Although widely used in the literature (see Alesina and La Ferrara, 2005; Ottaviano and Peri, 2006; Trax et al., 2015), the first measure treats groups as similar to each other. The inclusion of ethnic diversity effects in economic models lies in the preferences or technological characteristics. According to Bossert et al. (2011), one should therefore not just limit oneself to measuring fractionalization purely in terms of population shares, but also consider the distance between groups. Economic models that consider different population groups are based on the fact that they may have different preferences that would generate heterogeneity in economic decisions, or possible complementarities of skills that could affect economic performance in the urban area. This could not be accounted for by population shares alone. Equation 2.3 has a nice intuitive interpretation: it represents the average distance between all pairs of foreign people of the urban area.

I follow Bossert et al. (2011) and construct an N x N dissimilarity matrix $D = (d_{ij})_{i,j\in\{1,...,N\}}$ with the following properties: (i) the similarity values are in the interval [0, 1], assigning a value of 1 to perfect dissimilarity and a value of 0 to maximum similarity, i.e. $d_{ij} \in [0,1]$ for all $i, j \in \{1,...,N\}$, (ii) all values on the main diagonal that represent the dissimilarity of each group to itself are equal to 0 for all $i \in \{1,...,N\}$, (iii) the similarity matrix is considered to be symmetric, i.e. $d_{ij} = d_{ji}$. Here, the distance between population groups is measured by the geographic distance between the capitals of the countries from Behrens and Moussouni (2019), as ethnic distance has a strong geographic component (Bauernschuster et al., 2014).[9]

Figure 2.1 shows the diversity with and without geographic distances between

8. The fractionalization index measures the probability that, in a given urban area, two randomly selected individuals are from different countries. The idea behind the group distance is that the more different groups, the more difficult it is to predict correctly which group will be drawn.

9. I also consider other measures of group distance such as cultural and genetic distances. The results presented below do not change qualitatively. A brief description of these measures can be found in Appendix2.7.2.

groups, of each Canadian urban area compared to the urban area's average. Sainte-Marie (Quebec) has the lowest level of ethnic diversity, while Toronto (Ontario) has the highest level of ethnic diversity in Canada. Large cities (population 300,000 and over, outlined in cyan in the figure) have a higher level of diversity than the average Canadian urban area. Below-average diversity is most prevalent in Quebec and Atlantic provinces, while above-average diversity is found in Ontario and Western provinces. Figure 2.3 shows the same description is observed when the diversity measure includes cultural or genetic distance between groups, but with slightly less diversity in the western provinces and Ontario.

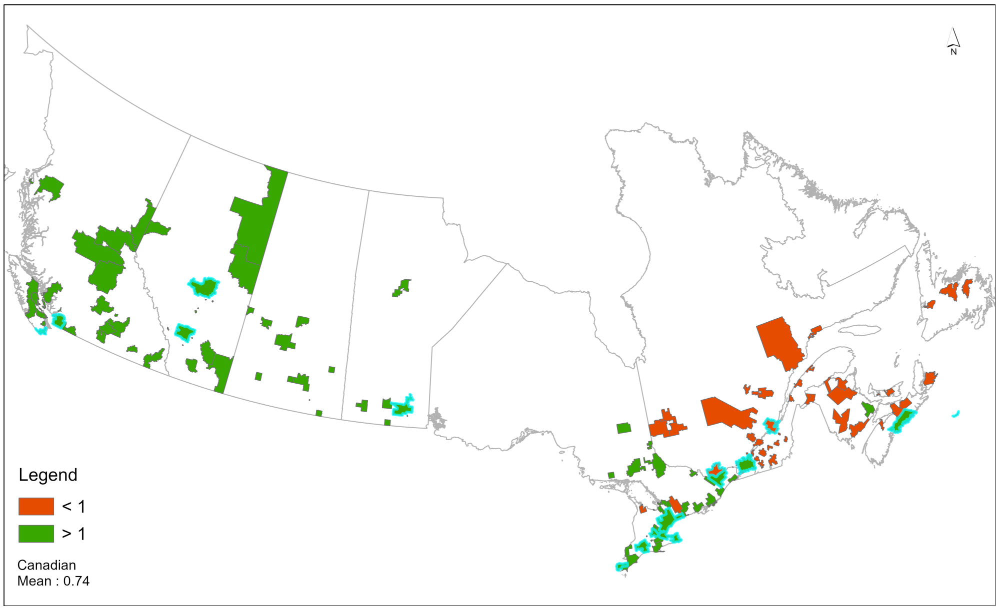
Manufacturing diversity

Diversity indexes similar to the previous one, which considers the share of Canadian manufacturing plants by sector, are constructed to explore the possible effects of manufacturing diversity. Manufacturing is an interesting industry to study because it seems to be the industrial sector most strongly correlated to local innovation. [10] The majority of patented innovations are those of the manufacturing industry because it is easier to identify innovation at this level than at the level of services where innovation can be, for example, organizational or process innovation. Carlino et al. (2007) showed in a study that examines the relationship between employment density and innovation, that although patent activity varies enormously across industries, the manufacturing share of employment in U.S. metropolitan areas is particularly positively related to local patent intensity. The primary source of data are the *Scott's National All Business Directories* that contain exhaustive information on establishments operating in Canada, with an extensive coverage of the manufacturing sector (NAICS 31–

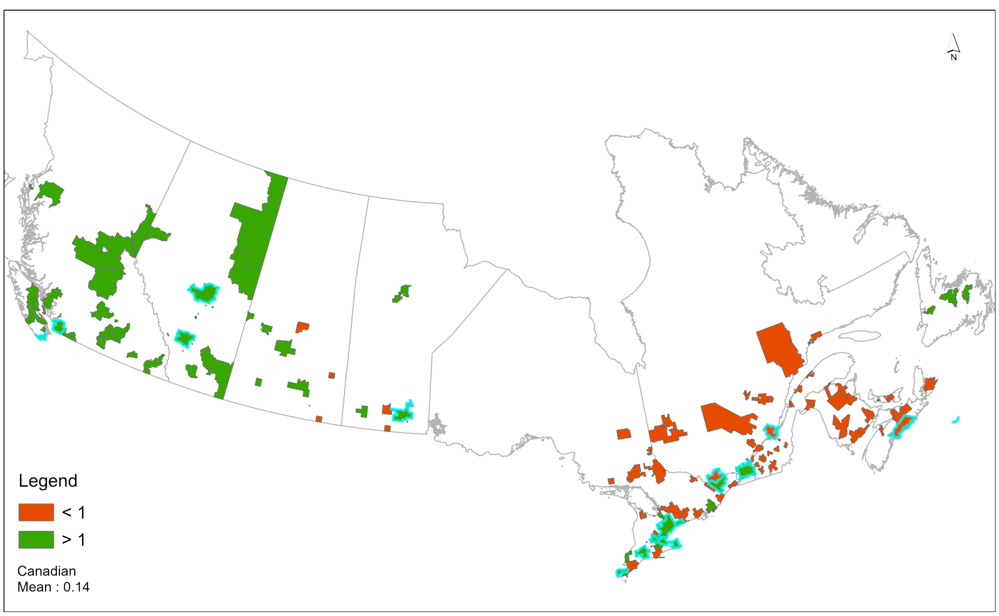
10. Researchers show that the level of patent applications and real GDP from manufacturing between 1995 and 2015 have varied in the same direction. See Susan Helper et al, 2016 Why does manufacturing matter? which manufacturing matters? and Canadian Intellectual Property Office, IP Canada Report 2016. This could be explained by the fact that manufacturing activity is the main driver of the type of innovation that produces patentable inventions, particularly in advanced economies such as Canada.

Figure 2.1: Relative ethnic diversity in Canadian Urban Areas

(a) Ethnic diversity with no distances between groups



(b) Ethnic diversity with geographic distances between groups



Notes: Ethnic diversity are measured relatively to the urban area average. A value of 1 on the map means that the urban area's growth rate is the same as all urban areas mean. Cyan contours outline cities with population of at least 300,000.

33). We have these data every two years from 2001 to 2017.[11] I add 1998 data

11. See Tables 2.9 in the Appendix 2.7.5 for a comparison between the Scott's National All

from Statistics Canada's Canadian Business Register, which is highly correlated with the Scotts database, as both databases describe the manufacturing plants in Canada. [12]

I also consider two measures of industrial diversity. In Appendix 2.7.3, I show how I get the two diversity measures from the same general expression. The first considers the share of manufacturing plants by sector in the urban area. This diversity is also measured by a simple fractionalization index. I choose the number of manufacturing plants instead of manufacturing employment, because the latter would make it difficult to disentangle the sectoral mix effect from the effect of the ethnic composition of employees on innovation activity. The index is expressed as follows:

$$\text{ManufDiv1}_c^t = 1 - \sum_{k=1}^{M} {\text{s}_{kc}^t}^2 \tag{2.4}$$

where s_{kc}^t is the share in manufacturing plants in sector k in the urban area c in period t.

The second measure of manufacturing diversity differs from the first by considering manufacturing plants groups as heterogeneous, and is constructed as follows:

$$\text{ManufDiv2}_c^t = \sum_{k=1}^{M} \sum_{l=1}^{M} \text{s}_{kc}^t \text{s}_{lc}^t d_{kl} \tag{2.5}$$

where s_{kc}^t and s_{lc}^t are the share in manufacturing plants from the 4 digit NAICS sectors k and l of urban area c in period t, M is total number of industries, and d refers to the distance between the two sectors. Here, the distance between

Business database and other Statistics Canada CBC databases.

12. 1998 was taken because it is the closest date to 1996 which displays industries in NAICS code used throughout the analysis instead of SIC code.

manufacturing plant groups is measured based on the patent citations flows between these plants across NAICS 4 digit industries. [13]

The correlation between the ethnic and industrial diversity measures (without distance) are around 1%, and the diversity measures (with distance) are around 15%. The idea is to see which diversity channel affects innovation the most. Is innovation most influenced by the interaction of people, or the complementarity of production between firms. This is the reason why ethnic diversity is in number of people and industrial diversity in number of firms (and not in number of people in firms), to dissociate the two as well as possible.

Figure 2.2 shows the manufacturing diversity with and without patent flows based distances, of each Canadian urban region compared to the average for all urban regions. Thompson (Manitoba), has the lowest level of manufacturing diversity, while Guelph (Ontario), has the highest level of manufacturing diversity in Canada. Large cities (population 300,000 and over, outlined in cyan in the figure) show, as with ethnic diversity, a higher level of manufacturing diversity than the average for Canadian urban areas. There is wide variation in this relative measure of diversity in small and medium-sized cities. A lower than average level of diversity is most prevalent in western Canada, while in eastern Canada there is a high level of manufacturing diversity. The importance of examining ethnic and manufacturing diversity can be seen, especially in provinces like Quebec that have a high level of manufacturing diversity and a low level of ethnic diversity. The western provinces have a relatively lower level of manufacturing diversity and a high level of ethnic diversity.

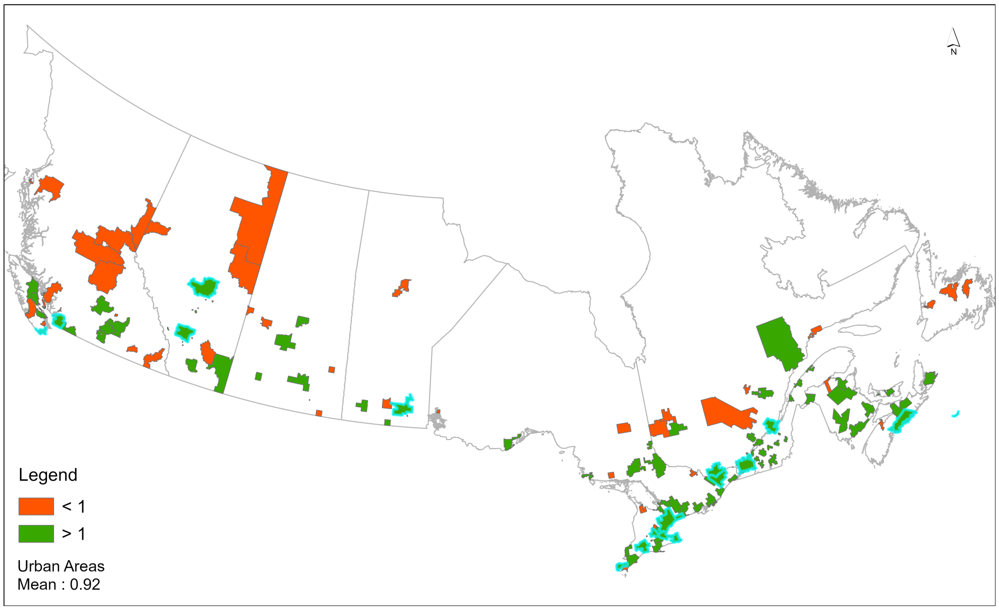
2.2.3 Additional data

The aim of the following analysis is to better understand whether and how diversity explains the level of innovation activity in urban areas. To do this, we need to control for many potential confounding factors, including initial city

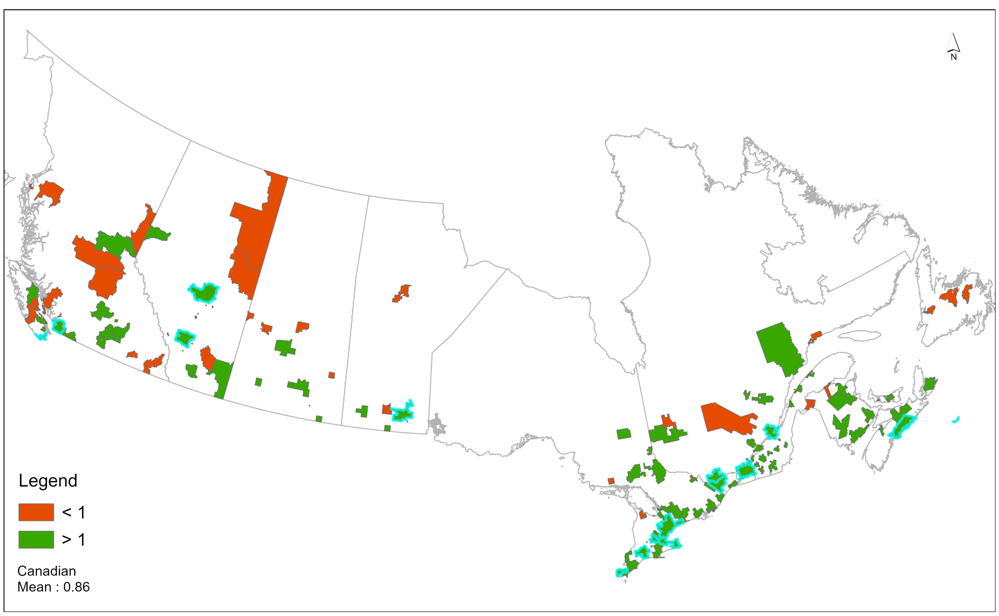
13. I also consider other measures of group distance based on labor flows and input-output sharing. The results presented below do not change qualitatively. A brief description of these measures can be found in Appendix2.7.2.

Figure 2.2: Relative manufacturing diversity in Canadian Urban Areas

(a) Manufacturing diversity with no distances between groups



(b) Manufacturing diversity with patent flows based distances between groups



Notes: Manufacturing diversity are measured relatively to the urban area average. A value of 1 on the map means that the urban area's growth rate is the same as all urban areas mean. Cyan contours outline cities with population of at least 300,000.

and geographical characteristics. Beyond the variety of the type of people and manufacturing plants, cities, especially larger ones, might be more innovative because of the overall level of their foreign population or manufacturing industry. To control for this possible size effect, I include in the regressions the share of people of foreign origin (excluding Canadian, British and French origins) and the share of manufacturing employment in the city. It is also particularly important to control for local inputs into the innovation process, such as human capital because the literature has shown that human capital contributes to growth and innovation in cities (e.g. Audretsch and Feldman, 2004; Lee, 2015). A proxy for the initial education level of the population is the share of residents with at least a university degree. The regressions also control for the influence of proximity to universities, a possible university city effect, by including the minimal distance to an university in the urban area. Finally, the regressions also include a measure of research inputs that is the sum of local university R&D expenditures divided by full-time enrollment in the urban area. This measure is intended to capture the intensive margin, that is, the R&D resources available to potential researchers. Additional details on the data sources used for these various covariates are provided in Appendix 2.7.1 and Table 2.5 presents descriptive statistics for these variables.

2.3 Innovation and diversity in cities: Regression analysis

This section present the empirical specification and the benchmark results.

2.3.1 Empirical specification

The specification applied to the data to analyze the effect of diversity at the city level is as follows:

$$\begin{aligned} log(\text{Innovation activity}^{t}_{c,r}) = & \alpha + \beta \text{EthnicDiv}^{t_0}_{c} + \delta \text{ManufDiv}^{t_0}_{c} + \gamma \text{X}^{t_0}_{c} + \theta_r + \tau_t \\ & + \varepsilon_{c,r,t} \end{aligned} \tag{2.6}$$

The dependent variable is the log of the average patents per working age population by working age population (15-64 years) of the period 2006-2011 and 2011-2016 in the urban area c. To mitigate bias induced by endogeneity or reverse causality, the independent variables are values at the beginning of each period t_0. The variables $\text{EthnicDiv}_c^{t_0}$ (which can be expressed as equation 2.2 or equation 2.3) and $\text{ManufDiv}_c^{t_0}$ (which can be expressed as equation 2.4 or equation 2.5), are the diversity indexes presented above at the initial period of period t_0 in the urban area c. $\text{X}_c^{t_0}$ is a vector of initial characteristics of urban area c which contains: [14] (i) the share of residents of foreign origin (which excludes Canadian, British and French origins, three founding nations of Canada), (ii) the share of manufacturing employment, (iii) the share of residents with a university degree, (iv) the (log) distance in meters to the closest university and (v) the sum of local university R&D expenditures divided by full-time enrollment in urban areas to capture the intensive margin-the R&D resources available to potential researchers. [15] θ_{r} is a regional fixed effect (Western provinces, Ontario, Quebec, and the Atlantic provinces), and ε_c is an error term. [16]

We chose to include the share of foreigners as a control to focus on the fractionalization effect of the population on innovation. Not including it does not allow us to know whether innovation increases because there are more people of foreign origin, or more people of various foreign origins. The assumption is that the large presence of different foreign groups could be more beneficial to idea fertilization, than the large presence of a single foreign group. Our specification therefore allows us to separate these two effects. Also, I exclude Canadian, British and French groups because they are disproportionately

14. Other variables that could be included in a more elaborate version of the chapter include dependence on resource sectors and proximity to the U.S. border. In Canada, large cities in and around metropolitan areas are more ethnically diverse than resource cities. Yet, during a resource boom, resource cities create jobs the fastest and generate very high wages.

15. The distance considered is the distance between the city center and the university. This avoids having several null distances in the database.

16. The results are not robust to the introduction of urban area fixed effects. It must be said that the diversity measures do not change much from one period to the next. There is little variability in the diversity measures over 5 years. The level of diversity 5 years ago will on average be about the same as the observed period.

larger in the population, which tends to give lower values than other smaller ethnic groups in the calculation of the fractionation index. The fractionalization index will measure relatively the same thing as the total share of foreigners in the city. However, the measure of ethnicity takes into account multiple relationships. Migrants of different generations who feel attached to other ethnic groups, mention this and this is reflected in the diversity measure. In this way, I do not neglect the origins and ethnicities within the Canadian national population.

Estimating the impact of diversity on innovation activity at the city level using OLS is likely to produce biased estimates of β and δ. It is possible that the OLS estimates do not control for bias not captured by the controls, such as reverse causality. I use instrumental variable estimation, to address this endogeneity problem.

Identifying the impact of population or industrial composition on local innovation is not trivial because of possible reverse causality. Diversity could increase innovation. Indeed, the exchange of complementary knowledge, skills and ideas between different firms and economic agents will tend to produce more output in terms of innovative activity. However, the choice of location of a population group or a firm in a given sector may be likely to be endogenous to the city's level of innovation. For example, a firm in a highly innovative sector such as physics or chemistry will locate in a city that develops such innovations in order to benefit from them. This reverse causality would lead to overestimating the impact of diversity on local innovation.

To address these endogeneity issues, the chapter relies on an IV strategy. In particular, I consider the "shift-share" instrument, which is a predicted index of local diversity calculated using the predicted shares of urban area residents or manufacturing plants. These shares are obtained by extrapolating observed shares in a base year with the national-level growth rates. Therefore, the predicted shares in an urban area in 2006 and 2011 for each ethnic groups (or each manufacturing plant groups), are attributed to the growth rate of that group at national level from 1996 to 2006 and from 1996 to 2011. To ensure that the initial shares in cities are as exogenous as possible to the national growth rate, the population (or number of plants) of the city is subtracted in the calculation of this rate. That leads to compute this equation :[17]

$$\widehat{(\mathrm{s}_{i,c})}^{t} = \mathrm{s}_{i,c}^{1996}[1 + (\mathrm{g}_i^{-c})_{1996-t}] \tag{2.7}$$

Once these 'predicted' shares are constructed for $t \in [2006, 2011]$, a 'predicted' diversity index for each city in $t \in [2006, 2011]$ is calculated as follows :

$$(\widehat{\mathrm{Div1}_{i,c}})^{t} = 1 - \sum_{i=1}^{N} \widehat{(\mathrm{s}_{i,c}^{t})}^{2} \tag{2.8}$$

$$(\widehat{\mathrm{Div2}_{i,c}})^{t} = \sum_{i=1}^{N} \sum_{j=1}^{N} \widehat{(\mathrm{s}_{i,c}^{t})} \widehat{(\mathrm{s}_{j,c}^{t})} d_{ij} \tag{2.9}$$

The predicted composition of the urban area is thus calculated on the basis of the initial composition of each group to which the growth rate of that group's share at the national level is assigned. This index thus varies only at the regional level.

2.3.2 Empirical results

Columns (1) and (2) of table 2.2 show the results of the OLS estimation of equation 2.6. The estimates represent semi-elasticity. The independent variables only are expressed in standard deviation. The dependent variable is measured in logarithm. The estimates show that higher manufacturing diversity is positively and significantly correlated with the level of innovation activity in cities. This result holds whether or not manufacturing diversity is measured by including distances between groups of plants by sector.

Ethnic diversity, on the other hand, is positively and significantly correlated

17. The reconstructed shares sum to 1.

with innovation activity in cities, only when measured by a greater fractionalization of the foreign population into ethnic groups while considering the distances between them. This measure of the compositional dimension of ethnic diversity better describes the distinction between groups, and better reflects the mix of diverse ideas and skills that would come from quite different groups. [18] This result corresponds to that of Agrawal et al. (2008) who examines how people proximity influences knowledge flows leading to higher level of innovation activity. They found that being co-located while being ethnically different increased the knowledge flow 12 times more than being ethnically similar. Desmet et al. (2009) examines the effect of linguistic diversity on the GDP of European countries, and show that the commonly used fractionalization index, which ignores linguistic distances, yields insignificant results.

The control variables show that cities that are initially more skilled are more related to local innovation activity. A larger overall number of people from foreign origins is positively and significantly associated with a higher level of innovation activity. Increasing the total share of manufacturing employment is positively correlated with the level of innovation activity.

The IV regressions in columns (1) and (2) of table 2.2 provide a similar picture as the previous regressions. Comparing these results with OLS columns (1) and (2), all findings are qualitatively robust and statistical significance remains strong. The more fractionalized the foreign population pool is in terms of ethnic groups, the higher the local innovation activity is - on average - in the respective location, again only with distance between groups. And, the more fractionalized the manufacturing plant are in terms of sectors, the higher the local innovation activity is - on average - in the urban area, both with and without distance groups. The coefficient on ethnic diversity is higher than that on manufacturing diversity in the IV estimates. This highlights that causality for

18. The relevance of including distances in the diversity measure is ultimately an empirical question. This tests whether this feature improves existing results, by comparing the distance-based index with the one that does not include distances. Including distances makes diversity statistically significant. It is a more accurate measure that better captures differences between groups and provides a better measure of diversity for ethnic groups.

Table 2.2: Innovation and diversity in Canadian Urban Areas

Dependent variable: (log) Patents per capita	OLS(1)	OLS(2)	IV(1)	IV(2)
Ethnic diversity	0.046		0.037	
	(0.052)		(0.143)	
Manufacturing diversity	0.096***		0.093***	
	(0.024)		(0.027)	
Ethnic diversity (geographic distance)		0.079**		0.138***
		(0.032)		(0.039)
Manufacturing diversity (patent distance)		0.091***		0.082***
		(0.023)		(0.026)
Initial share of foreign origin population	0.096**	0.086**	0.097**	0.076**
	(0.038)	(0.038)	(0.040)	(0.037)
Initial share of manufacturing employment	-0.003	-0.013	-0.003	-0.018
	(0.032)	(0.032)	(0.032)	(0.032)
Initial share of skilled people	0.182***	0.171***	0.182***	0.161***
	(0.032)	(0.033)	(0.032)	(0.034)
Minimal distance to university	-0.133***	-0.138***	-0.133***	-0.145***
	(0.044)	(0.045)	(0.045)	(0.046)
University RD spending per student	0.021	0.007	0.022	-0.005
	(0.035)	(0.035)	(0.035)	(0.034)
Region dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
R2 adjusted	0.33	0.34	n.a.	n.a.
Ethny IV estimate			0.20	1.09
Ethny IV p value			0.00	0.00
Ethny F statistic			12	207
Manuf. IV estimate			0.92	0.92
Manuf. IV p value			0.00	0.00
Manuf. F statistic			62	58
Urban Areas	308	308	308	308

Notes : The table presents OLS and 2SLS estimates. Coefficients are all measured in standard deviations. The dependent variable is the number of patents per 10,000 persons aged between 15 and 64 years. Diversity is measured by a generalized fractionalization index. Distance for ethnic diversity is geographic distance. Distance for manufacturing distance is based on patent citation flows. The "skilled" are the 15+ residents with at least a bachelor degree. Standard errors in parentheses are robust. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases and Statistics Canada boundary files.

ethnic diversity is a greater challenge than for manufacturing diversity.

Recent contributions discuss the conditions under which Bartik's instruments are valid. The proposed procedures apply in particular to estimates of economic variables measured in growth rates (see e.g. Adão et al., 2019; Borusyak et al., 2020; Goldsmith-Pinkham et al., 2020). Nevertheless, following the suggestions of Borusyak et al. (2020), I show in table 2.8, that the results are very stable, supporting the validity of Bartik's instrument even in the different context of our study.

2.3.3 Quantitative benchmarking

This section helps to show the economic significance of these effects, using the baseline results in table 2.2 to provide a quantitative comparison of the results. The estimates of the independent variables are expressed in standard deviation. The dependent variable is the number of patents per working age population. Considering that the overall share of foreigners is constant, as well as the other covariates, a one standard deviation increase in ethnic diversity (including geographic distance) induces an increase in local innovation activity of 17.7%. Similarly, increasing manufacturing diversity (including or not the distance between groups of plants) induces innovation gains of 13.6%. Thus we can see that ethnic diversity brings additional innovation gains of 4% more than manufacturing diversity. This additional gain goes up to nearly 12% if the distances between population groups is measured by cultural distance as shown in the table 2.13.

The ratio of the ethnic diversity index (with geographic distance) of Quebec City - which is in the top quartile - to that of Regina - which is in the bottom quartile - is 1.3, indicating that Quebec City (QC) is 1.3 times more diverse than Regina (SK) between 2006 and 2016. Thus moving from Regina's level of ethnic diversity to Quebec City's would increase the level of local innovation activity by 23%, almost a quarter of a percent, holding other variables constant. [19] The ratio between the manufacturing diversity index (with distance based on

19. It is possible to see a city move from the lowest to the highest percentiles of the distribution. Drazanova (2019) analyzes the ethnic fractionalization index annually covering the period 1945-2013. They show that there is significant persistence in ethnic diversity in several countries. For example, Britain and the Netherlands had similar levels of ethnic fractionalization in 2013, but since 1949, diversity has increased much faster in the Netherlands than in Britain. In contrast, ethnic fractionalization in Finland has remained stable over the past 50 years and is generally low.

input-output link) of Montreal (QC) - which is in the top quartile - to the oil city Wood Buffalo (AB) - which is in the low quartile - is 1.1. Thus moving from Wood Buffalo's level of manufacturing diversity to Montreal's would increase the level of local innovation activity by 13.6%, holding other variables constant. It provides a good idea of the economic importance of ethnic and manufacturing diversity to cities, and also how much greater the economic effects of ethnic diversity are.

2.4 Robustness checks and extended analyses

2.4.1 Inventor productivity

An issue may emerge when measuring local innovation activity that considers the number of patents according to the addresses of the associated inventors. The presence of productivity externalities in cities can be misleading in interpreting the effect of diversity on innovation activity. Indeed, Moretti (2021) has shown that when an inventor moves to a city where there is a large agglomeration of inventors in the same field, there is a significant increase in the number of patents produced by that inventor, in American cities. If this is the case in Canadian cities, it would be difficult to dissociate the effects of the specialization of inventors in cities, the effect of the ethnic composition of inventors on the level of local innovation activity.

In order to isolate this productivity effect between inventors of the same sector close to each other, I construct a new measure of innovation activity. Each patent (and our patent-inventor pairs) is linked to a probability of being used by a NAICS industry sector of 3 digits. I therefore duplicate each patent-inventor pair according to the different sectors to which they are linked. Thus in a postal code, if there are two inventors attached to the same patent and the same sector, I retain only one. In this way, I control the productivity gains resulting from the proximity of inventors in the same sector. I choose the postal code because it is the smallest spatial unit available.

The results are in Table 2.3. Diversity estimates now have a stronger effect on innovation activity. Overall, the effect of ethnic and manufacturing diversity remains robust to this specification, and remains positive and significant on innovation activity.

Table 2.3: Innovation and diversity in Canadian Urban Areas

Dependent variable:	All Patents		Unique Patents by sector	
	IV(1) Simple index	IV(2) Distance index	IV(3) Simple index	IV(4) Distance index
Ethnic diversity	0.077		0.124	
	(0.073)		(0.100)	
Manufacturing diversity	0.126***		0.272***	
	(0.039)		(0.074)	
Ethnic diversity (geographic distance)		0.177***		0.300***
		(0.034)		(0.059)
Manufacturing diversity (patent distance)		0.136***		0.290***
		(0.041)		(0.077)
Share of foreign origin population	0.137**	0.079	0.154	0.058
	(0.068)	(0.069)	(0.099)	(0.105)
Share of manufacturing employment	0.092***	0.110***	0.126**	0.155***
	(0.033)	(0.033)	(0.049)	(0.049)
Share of graduated people	0.273***	0.348***	0.344***	0.471***
	(0.037)	(0.042)	(0.056)	(0.060)
(log) Minimal distance to university	-0.018	-0.009	-0.027	-0.012
	(0.033)	(0.033)	(0.053)	(0.052)
University RD spending per student (1,000 dollars)	0.018	0.035	0.028	0.058
	(0.029)	(0.030)	(0.044)	(0.045)
Region dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Ethny IV estimate	0.56	1.43	0.56	1.43
Ethny IV p value	0.00	0.00	0.00	0.00
Ethny F statistic	29	107	29	107
Manuf. IV estimate	0.75	0.74	0.75	0.74
Manuf. IV p value	0.00	0.00	0.00	0.00
Manuf. F statistic	16	15	16	15
Times periods	310	310	310	310

Notes : The table presents OLS and 2SLS estimates. Coefficients are all measured in standard deviations. The dependent variable is the number of patents per 10,000 persons aged between 15 and 64 years. Diversity is measured by a generalized fractionalization index. Distance for ethnic diversity is geographic distance. Distance for manufacturing distance is based on patent citation flows. The "skilled" are the 15+ residents with at least a bachelor degree. Standard errors in parentheses are robust. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases and Statistics Canada boundary files.

2.4.2 Innovation value

Using patents as an indicator of innovation activity is also problematic because the value of patents is very highly asymmetric. Patents can differ in their value and their economic impact. I separate the patent applications that have not gone through the granting process from those that have (or are in the final stages of granting). Issued patents are more likely to have a more significant and prolonged effect on the local economy, than those that are in the process or have been rejected (e.g. Harhoff et al., 1999). In our data, between 1996 and 2016, 45% of the patent applications had the status of dead, withdrawn or expired.

I apply the benchmark model using all covariates and focus on the results IV. Table 2.12 shows that the results are robust to whether the patent is granted or not. Manufacturing and ethnic diversity remain positively and significantly correlated with innovation activity in cities.

2.4.3 Measures of distance between groups

I also analyze the effect of diversity on innovation activity by considering alternative measures of distance between groups. The previous regressions consider the geographical distance for ethnic diversity. I replace it with the cultural and the genetic distance between different groups of people according to their ethnic origin. For manufacturing diversity, I replace patent distance with the distance according to the sharing of input and output, and the flow of labor between the different manufacturing sectors. Table 2.6 shows pairwise correlation between all theses similarities measures. The population distances are poorly correlated and seem to describe different aspects of diversity, while the sectoral distances are highly correlated and easily substitutable. Results are displayed for IV estimates in table 2.13. The effect of ethnic and manufacturing diversity remains positive and significant regardless of the measure chosen. Note that the effect of ethnic diversity is higher when inter-group distances are measured by genetic distance and the effect of manufacturing diversity is higher when inter-group distances are measured by patent distance.

2.4.4 Big cities effects

As shown in section 2.2.2, large cities are generally places of high diversity compared to smaller ones, but also places of high innovation activity and presence of universities. Thus the effect of diversity on innovation activity might be disproportionately driven by larger cities. Although in equation 2.6, innovation activity is measured in terms of population, I consider several specifications to account for this city effect. I include in the baseline regressions a control for the initial population by adding the log of the total initial population or a dummy variable indicating whether the urban area population is greater than 300,000. In addition, I select a sample that eliminates the major Canadian provincial capitals: Charlottetown (PE), Edmonton (AB), Fredericton (NB), Halifax (NE), Quebec (QC), Regina (SK), St. John's (NL), Toronto (ON), Victoria (BC), Winnipeg (MB). I also select a sample that eliminates urban areas with more than 1 million people : Calgary (AB) Edmonton (AB) Ottawa (ON) Vancouver (BC) Toronto (ON) Montreal (QC). Table 2.14 shows that the estimates remain qualitatively similar to those of our baseline model.

2.4.5 Recent immigration

Several studies have shown that skilled immigration increases the level of innovation in cities, as these immigrants often come from fields such as science, technology, engineering, and mathematics which have a significant positive impact on the numbers of patents (e.g. Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010). In Canada, where immigration is largely skill-based, this is especially important. Since recent immigrants are counted among persons with foreign ethnic origins, it is difficult to know whether the effect of ethnic diversity is primarily through recent immigration or whether there is an effect specific to ethnic composition. To verify this, I use Canadian census data on the number of recent immigrants in the last 5 years in the urban area as a control in the regressions. The results are in Table 2.15. There is indeed a positive and significant effect of ethnic diversity on innovation activity even when controlling for immigration.

2.5 Technology class

This section focuses on the effect of ethnic and manufacturing diversity on innovation activity by patent class. Patents may not have the same economic value depending on the technological contribution of the innovation. Gambardella et al. (2008)estimate the economic value of patents by the price that the applicant of a granted patent would be willing to sell it for. They find that the most valuable patents are in the fields of chemicals and pharmaceuticals in Europe. Bessen (2008) also found that chemicals and pharmaceuticals have the highest value in U.S. patents, while computers-communications and "other" have the lowest values.

Using the U.S. patent classification system at 1 digit level, it is possible to have six technological classes: (i) chemical consisting of products used in agriculture, food, textile, coating, gas, organic compounds, (ii) computers and communications consisting of computer hardware, software, peripherals and storage, communications, (iii) drugs and medicals consisting of surgery, medical instruments, biotechnology and medicines, (iv) electrical and electronics consisting of electrical devices, electric lighting, nuclear, X-ray, power systems, (v) mechanical consisting of processing and handling of materials, metal working, engines and machinery, transportation, (vi) and other technological classes.

However, the use of technology class is an imperfect measure of patent value. The valuation of patents seems very subjective and depends on the use case of the analysis. But I can better measure the value of a patent with (i) the value of similar patents or patented products that have been sold and purchased before, or (ii) the cost of creating the IP asset (e.g., the cost of research and development as well as the cost of patent counseling and filing fees).

Table 2.4 gives the results of this estimation. The results show that ethnic and manufacturing diversity jointly have a positive and significant effect on the chemical, computers-communications and electrical-electronic innovation activity technology classes. The effect is strongest for ethnic diversity in the highly valued chemical class, while it is relatively similar for the other two low valued classes. This supports the results above that show that ethnic diversity has a larger effect on innovation activity, especially in chemical innovations which are among those with the greatest economic value. Manufacturing diversity also influences other technological classes.

Table 2.4: Innovation and diversity in Canadian Urban Areas

Dependent variable: (log) Patents per capita	Patent technology U.S. class					
	Chemical	Computers and Communications	Drugs and Medical	Electrical and Electronic	Mechanicals	Others
Ethnic diversity (geographic distance)	0.123***	0.077***	-0.017	0.067***	0.008	0.016
	(0.021)	(0.019)	(0.019)	(0.017)	(0.015)	(0.012)
Manufacturing diversity (patent distance)	0.067***	0.051**	0.030	0.054**	0.020	0.031**
	(0.025)	(0.022)	(0.020)	(0.021)	(0.017)	(0.012)
Share of foreign origin population	0.077**	-0.004	0.019	0.070*	0.035	0.031
	(0.033)	(0.035)	(0.048)	(0.039)	(0.038)	(0.030)
Share of manufacturing employment	0.032	0.048***	0.015	0.044***	0.013	0.029**
	(0.020)	(0.018)	(0.018)	(0.017)	(0.015)	(0.014)
Share of graduated people	0.116***	0.148***	0.080***	0.122***	0.044***	0.116***
	(0.026)	(0.030)	(0.027)	(0.024)	(0.016)	(0.021)
(log) Minimal distance to university	0.016	0.013	-0.009	0.006	-0.003	-0.003
	(0.018)	(0.017)	(0.018)	(0.016)	(0.013)	(0.012)
University RD spending per student (1,000 dollars)	0.012	0.025	0.061***	0.044***	0.023*	0.013
	(0.018)	(0.016)	(0.022)	(0.017)	(0.013)	(0.012)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Ethny IV estimate	1.43	1.43	1.43	1.43	1.43	1.43
Ethny IV p value	0.00	0.00	0.00	0.00	0.00	0.00
Ethny F statistic	107	107	107	107	107	107
Manuf. IV estimate	0.74	0.74	0.74	0.74	0.74	0.74
Manuf. IV p value	0.00	0.00	0.00	0.00	0.00	0.00
Manuf. F statistic	15	15	15	15	15	15
Times periods	310	310	310	310	310	310

Notes : The table presents 2SLS estimates. Coefficients are all measured in standard deviations. The dependent variable is the number of patents per 10,000 persons aged between 15 and 64 years. Diversity is measured by a generalized fractionalization index. Distance for ethnic diversity is geographic distance. Distance for manufacturing distance is based on patent citation flows. The "skilled" are the 15+ residents with at least a bachelor degree. Standard errors in parentheses are robust. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases and Statistics Canada boundary files.

2.6 Conclusion

In this chapter, I examined the effect of diversity on innovation activity in Canadian cities. I showed that having a greater fractionalization of people into ethnic groups, and of manufacturing firms into sectors, leads to higher levels of patents per working age population in Canadian urban areas between 2006 and 2016. The effects of ethnic diversity on innovation activity are primarily through differences between ethnic groups that ensure a mix of ideas and skills conducive to innovation. Also, even after controlling for the size of the manufacturing industry, the presence of different plants according to their sector provides a higher level of innovation activity in the city. I also show that ethnic diversity has stronger effects on local innovation activity than manufacturing diversity. An implication of these results is that investments that foster a diverse ecosystem of people and firms, not necessarily sharing apparent similarities, will help sustain economic growth in cities driven by innovation and technological progress.

2.7 Appendix to Chapter 2

This set of appendixes is organised as follows. Appendix 2.7.1 describes the data used in the analysis. Appendix 2.7.2 details the process of data. Appendix 2.7.3 explains the decomposition of fractionalization index used in the analysis. Appendix 2.7.4 discusses the robustness of the instrumental variables used in the analysis. Appendix 2.7.5 provides additional tables and figures. Appendix 2.8 displays additional results.

2.7.1 Data for the regressions

Census Data The Census data released by the Computing in the Humanities and Social Sciences (CHASS) data center at the University of Toronto contain a great deal of information on the socio-demographic characteristics of the residents as well as on the jobs they occupy. We use them to construct several of our controls on top of our dependent variables. Census data allow the calculation of some variables other than diversity indices that could influence the level of innovation activity in cities, such as human capital based on education, manufacturing employment and foreign population which excludes Canadian, British and French.

Geographic Data We will control in our regression analysis for several relevant geographic characteristic that may influence population growth are the city-level.

Distance Data: Universities are seen as important suppliers of inputs, both in terms of skilled labor and innovative ideas, but also as instrumental institutions that shape technological progress through a variety of mechanisms such as facilitating the formation of problem-solving networks, creating new enterprises, increasing the stock of knowledge, and producing skilled graduates(see Feldman, 1994; Feldman and Kogler, 2010). We thus calculate the distance separating each urban area from the nearest universities. The list of universities comes from the Association of Universities and Colleges of Canada (AUCC), which represents 97 Canadian public and private not-for-profit universities and university colleges. These universities are then geocoded through google based on their address.

Regions: Regional Development Agencies support manufacturers across Canada. [20] Specific regional public policies might also influence city-level population growth; we can think of Quebec, which has its own immigration policy, partly determined by its needs in terms of workforce. We thus build specific dummy variables for the Atlantic regions (New Brunswick, Newfoundland and Labrador, Nova Scotia, Prince Edward Island), the West (Alberta, British Columbia, Manitoba, Saskatchewan), Quebec and Ontario. [21]

Academic Research Data I will control in the regression analysis for the expenditures in R&D of universities that may influence innovation activity at the city-level. The data on university R&D expenditures is the Financial Information of Universities and Colleges (FIUC) of the Canadian Association of University Business Officers (CAUBO). The FIUC reports financial data by institution by region. There is information on expenditures by use and revenues by source. The author matched this information to the geocoded database of Canadian universities described above.

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20. These agencies are Atlantic Canada Opportunities Agency for Atlantic regions, Federal Economic Development Initiative and Federal Economic Development Agency for Ontario, Canada Economic Development for Quebec, and Western Economic Diversification Canada for Western region.

21. We do not use provincial dummies in our regressions because in some provinces, there are too few cities, such as in Atlantic Canada or in Manitoba and Saskatchewan, to allow for statistical inference based on within-province variations (see Table 2.10 in the Appendix).

Table 2.5 presents descriptive statistics on the variables used in this study. The average number of patents per working age population observed across Canadian urban areas is equal to 2.3. Between 2006 and 2016, in Canadian urban areas, the level of ethnic diversity was 84.4% and ranged from 4% to 26% on average when ethnic diversity is measured including distances between groups. The level of manufacturing diversity was 92.6% in Canadian urban areas and around 90% on average when manufacturing diversity is measured including inter-group distances. In 2006 and 2011, the share of people of foreign origin was 37.2%, the share of manufacturing jobs was 11.8% and the share of people with a university degree was 13.4%. In addition, the ratio of university R&D expenditures to the number of full-time students is 1.08. However, as the table illustrates, there is a great deal of variation across urban areas for all of these initial characteristics that will be helpful for our estimations.

Table 2.5: Descriptive statistics, urban area variables.

Variable	Obs	Mean	Std. Dev.	Minimum	Maximum
Innovation					
(log) Patents per working age population (10,000)	310	1.013	0.568	0	3.306
Ethnic diversity					
Index with no distance	310	0.844	0.078	0.515	0.959
Index with cultural distance	310	0.265	0.064	0.051	0.555
Index with geographic distance	310	0.222	0.038	0.137	0.370
Index with genetic distance	310	0.039	0.013	0.012	0.090
Manufacturing diversity					
Index with no distance	310	0.926	0.056	0.444	0.988
Index with labor flow distance	310	0.902	0.055	0.440	0.970
Index with patent flow distance	310	0.905	0.054	0.436	0.971
Index with input/ouput distance	310	0.912	0.056	0.442	0.974
Initial level					
% Initial share of foreign people	310	0.372	0.175	0.029	0.713
% Initial share of employment in manufacturing	310	0.118	0.080	0	0.341
% Initial people with university degree	310	0.134	0.053	0.050	0.358
University RD spending per studient	310	1.078	2.316	0	13.943
Geographic variables					
(log) Distance to nearest university (m)	310	10.807	1.251	6.652	13.070

2.7.2 Data processing

Distance between groups

These measures of distance between groups are used to construct diversity indices. This section provides a brief description of these measures.

Distance between population groups

Cultural distance: The intuition behind the construction of this measure is that people who share cultural traits and norms may be more likely to relate to each other by reproducing similar economic behaviors. Thus, culture would be a behavioral assessment of ethnic groups. The variable cultural distance refers to the distance between two different religions and ranges from 0 to 1. In particular, religion has shaped people's behavior and norms for several centuries. This variable compares the religion trees by giving lower values if two religions belong to the same sub-branch and higher values if they belong to different trees. Data come from Behrens and Moussouni (2019).

Genetic distance: Genetic data are common in the measurement of population proximities. Thus genetically closer populations would have tended to interact more in the past and are more likely to share common traits today, and thus demonstrate similar economic behavior. Two genetically distant people will claim to belong to two distant ancestors. However, it is difficult to separate genetic distance from cultural distance, as genetic traits and cultural traits are often related. The table 2.6 shows, however, that these two measures of distance are different. They will therefore be considered separately. Data come from Behrens and Moussouni (2019).

Geographical distance: It is measured by the geographic distance between the countries' capitals in kilometers. To reduce the geographic distance between zero and one, I calculate the following geographical distance measure : $d_{ij} = 1 - exp(-\lambda \text{capital\_distance})$ where λ refers to a distance decay parameter, set to a value such that the weight between two countries is 0.5 for the average distance between neighboring countries (see Trax et al., 2015). Thus, this measure of the distance between two countries tends to one as their geographical distance increases. Data come from Behrens and Moussouni (2019).

Distance between manufacturing plant groups

Input output distance: I use input-output matrices to calculate this distance measure. One element of this matrix provides the share of industry i's inputs that come from industry j $intput_{ij}$ and the share of industry i's outputs that are sold to industry j $output_{ij}$. Then, I select the maximum share between $intput_{ij}$ and $output_{ij}$ for each ij. The data comes from the 4-digit NAICS average of the manufacturing industry in Canada over the years 1998 to 2010. I then transform it to 1 - maximum share to represent the distance between i and j.

Labor flow distance: I use labor flow from the U.S. Bureau of Labor Statistics' Current Population Survey (CPS) to construct the measure of labor pooling distance. The data available in this source are the maximum labor movement shares in all 4-digit NAICS pairs between 2001 and 2006. I then transform them to 1 - maximum share to represent the distance between i and j.

Patent flow distance: Patent flow distance is measured using the United States Patent and Trademark Office's patent citing/city pairs. This database is a table that records the average number of citing/cited patents used over the period 1976-2006. The same method used for input-output is replicated to construct symmetric measures of patent flow by taking the maximum share between industry i's cited patent of industry j, and industry j's cited patent of industry i. I then transform it to 1 - maximum share to represent the distance between i and j.

Geographical structure

Census Metropolitan Areas (CMA) and Census Agglomerations (CA) are the ideal spatial units in Canada for the analysis of local labor markets since their boundaries are delineated based on the commuting patterns of residents. Provinces are too coarse a spatial scale, whereas dissemination areas (census blocks) are too fine to analyze population dynamics following local labor market shocks,

Table 2.6: Pairwise correlation of distance measures between countries and sectors.

Population groups distances			
	Cultural distance	Geographic distance	Genetic distance
Cultural distance	1		
Geographic distance	0.23	1	
Genetic distance	0.08	0.37	1

Manufacturing sectors distances			
	Labor flow	Patent used flow	Input-Output
Labor flow	1		
Patent used flow	0.88	1	
Input-Output	0.94	0.88	1

Notes: The first part of the table describes the distance measure correlations for between countries based on ethnic origins. The second part of the table describes the distance measure correlations for between NAICS 4-digit of manufacturing sectors.

because an inventor could easily work in one dissemination area and reside in another. Since each dissemination area belongs to a given urban area (CMA/CA), I aggregate the Census data available at the level of dissemination areas at the urban area level.

I obtain census data at the urban area (CMA/CA) level for 135 urban areas in 1996, 145 in 2001, 148 in 2006, 151 in 2011 and 157 in 2016. The differences between years are explained by the fact that from a statistical point of view, an urban area can lose its census agglomeration status and disappear, or (re)gain it and (re)appear. Note for example that if the population of the core of a CA declines below 10,000, the CA is removed. However, once an urban area becomes a CMA, it remains a CMA even if its total population declines below 100,000 or if the population of its core falls below 50,000.

There are 164 unique urban areas in total (CMA/CA) between 1996 and 2016, of which 127 are present in the 5 census years, 11 in 3 census years, 11 in 2 census years, 8 in 2 census years, and 7 in a single census year. I overlay each urban area for every year it appears, and we take the envelope of the overlaid boundaries. Magog (present in 2001) has been added to Sherbrooke in 2006, so we merge them. Saint-Jean-sur-Richelieu (present in 2001, 2006, 2011) has been added to Montreal in 2016, so we merge them. We get 162 urban areas whose boundaries in terms of municipalities are stable over time. Indeed, in this study, we want to capture innovation variation that are related to city diversity level, not to changes in geographical boundaries.

I keep in the sample only those agglomerations that have at least 10,000 inhabitants on average over the whole 1996-2016 period and for which we have all the necessary information for the econometric analysis. I end up with 155 stable urban areas. I calculate 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 total population of the "stabilized" urban area as we measure it. On average, we can see in Table 2.7 that this ratio is equal to 0.96 over the period 1996-2016, which means that the demographics of stabilized urban areas are quite similar to the demographics of the original urban areas.

Table 2.7: Population ratio between the actual and the stabilized urban areas

	Year				
	1996	2001	2006	2011	2016
Minimum	0.254	0.535	0.320	0.407	0.323
Mean	0.929	0.943	0.958	0.958	0.964
Maximum	1	1	1	1	1
Std. error	0.121	0.091	0.089	0.095	0.098

The boundaries of "actual" urban areas are those defined by Statistics Canada in a given census year. The boundaries of "stabilized" urban areas are defined by the envelope of the boundaries observed across the various census years.

2.7.3 Index decomposition

In most of the empirical and theoretical literature on diversity, the fractionalization index is determined by the probability that two randomly selected members of a given group belong to different language groups. Greenberg (1956) proposed a so-called B-index, which takes into account the distances between the groups:

$$\mathrm{B} = 1 - \sum_{i=1}^{N} \sum_{j=1}^{N} \mathrm{s}_i \mathrm{s}_j w_{ij}$$

where s_i and s_j are the group shares comprising the entire sample, the sum of which is equal to 1, and w_{ij} refers to the similarity between the two groups.

We can decompose the B-index as follows:

$$\mathrm{B} = 1 - \sum_{i=1}^{N}\sum_{i=1}^{N} \mathrm{s}_i \mathrm{s}_i w_{ii} - \sum_{i=1}^{N}\sum_{j=1 \neq i}^{N} \mathrm{s}_i \mathrm{s}_j w_{ij}$$

$$\mathrm{B} = 1 - \sum_{i=1}^{N} \mathrm{s}_i{}^2 w_{ii} - \sum_{i=1}^{N}\sum_{j=1}^{N} \mathrm{s}_i \mathrm{s}_j w_{ij}$$

This index can be expressed in two ways:

Simple index: For each term that includes different groups i and j, the similarity term w_{ij} is equal to 0, so that the term vanishes. If i and $j$are identical, $w_{ij} = 0$, so that the term is s_i x s_i. Therefore, the simple index collects only the s_i x s_i terms; all others will be equal to 0. The index is then rewritten as follows:

$$\text{Simple index} = 1 - \sum_{i=1}^{N} \mathrm{s}_i{}^2$$

which is the expression I use as the first measure of diversity in the estimates.

Distance-based index: For this index, we want to isolate only the component that takes into account distinct groups. Thus for each term that includes similar groups i and j, the similarity term $w_{ij} = 0$, so that this term disappears. If i and j are different, $w_{ij} \in [0, 1]$, so that only this term remains. Therefore, the index is written as follows:

$$\text{Distance index} = 1 - \sum_{i=1}^{N}\sum_{j=1}^{N} \mathrm{s}_i \mathrm{s}_j w_{ij}$$

By considering that $d_{ij} = 1 - w_{ij}$, it is easy to transform the index as follows:

$$\text{Distance index} = 1 - \sum_{i=1}^{N}\sum_{j=1}^{N} s_i s_j (1 - d_{ij})$$

$$\text{Distance index} = 1 - \sum_{i=1}^{N}\sum_{j=1}^{N} s_i s_j (1 - d_{ij})$$

With some algebra :

$$\text{Distance index} = 1 - \sum_{i=1}^{N} s_i \sum_{j=1}^{N} s_j + \sum_{i=1}^{N}\sum_{j=1}^{N} s_i s_j (1 - d_{ij})$$

with $\sum_{i=1}^{N} s_i \sum_{j=1}^{N} s_j = 1$:

$$\text{Distance index} = \sum_{i=1}^{N}\sum_{j=1}^{N} s_i s_j (1 - d_{ij})$$

which is the second measure of diversity used in the regression estimates.

2.7.4 IV validity

Following Borusyak et al. (2020) , I perform several checks to ensure the validity of the Bartik instruments used. First, I verify that the Bartik IV has sufficient variation to be relevant. With an average coefficient of variation above 73 p.p for ethnic diversity (and an average difference between the first and fourth quintile of 5 p.p.) and around 7 p.p for manufacturing diversity (and an average difference between the first and fourth quintile of 7 p.p.), it gives a satisfactory variation for instrumental estimates. In addition, to ensure that the sectoral and ethnic shares vary sufficiently across locations to give a good instrument, I calculate the 1 minus Herfindahl index of these shares at the national level. A high level of this measure would decrease the probability that a few industries or ethnic groups represent the largest share of the national level. It should be noted that for the ethnic shares, I have already removed the Canadian, British and French origin that represents the largest share. The statistic is equal to 94% for the ethnic shares (with a highest ethnic share of 17%) and equal to 97,5% for the sectoral shares (with a highest sectoral share of 6%). Third, it must be ensured that sectors or ethnic groups highly concentrated in urban areas with specific unobserved trends do not create a correlation between the instrument and the error term in the IV regressions. In order to verify this I construct an alternative Bartik instrument from which I remove sectors and ethnic groups that are highly concentrated geographically (top quartile). Table 2.8 shows that the results remain mostly stable. Overall, these checks confirm the validity of the Bartik instrument in the context of the study.

2.7.5 Additional tables and figures

Tables on data

Table 2.9: Comparing the Scott's National All database to the Canadian business counts (CBC).

	2001		2005		2009		2013		2017	
Province	CBC	Scott's	CBC	Scott's	CBC	Scott's	CBC	Scott's	CBC	Scott's
Alberta	5,843	3,935	5,416	3,482	5,351	3,597	4,882	3,144	4,095	2,891
British Columbia	8,797	6,212	8,261	5,400	7,697	5,031	6,933	4,148	5,984	3,966
Manitoba	1,883	1,654	1,741	1,489	1,605	1,280	1,481	1,108	1,049	1,061
New Brunswick	1,446	1,392	1,195	1,262	1,018	1,181	963	873	431	740
Newfoundland	757	576	629	544	508	482	522	364	244	320
Nova Scotia	1,832	1,677	1,483	1,506	1,225	1,312	1,106	970	666	816
Ontario	25,006	21,289	23,220	20,996	21,673	19,670	21,470	15,933	16,722	14,277
Prince Edward Island	354	328	292	327	256	282	211	199	114	154
Quebec	18,349	15,933	17,026	14,200	15,238	12,660	15,251	10,378	9,939	8,980
Saskatchewan	1,378	1,348	1,259	1,318	1,151	1,109	1,008	948	877	895
Territories		0		40		45		36		35
Canada	65,645	54,344	60,522	50,564	55,722	46,649	53,827	38,101	40,121	34,135
Cross-industry correlation	***0.908***		***0.939***		***0.937***		***0.931***		***0.773***	

Notes: Data are from Scott's National All databases and CBP (Table 33-10-0028-01 ,Table 33-10-0035-01). The descriptive statistics reported as "cross-industry" in the bottom panel of the table are computed across all 3 manufacturing digits industries (NAICS 311–339).

Table 2.8: Innovation and diversity in Canadian Urban Areas

Dependent variable: (log) Patents per capita		
	IV(1)	IV(2)
Ethnic diversity	0.065	
	(0.056)	
Manufacturing diversity	0.089***	
	(0.032)	
Ethnic diversity (geographic distance)		0.116***
		(0.037)
Manufacturing diversity (patent distance)		0.083***
		(0.026)
Initial share of foreign origin population	0.095**	0.080**
	(0.037)	(0.037)
Initial share of manufacturing employment	-0.002	-0.016
	(0.032)	(0.032)
Initial share of skilled people	0.181***	0.165***
	(0.031)	(0.033)
Minimal distance to university	-0.136***	-0.143***
	(0.046)	(0.045)
University RD spending per student	0.020	-0.001
	(0.034)	(0.034)
Region dummies	Yes	Yes
Time dummies	Yes	Yes
R2 adjusted	0.90	0.84
Ethny IV estimate	0.00	0.00
Ethny IV p value	976	249
Ethny F statistic	0.88	0.92
Manuf. IV estimate	0.00	0.00
Manuf. IV p value	43	58
Manuf. F statistic	308	308

Notes : Instruments used in regressions removes sectors and ethnic groups that are highly concentrated geographically. The table presents 2SLS estimates. Coefficients are all measured in standard deviations. The dependent variable is the number of patents per 10,000 persons aged between 15 and 64 years. The "skilled" are the 15+ residents with at least a bachelor degree. Standard errors in parentheses are robust. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases and Statistics Canada boundary files.

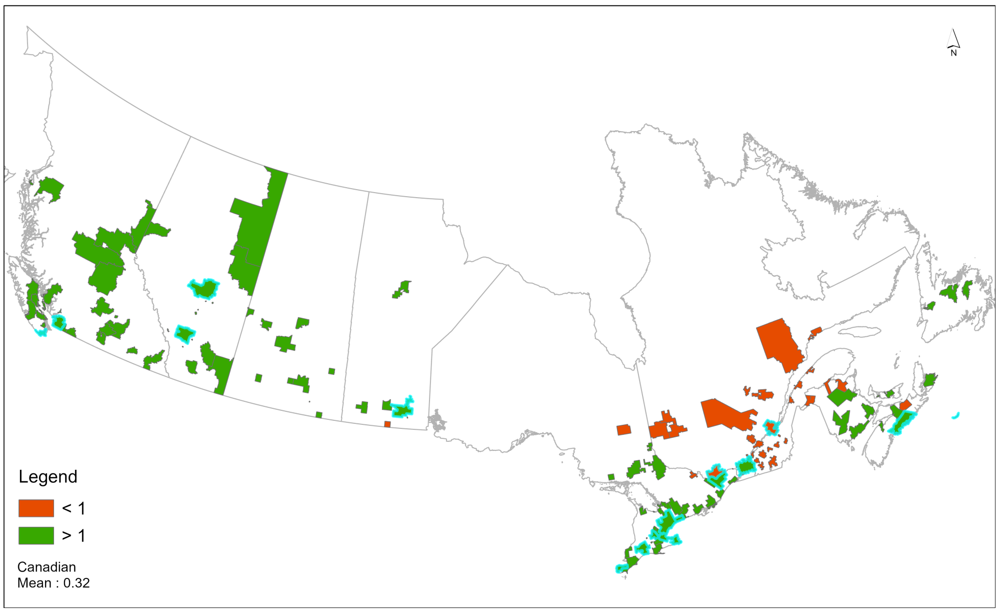
Table 2.10: Geographical breakdown of urban areas in Canada.

Region	Province	Total urban areas	Census metropolitan areas (CMA)	Census agglomeration CA	Minimum average population	Maximum average population
Western	Alberta	18	3	15	11,097	1,159,220
	British Columbia	26	4	22	13,609	2,214,755
	Manitoba	6	1	5	12,411	719,675
	Saskatchewan	10	2	8	10,074	254,852
		60	***10***	***50***	***10,074***	***2,214,755***
Atlantic	New Brunswick	7	2	5	15,080	132,529
	Newfoundland and Labrador	5	1	4	10,019	189,197
	Nova Scotia	5	1	4	25,933	379,159
	Prince Edward Island	2	0	2	16,355	64,537
		19	***4***	***15***	***10,019***	***379,159***

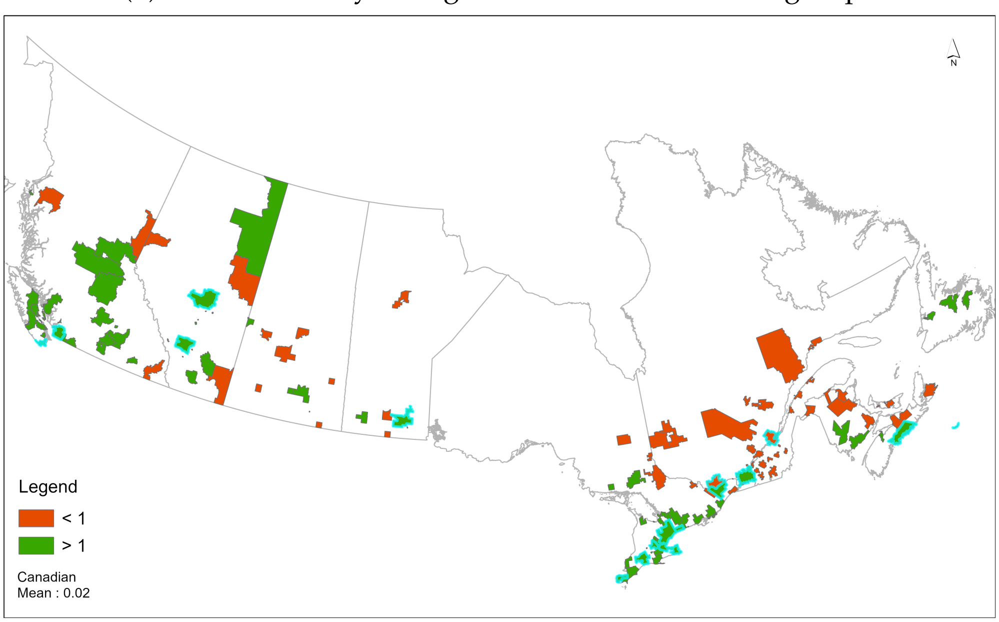
Figures on data

Figure 2.3: Relative ethnic diversity in Canadian Urban Areas

(a) Ethnic diversity with cultural distances between groups



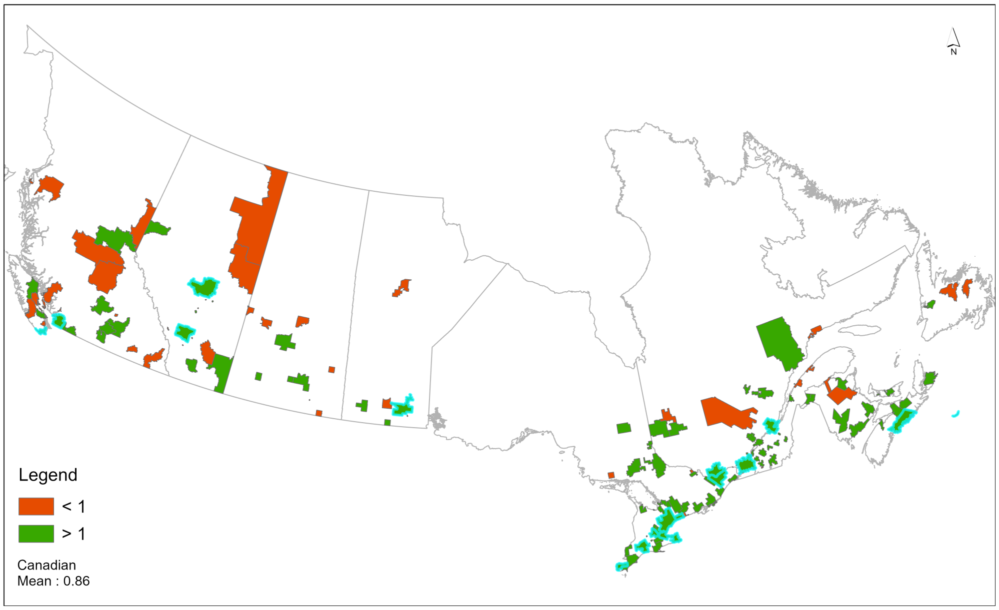
(b) Ethnic diversity with genetic distances between groups



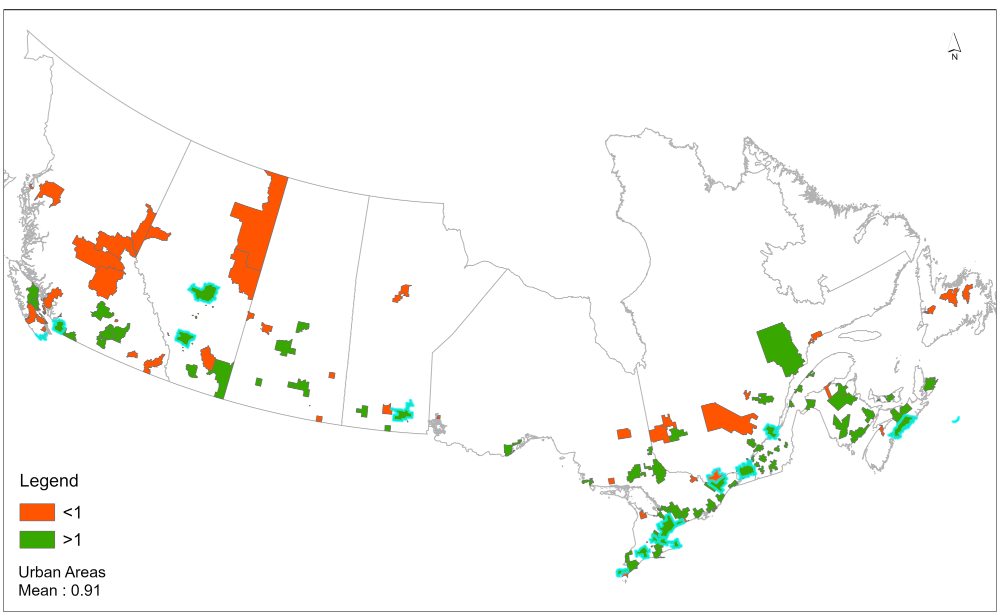
Notes: Ethnic diversity are measured relatively to the urban area average. A value of 1 on the map means that the urban area's growth rate is the same as all urban areas mean. Cyan contours outline cities with population of at least 300,000.

Figure 2.4: Relative manufacturing diversity in Canadian Urban Areas

(a) Manufacturing diversity with labor flow based distances between groups



(b) Manufacturing diversity with input/output based distances between groups



Notes: Manufacturing diversity are measured relatively to the urban area average. A value of 1 on the map means that the urban area's growth rate is the same as all urban areas mean. Cyan contours outline cities with population of at least 300,000.

2.8 Additional results

Table 2.11: Innovation and diversity in Canadian Urban Areas - Unique and Weighted Patent

Dependent variable: (log) Patents per capita	Single patents		Weighted patents	
	IV(1)	IV(2)	IV(3)	IV(4)
Ethnic diversity	-0.038		0.037	
	(0.120)		(0.143)	
Manufacturing diversity	0.065**		0.093***	
	(0.025)		(0.027)	
Ethnic diversity (geographic distance)		0.078**		0.138***
		(0.033)		(0.039)
Manufacturing diversity (patent distance)		0.057**		0.082***
		(0.025)		(0.026)
Initial share of foreign origin population	0.098***	0.079**	0.097**	0.076**
	(0.033)	(0.031)	(0.040)	(0.037)
Initial share of manufacturing employment	-0.003	-0.008	-0.003	-0.018
	(0.026)	(0.025)	(0.032)	(0.032)
Initial share of skilled people	0.133***	0.118***	0.182***	0.161***
	(0.028)	(0.029)	(0.032)	(0.034)
Minimal distance to university	-0.112***	-0.121***	-0.133***	-0.145***
	(0.040)	(0.040)	(0.045)	(0.046)
University RD spending per student	-0.011	-0.031	0.022	-0.005
	(0.028)	(0.027)	(0.035)	(0.034)
Region dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Ethny IV estimate	0.20	1.09	0.20	1.09
Ethny IV p value	0.00	0.00	0.00	0.00
Ethny F statistic	12	207	12	207
Manuf. IV estimate	0.92	0.92	0.92	0.92
Manuf. IV p value	0.00	0.00	0.00	0.00
Manuf. F statistic	62	58	62	58
Urban Areas	308	308	308	308

Notes : The table presents OLS and 2SLS estimates. Coefficients are all measured in standard deviations. The dependent variable is the number of patents per 10,000 persons aged between 15 and 64 years, based on the main inventor address. Diversity is measured by a generalized fractionalization index. Distance for ethnic diversity is geographic distance. Distance for manufacturing distance is based on patent citation flows. The "skilled" are the 15+ residents with at least a bachelor degree. Standard errors in parentheses are robust. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases and Statistics Canada boundary files.

Table 2.12: Innovation and diversity in Canadian Urban Areas - Patent Value

Dependent variable:	Patents per capita		Patents per capita (granted)		Patents per capita (no granted)	
	IV(1)	IV(2)	IV(3)	IV(4)	IV(5)	IV(6)
Ethnic diversity	0.037		0.110		0.028	
	(0.143)		(0.102)		(0.124)	
Manufacturing diversity	0.093^{***}		0.050^{***}		0.079^{***}	
	(0.027)		(0.017)		(0.024)	
Ethnic diversity (geographic distance)		0.138^{***}		0.116^{***}		0.100^{***}
		(0.039)		(0.033)		(0.033)
Manufacturing diversity (patent distance)		0.082^{***}		0.043^{**}		0.071^{***}
		(0.026)		(0.017)		(0.023)
Initial share of foreign origin population	0.097^{**}	0.076^{**}	0.059^{**}	0.049^{*}	0.088^{***}	0.072^{**}
	(0.040)	(0.037)	(0.030)	(0.029)	(0.033)	(0.031)
Initial share of manufacturing employment	-0.003	-0.018	0.001	-0.015	-0.002	-0.012
	(0.032)	(0.032)	(0.025)	(0.025)	(0.027)	(0.028)
Initial share of skilled people	0.182^{***}	0.161^{***}	0.116^{***}	0.103^{***}	0.155^{***}	0.140^{***}
	(0.032)	(0.034)	(0.025)	(0.027)	(0.027)	(0.029)
Minimal distance to university	-0.133^{***}	-0.145^{***}	-0.029	-0.034	-0.132^{***}	-0.141^{***}
	(0.045)	(0.046)	(0.035)	(0.035)	(0.035)	(0.035)
University RD spending per student	0.022	-0.005	0.016	-0.001	0.015	-0.005
	(0.035)	(0.034)	(0.027)	(0.028)	(0.030)	(0.029)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Ethny IV estimate	0.20	1.09	0.20	1.09	0.20	1.09
Ethny IV p value	0.00	0.00	0.00	0.00	0.00	0.00
Ethny F statistic	12	207	12	207	12	207
Manuf. IV estimate	0.92	0.92	0.92	0.92	0.92	0.92
Manuf. IV p value	0.00	0.00	0.00	0.00	0.00	0.00
Manuf. F statistic	62	58	62	58	62	58
Urban Areas	308	308	308	308	308	308

Notes : The table presents OLS and 2SLS estimates. Coefficients are all measured in standard deviations. The dependent variable is the number of patents per 10,000 persons aged between 15 and 64 years. Diversity is measured by a generalized fractionalization index. Distance for ethnic diversity is geographic distance. Distance for manufacturing distance is based on patent citation flows. The "skilled" are the 15+ residents with at least a bachelor degree. Standard errors in parentheses are robust. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases and Statistics Canada boundary files.

Table 2.13: Innovation and diversity in Canadian Urban Areas - Multiple innovation measures

Dependent variable: (log) Patents per capita									
	IV(1)	IV(2)	IV(3)	IV(4)	IV(5)	IV(6)	IV(7)	IV(8)	IV(9)
Ethnic diversity (cultural distance)	0.187^{***} (0.057)			0.191^{***} (0.058)			0.189^{***} (0.058)		
Ethnic diversity (geographic distance)		0.134^{***} (0.039)			0.138^{***} (0.039)			0.135^{***} (0.039)	
Ethnic diversity (genetic distance)			0.123^{***} (0.034)			0.127^{***} (0.035)			0.124^{***} (0.035)
Manufacturing diversity (labor distance)	0.094^{***} (0.026)	0.087^{***} (0.025)	0.089^{***} (0.026)						
Manufacturing diversity (patent distance)				0.089^{***} (0.026)	0.082^{***} (0.026)	0.084^{***} (0.026)			
Manufacturing diversity (input/ouput distance)							0.097^{***} (0.026)	0.090^{***} (0.025)	0.091^{***} (0.026)
Initial share of foreign origin population	0.089^{**} (0.037)	0.078^{**} (0.036)	0.094^{***} (0.036)	0.086^{**} (0.037)	0.076^{**} (0.037)	0.092^{**} (0.036)	0.088^{**} (0.037)	0.077^{**} (0.037)	0.093^{***} (0.036)
Initial share of manufacturing employment	-0.006 (0.031)	-0.016 (0.032)	-0.010 (0.032)	-0.008 (0.032)	-0.018 (0.032)	-0.012 (0.032)	-0.006 (0.031)	-0.016 (0.032)	-0.010 (0.032)
Initial share of skilled people	0.163^{***} (0.034)	0.161^{***} (0.034)	0.171^{***} (0.033)	0.163^{***} (0.034)	0.161^{***} (0.034)	0.171^{***} (0.033)	0.162^{***} (0.034)	0.160^{***} (0.034)	0.170^{***} (0.033)
Minimal distance to university	-0.136^{***} (0.045)	-0.141^{***} (0.045)	-0.136^{***} (0.046)	-0.140^{***} (0.046)	-0.145^{***} (0.046)	-0.140^{***} (0.046)	-0.135^{***} (0.046)	-0.140^{***} (0.046)	-0.135^{***} (0.046)
University RD spending per student	0.001 (0.034)	-0.004 (0.034)	0.004 (0.034)	-0.000 (0.034)	-0.005 (0.034)	0.003 (0.034)	-0.000 (0.034)	-0.005 (0.034)	0.004 (0.034)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethny IV estimate	0.87	1.09	0.97	0.87	1.09	0.97	0.87	1.09	0.97
Ethny IV p value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Ethny F statistic	121	206	105	122	207	104	122	207	105
Manuf. IV estimate	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92
Manuf. IV p value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Manuf. F statistic	64	64	64	57	58	58	68	69	69
Urban Areas	308	308	308	308	308	308	308	308	308

Notes : The table presents 2SLS estimates. Coefficients are all measured in standard deviations. The dependent variable is the number of patents per 10,000 persons aged between 15 and 64 years. The "skilled" are the 15+ residents with at least a bachelor degree. Standard errors in parentheses are robust. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases and Statistics Canada boundary files.

Table 2.14: Innovation and diversity in Canadian Urban Areas - City size

Dependent variable:	Patents per capita (All cities)		Patents per capita (All cities)		Patents per capita (All cities)		Patents per capita (No big cities)	
	IV(1)	IV(2)	IV(3)	IV(4)	IV(5)	IV(6)	IV(7)	IV(8)
Ethnic diversity	0.037		-0.021		-0.185		0.002	
	(0.143)		(0.153)		(0.209)		(0.182)	
Manufacturing diversity	0.093***		0.097***		0.045		0.094***	
	(0.027)		(0.026)		(0.034)		(0.027)	
Ethnic diversity (geographic distance)		0.138***		0.106**		0.097**		0.158***
		(0.039)		(0.047)		(0.048)		(0.061)
Manufacturing diversity (patent distance)		0.082***		0.086***		0.065**		0.084***
		(0.026)		(0.025)		(0.030)		(0.026)
Initial share of foreign origin population	0.097**	0.076**	0.096**	0.077**	0.112***	0.079**	0.110**	0.083**
	(0.040)	(0.037)	(0.040)	(0.037)	(0.040)	(0.036)	(0.043)	(0.038)
Initial share of manufacturing employment	-0.003	-0.018	-0.017	-0.022	-0.012	-0.013	-0.001	-0.008
	(0.032)	(0.032)	(0.032)	(0.032)	(0.034)	(0.032)	(0.036)	(0.033)
Population density			0.079***	0.050				
			(0.030)	(0.032)				
Log of initial population					0.143**	0.056		
					(0.059)	(0.045)		
Initial share of skilled people	0.182***	0.161***	0.181***	0.163***	0.155***	0.152***	0.184***	0.167***
	(0.032)	(0.034)	(0.032)	(0.034)	(0.036)	(0.036)	(0.033)	(0.036)
Minimal distance to university	-0.133***	-0.145***	-0.103**	-0.125***	-0.102**	-0.133***	-0.128***	-0.140***
	(0.045)	(0.046)	(0.047)	(0.048)	(0.048)	(0.046)	(0.046)	(0.047)
University RD spending per student	0.022	-0.005	0.029	0.004	-0.013	-0.017	-0.002	-0.030
	(0.035)	(0.034)	(0.035)	(0.035)	(0.035)	(0.034)	(0.041)	(0.039)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethny IV estimate	0.20	1.09	0.20	1.06	0.16	1.00	0.18	1.04
Ethny IV p value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Ethny F statistic	12	207	11	262	13	242	9	365
Manuf. IV estimate	0.92	0.92	0.92	0.92	0.90	0.89	0.92	0.92
Manuf. IV p value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Manuf. F statistic	62	58	61	57	65	115	61	61
Urban Areas	308	308	308	308	308	308	288	288

Notes : The table presents OLS and 2SLS estimates. Coefficients are all measured in standard deviations. The dependent variable is the number of patents per 10,000 persons aged between 15 and 64 years. Diversity is measured by a generalized fractionalization index. Distance for ethnic diversity is geographic distance. Distance for manufacturing distance is based on patent citation flows. The "skilled" are the 15+ residents with at least a bachelor degree. Standard errors in parentheses are robust. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases and Statistics Canada boundary files..

Table 2.15: Innovation and diversity in Canadian Urban Areas - Recent Immigration

Dependent variable:	Patents per capita		Patents per capita (Recent immigration)	
	IV(1)	IV(2)	IV(3)	IV(4)
Ethnic diversity	0.037		-0.024	
	(0.143)		(0.155)	
Manufacturing diversity	0.093***		0.082***	
	(0.027)		(0.028)	
Ethnic diversity (geographic distance)		0.138***		0.104**
		(0.039)		(0.041)
Manufacturing diversity (patent distance)		0.082***		0.076***
		(0.026)		(0.027)
Initial share of foreign origin population	0.097**	0.076**	0.084**	0.067*
	(0.040)	(0.037)	(0.038)	(0.036)
Initial share of manufacturing employment	-0.003	-0.018	-0.016	-0.021
	(0.032)	(0.032)	(0.031)	(0.031)
Initial share of skilled people	0.182***	0.161***	0.156***	0.146***
	(0.032)	(0.034)	(0.032)	(0.034)
Initial share of recent immigrants			0.103***	0.075**
			(0.036)	(0.034)
Minimal distance to university	-0.133***	-0.145***	-0.119***	-0.133***
	(0.045)	(0.046)	(0.045)	(0.044)
University RD spending per student	0.022	-0.005	0.020	-0.002
	(0.035)	(0.034)	(0.034)	(0.034)
Region dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Ethny IV estimate	0.20	1.09	0.19	1.07
Ethny IV p value	0.00	0.00	0.00	0.00
Ethny F statistic	12	207	10	206
Manuf. IV estimate	0.92	0.92	0.92	0.92
Manuf. IV p value	0.00	0.00	0.00	0.00
Manuf. F statistic	62	58	60	62
Urban Areas	308	308	308	308

Notes : The table presents OLS and 2SLS estimates. Coefficients are all measured in standard deviations. The dependent variable is the number of patents per 10,000 persons aged between 15 and 64 years. Diversity is measured by a generalized fractionalization index. Distance for ethnic diversity is geographic distance. Distance for manufacturing distance is based on patent citation flows. The "skilled" are the 15+ residents with at least a bachelor degree. Standard errors in parentheses are robust. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases and Statistics Canada boundary files..

CHAPTER III

DIVERSITY, LOCAL LABOR MARKET AND RESILIENCE.

Abstract

I combine establishment-level and Canadian census data for the period 2006–2016 to study the impact of manufacturing diversity on city-level employment. I find that manufacturing diversity leads to higher employment growth, especially male employment, and less skilled people. I also find significant positive spillover effects of manufacturing diversity on local employment in other industries such as construction, arts and recreation, and professional services. Moreover, cities that innovate more have a greater effect of manufacturing diversity on their local employment growth. Finally, manufacturing diversity makes cities more resilient and helps them retain employment after negative shocks to local labor demand.

Keywords: Canadian cities; industrial diversity; economic resilience; local labor market.
JEL Classification Codes: J21, O3, R11, R23.

3.1 Introduction

Urban resilience is an important issue for the development of cities in the face of disasters and unexpected events that affect local populations and firms. In particular, the emergence of the current COVID-19 pandemic has threatened some industries and forced cities to re-evaluate and address resilience. Many factors such as economic structure influence the resilience of cities (Martin and Sunley, 2015), and this paper focuses on the role of manufacturing diversity as an engine of growth in local labor markets and a factor of resilience in cities.

In addition to simply studying a relationship between employment and manufacturing diversity, I also study the mechanism by which diversity affects employment by mitigating the initial effects of local shocks on employment. I examine the effect of manufacturing diversity, as measured by the manufacturing employment mix by sector, on employment growth, especially in the presence of big manufacturing plant closures. Industrial diversity within a region fosters technological innovation through knowledge and technology spillovers between sectors in the same region, leading to local employment growth (Glaeser et al., 1992). Besides, regions with more concentrated industrial structures are subject to greater volatility in their economic growth and more vulnerable to local shocks leading to job destruction and reduced hiring. [1] A more diversified regional production system would reduce dependence on a single industry, and allow the region to avoid the severe fluctuations in employment and income that come with business cycle (Baldwin and Brown, 2004; Essletzbichler, 2007). Because firms in a diverse economy have the ability to hire displaced workers from other industries, diverse regional economies are assumed to be more stable and resilient (Dissart, 2003; Frenken et al., 2007). The chapter also examines the effect of manufacturing diversity on employment by gender, education, and industry, and also how the effect of manufacturing diversity differs by the city's initial level of innovation. The propensity to consume and the need for amenities and services differ by gender and education.

1. Detroit, Cleveland and Youngstown are all examples of the decline of specialized cities.

In addition, the contribution of industrial sectors to GDP varies considerably, with manufacturing, construction, mining and FIRE services being the major contributors in recent years.[2]

I find that manufacturing diversity leads to higher employment growth, especially in arts, recreation and entertainment services, construction services, and professional services , which seem to be strongly connected to the manufacturing industry, particularly through input-output links. I also show that manufacturing diversity is skewed toward the employment of men relative to women, and to a higher growth in the share of people without a university degree, characteristic of jobs in construction, manufacturing and recreation services. I also show that innovation generates additional effects from industrial diversity on employment growth. Finally, I show that cities that are initially more diverse are more resilient to large negative employment shocks. Cities with a high level of manufacturing diversity have seen employment remain relatively stable (or even keep growing) when large manufacturing plants have closed. Of the three dissertation chapters, the third chapter confirms some things we already know, such as the ability of diverse cities to be resilient in the face of economic shocks, particularly in their ability to retain employment. The added value of this paper is that it explores other little-studied research questions such as the effects of manufacturing diversity on specific sectors, on skilled labor, and on gender balance.

These findings are important for several reasons. First, studying the effect of industrial diversification on economic growth during a recession can help provide useful information for longer-term policy decisions, such as determining the need for policies to better withstand economic shocks like the one generated by the COVID 19. They are also important for the analysis of the government's strategy, which encourages the diversification of its economy through regional policies and development agencies.[3] Measuring the economic effects

2. See Table 36-10-0487-01, Statistics Canada.

3. Canada's Jobs and Growth Fund provides $700 million nationally over three years to businesses and organizations to help them create jobs and build resilience through diversifica-

of diversity is then important to understand how these policies affect local economies.

To estimate the effect of manufacturing diversity on employment growth in Canadian urban areas, the paper combines establishment-level data and population census data from 2006 to 2016. Identifying the impact of manufacturing diversity on local employment is difficult due to possible reverse causality. People come to the diverse cities to take advantage of the variety of employment opportunities. In addition, firms come to benefit from the variety of inputs and access to a diverse workforce, including the reemployment of displaced workers (Frenken et al., 2007). The diversity of industries within a region also fosters technological innovation through knowledge and technology spillovers and stimulate city growth (e.g. Glaeser et al., 1992). However, the growth of heterogeneous population and firms understandably affects the level of industrial diversity in the city. This reverse causality would lead to overestimating the impact of manufacturing diversity on local employment. It is also possible that there are measurement errors in the data collection, for example, companies providing incorrect information about their NAICS industry at the 6 digits level. In addition, in our data many companies provide more than one industry. I retain the primary reported activity, and thus the diversity measure does not account for this. All of this would tend to create a downward bias. To address endogeneity, the paper uses an IV strategy. The treatment variable is the manufacturing diversity index. I instrument it with a predicted manufacturing diversity index computed with the predicted shares of manufacturing employment by sector. Predicted shares are calculated as the interaction between a historical share (of 85 4-digit NAICS sectors), and the observed growth rate of each sector in Canada. Finally, I also control for observable characteristics that may influence employment at the city level, such as the share of manufacturing employment, the share of skilled people, the initial level of total employment and unemployment rate, proximity to large cities and the maritime coasts, climate and regional policy differences through big region fixed effects.

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tion and transition to a green economy starting in 2020.

This paper is related to two strands of the literature. First, it builds on previous work that examines the relationship between diversity and economic performance. Empirical studies on the subject have revealed a positive effect of industrial diversity on economic growth through increased employment (e.g. Glaeser et al., 1992; Boschma et al., 2012), productivity (e.g. Frenken et al., 2007), income (e.g. Pede, 2013) and innovation (e.g. Feldman and Audretsch, 1999; Duranton and Puga, 2001). Previous research has also shown that sociocultural diversity increases wages and rents (e.g. Ottaviano and Peri, 2006), employment (e.g. Lee, 2011), but has mixed effects on productivity (e.g. Parrotta et al., 2014; Trax et al., 2015). It has also been argued that economic diversity contributes to economic stability by providing an employment insurance to regions during cyclic downturns (e.g. Dissart, 2003; Izraeli and Murphy, 2003; Brown and Greenbaum, 2017). Rather than focusing on the economic stability of a region after a single shock in a given period, which is typical in this literature, the paper examines the effect of negative demand shocks on the labor market over a 10-year period. This allows for an analysis of the ability of regions to maintain their stability over the long run. Another important contribution is to analyze the effect of industrial diversity on employment by gender, education and industry. Furthermore, I analyze the effect of manufacturing diversity in the presence of innovation in cities.

Second, the paper contributes to the recent literature on the resilience of local economies. Cerra and Saxena (2008) find that economies that experience severe or frequent economic or political disruptions have lower overall growth rates. Such evidence is motivating researchers to understand what economic structure might enable countries and cities to better cope with economic shocks. Several papers investigate whether clusters are conducive to resilience in cities. Martin et al. (2011) show that French exporters were more affected by the 2008 trade collapse when they were located near other exporters or targeted by cluster policies. Behrens et al. (2020) show that plants in Canadian textile clusters are no more successful in surviving or adapting by changing their primary industry than those located outside of clusters. Delgado and Porter (2017), show that industries located near other related industries experienced higher employment growth than unrelated industries during the great recession of 2007-2009. Other papers have examined whether certain sectors of economic activity contribute to making cities resilient, such as Behrens et al. (2021b) who show that the presence of certain services, such as education, health, arts and culture, is contributing to the demographic resilience of cities. Unlike those studies, this paper examines how manufacturing diversity is a factor of resilience for local employment after a negative shock to the local labor market.

The rest of the paper is organized as follows. Section 3.2 describes the data used in the empirical analysis. Section 3.3 presents OLS and IV results on the impact of manufacturing diversity on employment growth. Section 3.4 examines the effect of manufacturing diversity on employment groups. Section 3.5 discusses the effect of manufacturing diversity in the presence of innovation in cities. Section 3.6 analyzes the effect of manufacturing diversity as a factor of urban resilience in the face of a local shock. Section 3.7 concludes.

3.2 Data and descriptive statistics

In this section, I describe the establishment-level database I use to measure manufacturing diversity, as well as the demographic, economic, and geographic variables that are controlled for in the empirical analysis. I also provide descriptive statistics that motivate further analysis.

3.2.1 Establishment-level data and manufacturing diversity

I use the *Scott's National All Business Directories* to construct the measure of manufacturing diversity. This database contains exhaustive information on establishments operating in Canada, with an extensive coverage of the manufacturing sector (NAICS 31–33). Compared to other manufacturing plant databases, it provides more information on small plants and tracks plants and their basic information over several years.[4] Information on manufacturing plants is

4. Scott's database is probably the best alternative to restricted-access datasets such as Statistics Canada's Annual Survey of Manufacturers or the Business Register. See Tables 3.10, 3.11, and 3.12 in the Appendix for a comparison between the Scott's National All Business database and other Statistics Canada databases listing establishments.

available every two years from 2001 to 2017. I only need 2007 for the analysis here. This study will primarily use information on the plant's sector by 6-digit NAICS code (aggregated to 4-digits), its number of employees, and complete address information that allows to geocode the plants and to assign them to cities. [5]

Table 3.1 provides an overview of the geographic structure of manufacturing in Canada in 2007. Most manufacturing plants are located in Quebec and Ontario. Table 3.13 shows a wide variation in the distribution of plants in the NAICS 4-digit sectors in 2007. I add 1998 data from Statistics Canada's Canadian Business Register, which is highly correlated with the Scotts database, in order to have information on manufacturing plants about 10 years earlier, useful for instrument construction. [6].

Table 3.1: Geographic breakdown of manufacturing plants in Canada.

		2007	
Region	Province	# of plants	Avg. jobs
Western	Alberta	3,723	36.4
	British Columbia	5,267	30.2
	Manitoba	1,405	36.7
	Saskatchewan	1,203	24.0
		11,598	***32.3***
Atlantic	New Brunswick	1,167	32.8
	Newfoundland and Labrador	517	41.0
	Nova Scotia	1,354	27.7
	Prince Edward Island	309	23.4
		3,347	***31.1***
Ontario	Ontario	***20,301***	***35.6***
Quebec	Quebec	***12,992***	***35.8***
Canada		**48,288**	**30.9**

Notes: Data from the Scott's National All Business Directories. The table is based on manufacturing plants (NAICS 31–33). The three territories (Northwest Territories, Nunavut, and Yukon) are not reported in the table but are included in the total.

This paper examines the effect of manufacturing diversity in 2007 on employ-

5. More information on the geocoding procedure is provided in Appendix 3.8.2.

6. 1998 was chosen because it is the closest date to 1996 that lists industries in the NAICS code used throughout the analysis instead of the SIC code

ment and unemployment growth in urban areas in Canada between 2006 and 2016. The analysis presented here is based on 155 Canadian urban areas. I use the 4-digit NAICS classification to measure manufacturing diversity.

I consider two measures of diversity.[7] The first considers the share of manufacturing employment by sector in the urban area. This diversity is measured by a simple fractionalization index.

The index is expressed as follows:

$$\text{ManufDiv1}_c = 1 - \sum_{i=1}^{N} \text{s}_{ic}{}^2 \tag{3.1}$$

where s_{ic} is the share of manufacturing employment in sector i in the urban area c in 2007.

The second measure of manufacturing diversity differs from the first by considering manufacturing plants groups as heterogeneous, and is constructed as follows:

$$\text{ManufDiv2}_c = \sum_{i=1}^{N} \sum_{j=1}^{N} \text{s}_{ic} \text{s}_{jc} d_{ij} \tag{3.2}$$

where s_{ic} and s_{jc} are the share in manufacturing employment from the 4 digit NAICS sectors i and j of urban area c in 2007, N is total number of industries, and d_{ij} refers to the distance between the two sectors. Here, the distance between manufacturing plant groups is measured based on the input-output sharing between these plants across NAICS 4 digit industries.[8]

7. In Appendix 3.8.3, I show how I get the two diversity measures from the same general expression.

8. Other measures of group distance based on labor flows and patent citations flows do not change qualitatively the results.

Turning to the geographic aspects of manufacturing, Figure 3.1 shows the simple manufacturing diversity index, of each Canadian urban area compared to the average for all urban areas. There is substantial heterogeneity across Canadian provinces. Grand Falls-Windsor (Newfoundland and Labrador), has the lowest level of manufacturing diversity, while Montreal (Quebec), has the highest level of manufacturing diversity in Canada. Large cities (population 300,000 and over, outlined in cyan in the figure) show a higher level of manufacturing diversity than the average for Canadian urban areas. There is wide variation in this relative measure of diversity in small and medium-sized cities. Urban areas in British Columbia, Atlantic Canada (New Brunswick, Newfoundland and Labrador, Nova Scotia, Prince Edward Island) and northern Quebec have a lower level of manufacturing diversity than the average Canadian urban area. Those in Alberta and Ontario have higher than average levels of manufacturing diversity. I find a similar description when I consider the manufacturing diversity with input-output based distances, of each Canadian urban area compared to the average for all urban areas. [9]

3.2.2 Labor data

I use data from the Canadian census released by the Computing in the Humanities and Social Sciences (CHASS) data center at the University of Toronto. I aggregate the information to the level of urban areas. The database provides information on employment and population characteristics such as gender, education, and industry for the years 2001, 2006, 2011, and 2016. [10]

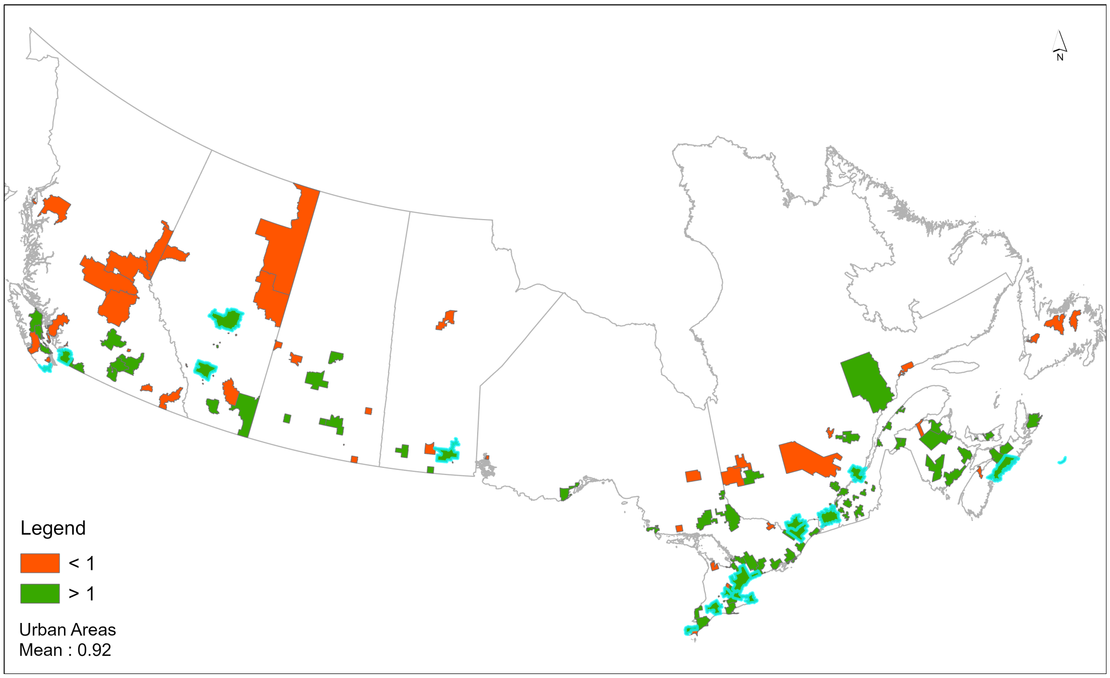
Urban areas—defined as census metropolitan areas (CMA) and census agglomerations (CA)—consist of one or more neighboring municipalities located around a core area and strongly interconnected in terms of commuting flows. [11] By construction, most people living in an urban area also work there. Thus, urban

9. See Figure 3.3 in Appendix 3.8.4.

10. Additional details are provided in Appendix 3.8.1.

11. A description of the distribution of urban areas by province is provided in Table 3.14.

Figure 3.1: Relative manufacturing diversity in Canadian Urban Areas



Notes: Manufacturing diversity are measured relatively to the urban area average. A value of 1 on the map means that the urban area's growth rate is the same as all urban areas mean. Cyan contours outline cities with population of at least 300,000.

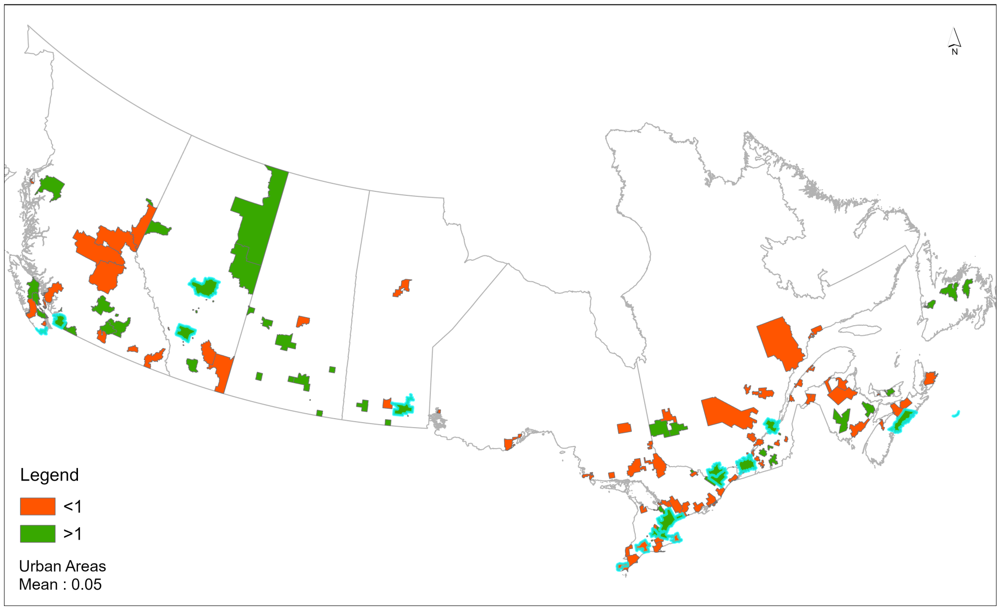
areas are the right spatial unit to investigate the links between manufacturing diversity and labor. The analysis is based on 155 Canadian urban areas whose boundaries are stable between 1996 and 2016. [12] After eliminating some outliers, it remains 155 urban areas.

Figure 3.2 shows there is wide variation in employment growth rates across Canadian urban areas. Among cities with a population of over 100,000, Saskatoon, Saskatchewan experienced the highest employment growth with a 23.7% increase from an initial employment of 125,535. Chatham-Kent, Ontario had the largest decrease in employment with a 11% decrease from an initial popu-

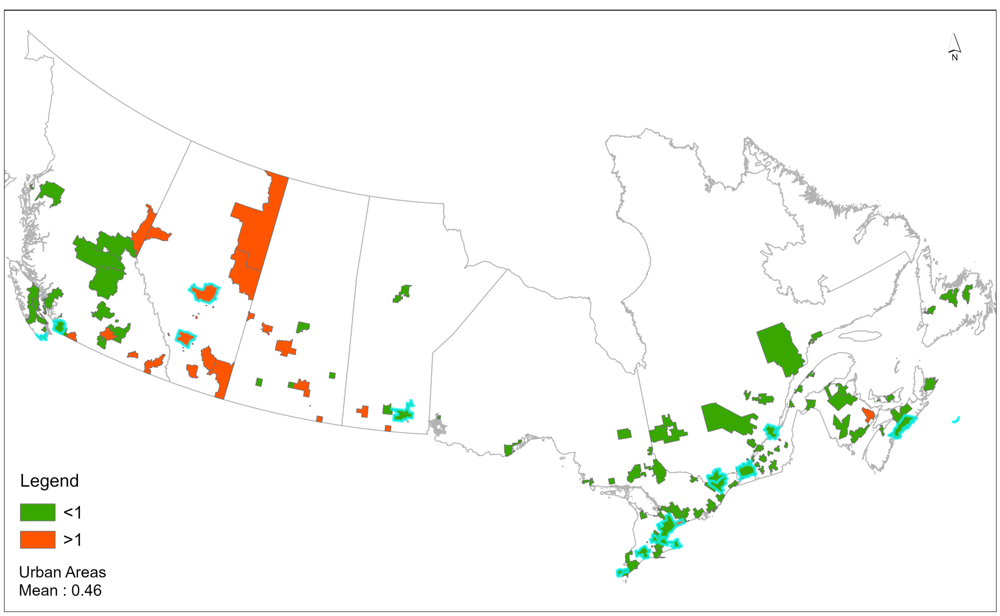
12. Statistics Canada uses population thresholds to define urban areas. Hence, their number has changed from 135 in 1996 to 156 in 2017. I keep all the areas that appear as an urban area for at least one of the census years under study. Statistics Canada also adjusts the boundaries of urban areas over time. In order to have a stable geography, I take for each of them the envelope of the boundaries observed over the four census periods. More details are provided in Appendix 3.8.2.

Figure 3.2: Relative employment growth rates in Canadian urban areas

(a) Relative employment growth rates



(b) Relative unemployment growth rates



Notes: Growth rates are measured relatively to all urban areas average. A value of 1 on the map means that the urban area's growth rate is the same as the overall mean. Cyan contours outline cities with population of at least 300,000.

lation of 51,670. Large cities (with 300,000+ inhabitants, outlined in cyan on the figure) all experienced employment growth (except Windsor, Ontario), with growth rates usually in excess of the urban area average. On the opposite, small- and medium-sized cities experienced either employment growth or employment decline. The majority of urban areas in Eastern Canada experienced lower employment growth than the urban area average, particularly in the Atlantic provinces and in the peripheral parts of Ontario and Quebec. [13] In Western Canada, below-average employment growth is mostly observed in British Columbia, whereas Alberta had growth levels above the overall average. Turning to the unemployment growth rates, the majority of urban areas have experienced lower growth than the average for urban areas, particularly in Eastern Canada. It is also noticeable that the provinces of Alberta and Saskatchewan, which have seen higher than average employment growth, also have higher than average unemployment growth. Since the end of the resource boom in 2014, Canada has experienced a period of slow overall growth and the labor market has undergone a substantial reallocation of labor resources away from resource-rich regions (Alberta, Saskatchewan) due to job losses and a gradual recovery of employment and production in central Canada (Ontario and Quebec) (Riddell, 2018).

3.2.3 Additional data

This study examines the effect of manufacturing diversity on the growth of local labor outcomes such as employment and unemployment. In order to control for many potential confounders, I add other characteristics that influence these growths, such as the human capital of the city, the initial unemployment rate, the share of manufacturing industry, and the initial level of employment. I also consider geographic characteristics such as climate, access to the coast and to the big cities, and differences in regional public policies by using fixed effects for Atlantic Provinces, Western Provinces, Quebec and Ontario. [14] I also

13. See, e.g., Johnson (2002) and Polèse and Shearmur (2002) for a more detailed description of the decline of the workforce in Atlantic Canada.

14. I do not use provincial dummies in our regressions because in some provinces, there are too few cities, such as in Atlantic Canada or in Manitoba and Saskatchewan, to allow for

use patent data to better understand if innovation can contribute to a more dynamic labor market in diverse cities. Table 3.7 in Appendix 3.8.1 presents descriptive statistics for these variables.

3.3 Manufacturing diversity and local labor market: Regression analysis

There are three important transmission channels (Frenken et al., 2007) . The first concerns spillovers between diverse sectors. Because spillovers are spatially bounded, a region with a distinct composition of complementary sectors will experience higher growth rates than a region with sectors that are not complementary. The second channel is to view diversity as a hedging strategy for a region against external demand shocks. A high degree of sectoral diversity in a regional economy implies that a negative demand shock to one of these sectors will have only mild negative effects on growth and employment. In contrast, a region that specializes in a single sector, or a group of sectors whose demand is correlated, runs the risk of a serious slowdown in growth and high unemployment rates following a demand shock. Finally, the third channel concerns the long-term effect of diversity on the economic system. An economy with low industrial diversity could over time suffer from structural unemployment and eventually stagnate (**?**). The development of new sectors would help to absorb labor that has become redundant in the pre-existing sectors that are dominant in rural areas. This stagnation is explained by a combination of productivity increases and demand saturation in the pre-existing sectors, characterizing the dynamics of the product life cycle in each sector.

The mechanisms of transmission of the effects of diversity to different employment sectors can be characterized by the input-output relationships or the technological intensity of the industry. On the one hand, firms within industries that share strong and dynamic input-output linkages benefit from diversity because the exchange of ideas, knowledge and processes occurs more easily (Forni and Paba, 2002). On the other hand, industries whose firms are technologically closer because they operate in an R&D-intensive sector are more

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statistical inference based on within-province variations (see Table 3.14 in the Appendix).

likely to be involved in the exchange of new ideas and thus to benefit from real spillovers (Griliches, 1992).

I present in this section the empirical specification and the baseline results.

3.3.1 Empirical specification

First, I examine the effect of manufacturing diversity on city-level growth rates of population, employment and unemployment, y. The baseline specification is the following:

$$\text{growth rate of } y_{c,r}^{2006-2016} = \alpha \times \text{ManufDiv}_c^{2007} + \beta \times \text{X}_c^{2006} + \theta_r + \varepsilon_{c,r} \qquad (3.3)$$

where X_c^{2006} is a vector of initial city characteristics, θ_r are regional fixed effect (Western provinces, Ontario, Quebec, and the Atlantic provinces), and $\varepsilon_{c,r}$ is an error term. The vector of initial city characteristics in 2006 contains: (i) the log of initial employment; (ii) the share of residents with a university degree, (iii) the share of manufacturing employment; (iv) the level of unemployment rate; (v) the January and July maximum temperatures; (vi) the log distance to the closest coast; and (vii) the log distance to the closest urban center with at least 300,000 inhabitants. The variable of interest is the manufacturing diversity index.

Estimating the impact of manufacturing diversity on city-level local labor outcomes using OLS is likely to yield a biased estimate of α. Indeed, it is plausible that manufacturing diversity and employment are simultaneously determined by changes in other dimensions of the local environment (changes in the quality of infrastructure, for example). It is also likely that equation (3.3) suffers from reverse causality. On the one hand, positive spillovers from diversity may attract people (such as the exchange of ideas, knowledge and processes) or firms (such as the variety of employment opportunities, labor and inputs). On the other hand, having a growing population increases the need for variety, and this attracts more diverse firms to meet that demand.

I consider the "shift-share" instrument À la Card (2001), which is a predicted index of local diversity of manufacturing employment in urban areas. These shares are obtained by extrapolating observed shares in a base year with the national-level growth rates. Therefore, the predicted shares in an urban area in 1998 for each manufacturing sector, are attributed to the growth rate of that group at national level from 2007 to 2016. To ensure that the initial shares in cities are as exogenous as possible to the national growth rate, the employment of the city is subtracted in the calculation of this rate. That leads to compute this equation :

$$\widehat{(\mathrm{s}_{i,c})}^{2007} = \mathrm{s}_{i,c}^{1998}[1 + (\mathrm{g}_i^{-c})_{1998-2007}] \tag{3.4}$$

Once these 'predicted' shares are constructed for 2007, a 'predicted' diversity index for each city in 2007 is calculated as follows :

$$(\widehat{\mathrm{ManufDiv}}_{i,c})^{2007} = 1 - \sum_{i=1}^{N} \widehat{(\mathrm{s}_{i,c}^{2007})}^{2} \tag{3.5}$$

The predicted composition of the urban area is thus calculated on the basis of the initial composition of each manufacturing sector to which the growth rate of that group's share at the national level is assigned.

3.3.2 Results

Columns (1)–(3) of Table 3.2 show results of the OLS estimation of equation (3.3). Three outcome variables are considered: the growth rate of the total population, the growth rate of the total employment and the growth rate of the total unemployment. The treatment variable is the fractionalization index measuring the diversity of manufacturing employment by sector (with and without distances between groups). The OLS results show that manufacturing diversity is positively correlated with population and employment growth and is not correlated with unemployment growth at the city-level, with relatively close estimates between population and employment. The IV regressions in columns (4)–(6) of Table 3.2 provide a comparable picture. For total population and employment growth, the coefficient on the manufacturing diversity remains positive, but its size increases in absolute value compared to the OLS estimate.

The fact that the coefficient on manufacturing diversity becomes more positive with IV for total population and employment growth may reflect to some extent a downward bias due to possible measurement errors in manufacturing diversity mentioned above. Overall, the results show that manufacturing diversity has led to an increase in population, especially in employment in Canadian urban areas. The effect is quantitatively sizable. A one-standard deviation in the manufacturing diversity induces a increase in the employment growth rate by 0.2% (which exhibit large variation with a mean 0.467 of and a standard deviation of 0.728) .

Table 3.2: Manufacturing diversity and local growth in Canadian cities

Dependent variable y: Growth of	Total Population		Total Employment		Total Unemployment		Total Population		Total Employment		Total Unemployment	
	OLS(1) Simple index	OLS(2) Distance index	OLS(3) Simple index	OLS(4) Distance index	OLS(5) Simple index	OLS(6) Distance index	IV(1) Simple index	IV(2) Distance index	IV(3) Simple index	IV(4) Distance index	IV(5) Simple index	IV(6) Distance index
Manufacturing diversity	0.179*		0.159**		0.038		0.255***		0.199***		0.046	
	(0.068)		(0.044)		(0.021)		(0.057)		(0.047)		(0.035)	
Manufacturing diversity (input/output distance)		0.186*		0.167**		0.037		0.263***		0.213***		0.051
		(0.066)		(0.039)		(0.020)		(0.060)		(0.046)		(0.037)
Ln Total initial employment	-0.176	-0.177	-0.161	-0.163	-0.144	-0.144	-0.206**	-0.207**	-0.177***	-0.180***	-0.147**	-0.149***
	(0.114)	(0.114)	(0.097)	(0.095)	(0.067)	(0.066)	(0.089)	(0.091)	(0.066)	(0.067)	(0.058)	(0.057)
Share of 15+ with a university degree	0.163	0.162	0.253	0.252	-0.140	-0.141	0.171	0.169	0.258**	0.257**	-0.139	-0.139
	(0.149)	(0.150)	(0.145)	(0.146)	(0.105)	(0.105)	(0.121)	(0.123)	(0.116)	(0.118)	(0.088)	(0.088)
Share of manufacturing employment	-0.104*	-0.098*	-0.152**	-0.147**	-0.198	-0.196	-0.114***	-0.105***	-0.157***	-0.151***	-0.199**	-0.198**
	(0.039)	(0.035)	(0.048)	(0.045)	(0.101)	(0.100)	(0.036)	(0.032)	(0.038)	(0.037)	(0.084)	(0.083)
Unemployment rate	-0.370	-0.365	-0.133	-0.128	-0.515	-0.514	-0.361	-0.353	-0.128	-0.121	-0.514*	-0.512*
	(0.273)	(0.271)	(0.266)	(0.264)	(0.325)	(0.325)	(0.226)	(0.225)	(0.220)	(0.220)	(0.271)	(0.272)
January maximum temperature	0.101	0.099	0.058	0.055	0.194*	0.194*	0.087	0.084	0.050	0.047	0.193***	0.191***
	(0.066)	(0.065)	(0.139)	(0.138)	(0.077)	(0.077)	(0.058)	(0.054)	(0.122)	(0.119)	(0.063)	(0.064)
July maximum temperature	-0.015	-0.018	0.017	0.014	-0.149	-0.150	-0.020	-0.024	0.014	0.010	-0.150*	-0.151*
	(0.098)	(0.098)	(0.081)	(0.081)	(0.105)	(0.105)	(0.085)	(0.085)	(0.071)	(0.071)	(0.088)	(0.088)
Log distance to nearest coastline	0.024	0.026	0.019	0.020	0.122	0.122	0.026	0.027	0.020	0.021	0.122	0.123
	(0.057)	(0.057)	(0.022)	(0.022)	(0.092)	(0.092)	(0.048)	(0.048)	(0.019)	(0.019)	(0.077)	(0.077)
Log distance to nearest big city	-0.036	-0.036	-0.032	-0.033	-0.050	-0.050	-0.040***	-0.040***	-0.034**	-0.035**	-0.051**	-0.051**
	(0.018)	(0.017)	(0.019)	(0.019)	(0.028)	(0.028)	(0.015)	(0.015)	(0.016)	(0.015)	(0.023)	(0.023)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate							0.890	0.890	0.890	0.890	0.890	0.890
IV P value							0.000	0.000	0.000	0.000	0.000	0.000
IV Partial R2							0.64	0.63	0.64	0.63	0.64	0.63
First stage F statistic							35	34	35	34	35	34
Adjusted R2	0.37	0.37	0.23	0.23	0.57	0.57						
Urban Areas	155	155	155	155	155	155	155	155	155	155	155	155

Notes : The table presents OLS and 2SLS estimates. Coefficients are all measured in standard deviations. Diversity is measured by a generalized fractionalization index. The "skilled" are the 15+ residents with at least a bachelor degree. Temperatures are in Celsius and distances in meters. A big city is a city with at least 300,000 residents. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Scott's National All databases, Statistic Canada's Census 2006-2016 and boundaries files, Environment Canada's weather data.

Regarding the effects of the controls, the results are intuitive. Proximity to large urban centers is attractive for workers who certainly favor large markets with better employment opportunities. Cities with a higher initial share of manufacturing jobs and unemployment rates experienced a decrease in total population (including employment and unemployment). Initial cities with a higher share of skilled workers experienced an increase in total employment. The regressions also show that the population of large cities grew more slowly.

3.3.3 Robustness checks

Recent contributions discuss the conditions under which Bartik instruments are valid and propose procedures to ensure they can be used safely (see e.g. Adão et al., 2019; Borusyak et al., 2020; Goldsmith-Pinkham et al., 2020). Following the suggestions made by Borusyak et al. (2020), I do three things.

First, I assess the relevance of the instrument by measuring one minus the Herfindahl index of manufacturing employment shares at the national level. If a few specific groups account for the largest share of national level, it is unlikely that group shares will vary enough across locations to provide a good IV. Here, this statistic is equal to 0.97 (with a highest sectoral share of 6%), which suggests there is a reasonable degree of variation in industry shares. The Bartik IV can be considered as a relevant IV.

Second, I report in Table 3.16 a placebo test where the dependent variable is the population growth rate between 1996 and 2006 instead of 2006 and 2016. This placebo amounts to a test for the parallel trend assumption. The coefficients on population, employment and unemployment growth in the IV regressions are statistically insignificant. [15]

Third, another concern with the benchmark IV regressions is that if some industries are highly concentrated in urban areas with specific unobserved trends, there could be a correlation between the instrument and the error term in the IV regressions. To take care of this issue, we build an alternative Bartik instrument from which we remove the industries that are the most highly geographically concentrated (top quartile). As can be seen in Table 3.17, the results are very

15. For the placebo test of unemployment, I do not control for the initial level of unemployment, which in the pre-trend analysis becomes the final level.

stable. Overall, these checks confirm the validity of the Bartik instrument in the context of the study.

3.4 Local labor outcomes

In Table 3.3, I look at the effect of manufacturing diversity on the evolution of the share of different groups in the overall employment. Compared to the previous results, it allows to assess whether the growth for a given group is affected by manufacturing diversity differently from that of the overall employment.

An advantage of analyzing industrial diversity over other sectors is the availability of data at the local level over several years. In addition, the manufacturing sector is the sector that has the most different sub-sectors. It is also the sector that makes a significant contribution to the modern economy in terms of wealth creation (over 10% of Canada's total GDP) and exports (68% of all Canadian merchandise exports). In addition, it is a sector that has modernized by becoming more innovative, high-tech, and relies on a highly skilled workforce (such as designers, researchers, programmers, engineers, technicians). The impact of diversity in this industry is therefore very interesting to explore.

The diversity of the manufacturing sector has a greater effect on non-highly skilled individuals within local populations. I also find a positive relationship between manufacturing diversity and the ratio of male to female employees. Male or low-skilled labor-intensive industries are manufacturing, construction, and arts and entertainment (and somewhat professional services). [16].

I then examine how employment by industry has been affected by manufacturing diversity. Thanks to the information on local employment at the NAICS 2-digit level available in the Census data, I am able to consider (i) manufacturing,

16. People without bachelor's degree or higher are 94% in Construction, 78% in Manufacturing, 68% in arts and recreation, 56% in Professional services according to the 2010 Labour Force Survey from Statistics Canada. Male employment is 88.5% in Construction services, 57% in Professional services and 54% in arts and recreation services between 2006 and 2016 in Canada. See Table 14-10-0023-01, Labour force characteristics by industry, 2006-2016, Statistics Canada.

Table 3.3: Manufacturing diversity and employment groups in Canadian cities

Dependent variable y: Growth of	Total Employment		Male to female employee ratio		Manufacturing Share		Skilled Share	
	IV(1) Simple index	IV(2) Distance index	IV(3) Simple index	IV(4) Distance index	IV(5) Simple index	IV(6) Distance index	IV(7) Simple index	IV(8) Distance index
Manufacturing diversity	0.199***		0.107***		-0.015		-0.123**	
	(0.047)		(0.040)		(0.040)		(0.057)	
Manufacturing diversity (input/output distance)		0.213***		0.114***		-0.033		-0.121**
		(0.046)		(0.042)		(0.043)		(0.055)
Ln Total initial employment	-0.177***	-0.180***	-0.016	-0.018	0.001	0.008	0.051	0.049
	(0.066)	(0.067)	(0.108)	(0.110)	(0.033)	(0.035)	(0.057)	(0.054)
Share of 15+ with a university degree	0.258**	0.257**	0.354***	0.353***	-0.018	-0.020	0.414***	0.416***
	(0.116)	(0.118)	(0.083)	(0.082)	(0.042)	(0.041)	(0.017)	(0.017)
Share of manufacturing employment	-0.157***	-0.151***	0.011	0.014	-0.704***	-0.703***	-0.127	-0.132
	(0.038)	(0.037)	(0.204)	(0.206)	(0.122)	(0.120)	(0.131)	(0.129)
Unemployment rate	-0.128	-0.121	0.166	0.170	-0.173*	-0.176**	-0.277***	-0.280***
	(0.220)	(0.220)	(0.113)	(0.113)	(0.088)	(0.087)	(0.084)	(0.087)
January maximum temperature	0.050	0.047	-0.088	-0.090	0.036	0.040	-0.045**	-0.045**
	(0.122)	(0.119)	(0.182)	(0.181)	(0.082)	(0.084)	(0.023)	(0.022)
July maximum temperature	0.014	0.010	0.056	0.054	-0.008	-0.007	0.056	0.058
	(0.071)	(0.071)	(0.047)	(0.047)	(0.018)	(0.017)	(0.045)	(0.045)
Log distance to nearest coastline	0.020	0.021	-0.042**	-0.041**	0.032	0.032	-0.055***	-0.055***
	(0.019)	(0.019)	(0.017)	(0.017)	(0.023)	(0.022)	(0.016)	(0.016)
Log distance to nearest big city	-0.034**	-0.035**	0.023	0.022	0.009	0.010	0.002	0.002
	(0.016)	(0.015)	(0.025)	(0.026)	(0.011)	(0.012)	(0.014)	(0.013)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	0.890	0.890	0.890	0.890	0.890	0.890	0.890	0.890
IV P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IV Partial R2	0.64	0.63	0.64	0.63	0.64	0.63	0.64	0.63
First stage F statistic	35	34	35	34	35	34	35	34
Urban Areas	155	155	155	155	155	155	155	155

Notes : The table presents 2SLS estimates. Coefficients are all measured in standard deviations. Diversity is measured by a generalized fractionalization index. The "skilled" are the 15+ residents with at least a bachelor degree. Temperatures are in Celsius and distances in meters. A big city is a city with at least 300,000 residents. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases, Statistic Canada's Census 2006-2016 and boundaries files, Environment Canada's weather data.

(ii) construction services, (iii) arts, entertainment and recreation services, (iv) professional services composed of the information, finance, real estate, scientific and technical, management and administrative support services, (v) trade and transport services composed of the retail trade, wholesale trade, transport and warehousing sectors, (vi) education and health services, and (vii) accomodation and food services.[17] The results in Table 3.4 report the simple index measure of manufacturing diversity. The distance index measure gives qualitatively the same results reported in the Table 3.18 in the Appendix. I find that the construction, arts, entertainment and recreation, and professional services

17. Manufacturing correspond to NAICS 31, 32 and 33, construction services to NAICS 23, arts, entertainment and recreation services to NAICS 71, professional services to NAICS 51 to 56, trade and transport services to NAICS 41, 44, 48 and 49, education and health services to NAICS 61 and 62, and finally accomodation and food services to NAICS 72.

industries are positively affected by manufacturing diversity.

A diverse industrial environment supports the diffusion of technological or knowledge externalities and innovative activities, thus leading to local economic growth. To the extent that some ideas diffuse and can be used by firms, local industrial heterogeneity may facilitate faster diffusion of ideas, especially when two sectors are closely linked (through shared inputs and outputs, for example) or when innovations from one sector can be used in another sector (Combes, 2000). The main hypothesis here is that the effect of industrial diversity on employment differs across sectors, as they do not benefit equally from technological or knowledge externalities generated by the diverse economic structure.

Manufacturing sectors are more likely to exchange ideas and technologies with each other because of the input-output linkages between them. This leads to manufacturing job growth in a highly diverse city. In addition, studies show that manufacturing has multiplier effects on other industries (e.g. Behrens et al., 2021b). For example, the growth in manufacturing employment would support growth in construction and professional services (manufacturing plants consume a lot of professional services, for example) and cultural services (through higher local consumer demand, due to the growth in manufacturing jobs that pay well on average).

Overall, the significant positive effects of manufacturing diversity that we observe across several industries show that manufacturing diversity has heterogeneous effects on employment by gender, education, and industry. This may explain why this diversity so significantly affects local employment.

3.5 Innovation activity

I use the Canadian patent database digitized by the CD Howe Institute to construct measures of innovation activity. This database provides detailed information on the patent as well as the postal code of the place of residence of the inventors associated with the patent. Patents are then assigned to urban areas based on the residential address of all inventors named on the patent. It

Table 3.4: Manufacturing diversity and employment by industry in Canadian cities

Dependent variable y: Growth of	Manufacturing industry	Construction services	Arts, entertainment and recreation services	Professional services	Trade and transport services	Education and health services	Accomodation and food services
	IV(1) Simple index	IV(2) Simple index	IV(3) Simple index	IV(4) Simple index	IV(5) Simple index	IV(6) Simple index	IV(7) Simple index
Manufacturing diversity	0.134**	0.191***	0.275***	0.149**	-0.057	0.070	-0.065
	(0.053)	(0.023)	(0.044)	(0.075)	(0.073)	(0.094)	(0.060)
Ln Total initial employment	-0.004	0.017	-0.266***	-0.133*	-0.084***	-0.127***	-0.018
	(0.079)	(0.064)	(0.025)	(0.076)	(0.029)	(0.031)	(0.086)
Share of 15+ with a university degree	0.037	0.106***	0.186*	-0.027	0.132	-0.058	0.063
	(0.043)	(0.039)	(0.106)	(0.236)	(0.088)	(0.139)	(0.121)
Share of manufacturing employment	-0.050	0.178**	-0.032	0.005	0.005	-0.135	-0.029
	(0.145)	(0.080)	(0.028)	(0.107)	(0.110)	(0.099)	(0.099)
Unemployment rate	-0.463*	0.101	-0.188	-0.322**	-0.313	-0.292***	-0.137
	(0.241)	(0.207)	(0.118)	(0.147)	(0.199)	(0.095)	(0.276)
January maximum temperature	-0.066	-0.286**	0.175**	0.005	0.191***	0.126***	0.074
	(0.128)	(0.145)	(0.080)	(0.056)	(0.037)	(0.044)	(0.120)
July maximum temperature	0.028	-0.153	-0.107	-0.022	0.031	0.072	0.186***
	(0.047)	(0.096)	(0.088)	(0.040)	(0.057)	(0.053)	(0.028)
Log distance to nearest coastline	0.036**	0.061	0.009	-0.022*	0.015	0.010	-0.011
	(0.017)	(0.040)	(0.016)	(0.013)	(0.028)	(0.035)	(0.036)
Log distance to nearest big city	0.013	-0.000	-0.039***	-0.040**	-0.025	-0.014**	-0.033
	(0.016)	(0.010)	(0.013)	(0.020)	(0.016)	(0.007)	(0.024)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	0.890	0.890	0.890	0.890	0.890	0.890	0.890
IV P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IV Partial R2	0.64	0.64	0.64	0.64	0.64	0.64	0.64
First stage F statistic	35	35	35	35	35	35	35
Urban Areas	155	155	155	155	155	155	155

Notes : The table presents 2SLS estimates. Coefficients are all measured in standard deviations. Diversity is measured by a simple fractionalization index. The "skilled" are the 15+ residents with at least a bachelor degree. Temperatures are in Celsius and distances in meters. A big city is a city with at least 300,000 residents. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases, Statistic Canada's Census 2006-2016 and boundaries files, Environment Canada's weather data.

allows the construction of patent-inventor pairs by working age population in each Canadian urban area. I construct the measure of the innovation activity (which is the number of patent-inventors per working age population in 2006) in urban area c as follows :

$$\text{Innovation activity}_c = \frac{\text{\# patent-inventors}}{\text{Working age population}} \times 10,000 \tag{3.6}$$

The innovation activity is heterogeneous across provinces, ranging from 0 to 14 (with a Canadian average of 2.4). The majority of urban areas in the western provinces of Quebec experienced higher innovation activity than the Canadian average, while the most urban areas in Atlantic Canada experienced lower innovation activity than the Canadian average.

The results in the Table 3.5 shows that innovation activity increases employment and decreases unemployment. Cities that are initially more innovative have a larger positive effect of industrial diversity on employment growth and a larger negative effect on unemployment growth. There must be some innovation base for interaction that facilitates the exchange of existing ideas and the generation of new ideas between diverse industries (e.g. Duranton and Puga, 2001). Thus, cities with higher levels of innovation would have a greater platform for the exchange of ideas and knowledge, which would benefit the variety of industries to stimulate growth within the city.

Table 3.5: Manufacturing diversity and innovation in Canadian cities

Dependent variable *y*: Growth of	Total Population		Total Employment		Total Unemployment	
	IV(1) Simple index	IV(2) Distance index	IV(3) Simple index	IV(4) Distance index	IV(5) Simple index	IV(6) Distance index
Manufacturing diversity	0.240***		0.121***		0.104***	
	(0.084)		(0.045)		(0.030)	
Manufacturing diversity x Innovation	0.106		1.992***		-1.893***	
	(0.589)		(0.504)		(0.391)	
Manufacturing diversity (input/output distance)		0.252***		0.141***		0.115***
		(0.084)		(0.042)		(0.033)
Manufacturing diversity x Innovation		0.024		1.803***		-2.018***
		(0.500)		(0.479)		(0.307)
Innovation activity	-0.053	-0.136	1.807***	1.620***	-1.943***	-2.066***
	(0.548)	(0.463)	(0.477)	(0.450)	(0.423)	(0.341)
Ln Total initial employment	-0.202**	-0.203**	-0.188***	-0.190***	-0.130**	-0.131**
	(0.088)	(0.091)	(0.064)	(0.065)	(0.058)	(0.057)
Share of 15+ with a university degree	0.101	0.100	0.156	0.158	-0.140*	-0.137*
	(0.117)	(0.117)	(0.107)	(0.110)	(0.072)	(0.071)
Share of manufacturing employment	-0.136***	-0.126***	-0.208***	-0.199***	-0.180**	-0.179**
	(0.030)	(0.029)	(0.044)	(0.043)	(0.075)	(0.072)
Unemployment rate	-0.357*	-0.349*	-0.146	-0.138	-0.491*	-0.486*
	(0.211)	(0.211)	(0.206)	(0.208)	(0.264)	(0.262)
January maximum temperature	0.082	0.079	0.059	0.053	0.177***	0.174***
	(0.056)	(0.053)	(0.118)	(0.115)	(0.065)	(0.065)
July maximum temperature	-0.023	-0.027	0.012	0.008	-0.152*	-0.153*
	(0.082)	(0.082)	(0.069)	(0.069)	(0.086)	(0.086)
Log distance to nearest coastline	0.010	0.011	0.001	0.002	0.118	0.119
	(0.045)	(0.045)	(0.018)	(0.019)	(0.079)	(0.079)
Log distance to nearest big city	-0.034**	-0.035***	-0.029**	-0.029**	-0.048**	-0.048**
	(0.013)	(0.013)	(0.014)	(0.013)	(0.024)	(0.024)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	0.991	0.991	0.991	0.991	0.991	0.991
IV P value	0.000	0.000	0.000	0.000	0.000	0.000
IV Partial R2	0.66	0.65	0.66	0.65	0.66	0.65
First stage F statistic	64	111	64	111	64	111
Urban Areas	154	154	154	154	154	154

Notes : The table presents 2SLS estimates. Coefficients are all measured in standard deviations. Diversity is measured by a generalized fractionalization index. Distance for manufacturing distance is based on input-output flows. The "skilled" are the 15+ residents with at least a bachelor degree. Distances are in meters. Temperatures are in Celsius and distances in meters. A big city is a city with at least 300,000 residents. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases, Statistic Canada's Census 2001-2016 and boundaries files, Environment Canada's weather data.

3.6 Urban resilience

In this section the paper analyzes the effects of manufacturing diversity on resilience and examines how it affects employment during economic shocks.

In chapter 1, the observed shock is the job loss rate, and in chapter 2, the closure rate. The instruments constructed are therefore slightly different, one being a bartik with employment, and the other being a bartik with the number of plants. But, both chapters show that negative demand shocks have decreased the growth rate of population and employment. Moreover, in terms of resilience factors, in chapter 1, public services and recreation play an important role, while in chapter 3, it is manufacturing diversity.

In this study, resilience will be defined as the ability of the urban area to maintain employment during a crisis. An urban area is considered to have suffered a local shock if it has experienced a significant loss of employment with a specific industry being responsible for part of that decline (Brown and Greenbaum, 2017). The measure of local shock is the number of closures in the urban area in 2017 of large manufacturing plant (50+ employees) from 2007 relative to the initial level of manufacturing plants in the urban area. It is defined as follows:

$$\text{Closure rate} \quad = \quad \frac{\text{\# Large plants present in 2007 but not in 2017}}{\text{\# Plants present in 2007}}, \qquad (3.7)$$

The expected result is that this type of shock will negatively affect the local economy but that more industrial diversified economies will be more resilient to this shock. Behrens et al. (2021b) have shown that large manufacturing plant closures have negative multiplier effects on employment in other industries in Canadian urban areas. Thus, it is a local shock with a significant impact on the local economy.

One might ask whether the recovery in employment is different across cities because they respond differently to the same shock or because they were hit by different shocks? In this chapter, we consider the closure rate of large firms, which differs across cities. In this sense, it is more about the magnitude of different shocks in cities. One thing might have been to consider a national shock that affects all cities relatively equally. Brown and Greenbaum (2017)), on the other hand, examined the effect of industrial diversity on the resilience of cities to local and national shocks. They find that the impact of a national shock on employment has a similar but larger impact on unemployment than a sudden and significant decline in local employment.

Figure 3.4 in the Appendix shows a particularly striking heterogeneity of this shock when comparing the local closure rate to that observed on average in Canadian urban areas. Urban areas in Western Canada have a lower rate of manufacturing job loss than urban areas in Eastern Canada, particularly in the manufacturing belt. Table 3.15 in the Appendix shows that sectors with the highest job loss rates are the chemical, metal, wood product, transportation equipment, and textile and clothing sectors.

As expected, the negative local labor market shock leads to a decline in the total population and thus in employment (and unemployment) as people leave the city (Behrens et al., 2021b). The results in Table 3.6 also show that manufacturing diversity is a resilience factor for cities; cities with a higher level of manufacturing diversity are rather insensitive to large plant closures. These results are consistent with those of Brown and Greenbaum (2017) who show that in Ohio, USA, counties with greater industrial diversity tended to experience relatively lower unemployment rates when the local (and national) economy experienced employment shocks. In the estimates, the initial size of the urban area and the share of manufacturing employment are considered to isolate only the effect of manufacturing diversity. Thus, even if an urban area is small, it can enjoy the benefits of industrial diversity as a resilience factor.

The results also show that while manufacturing diversity does not have a direct effect on unemployment, manufacturing diversity in the presence of negative local shocks stabilizes the level of unemployment.

Table 3.6: Manufacturing diversity and local labor shock in Canadian cities

Dependent variable *y*: Growth of	Total Population		Total Employment		Total Unemployment	
	IV(1) Simple index	IV(2) Distance index	IV(3) Simple index	IV(4) Distance index	IV(5) Simple index	IV(6) Distance index
Manufacturing diversity	0.215***		0.144**		-0.002	
	(0.068)		(0.058)		(0.047)	
Manufacturing diversity x Local shock	2.197*		2.923***		2.323**	
	(1.183)		(0.467)		(1.105)	
Manufacturing diversity (input/output distance)		0.217***		0.142**		0.003
		(0.067)		(0.057)		(0.048)
Manufacturing diversity x Local shock		2.219**		3.285***		2.085**
		(0.988)		(0.504)		(0.883)
Local shock closure rate	-2.202*	-2.225**	-2.918***	-3.280***	-2.292**	-2.058**
	(1.152)	(0.961)	(0.471)	(0.494)	(1.090)	(0.870)
Ln Total initial employment	-0.228***	-0.229***	-0.206***	-0.213***	-0.170***	-0.169***
	(0.085)	(0.087)	(0.070)	(0.070)	(0.064)	(0.061)
Share of 15+ with a university degree	0.181	0.181	0.272**	0.276**	-0.125	-0.124
	(0.110)	(0.113)	(0.106)	(0.109)	(0.079)	(0.080)
Share of manufacturing employment	-0.111***	-0.094***	-0.158***	-0.139***	-0.209***	-0.200***
	(0.030)	(0.026)	(0.024)	(0.028)	(0.071)	(0.066)
Unemployment rate	-0.299	-0.285	-0.049	-0.023	-0.457*	-0.455*
	(0.200)	(0.199)	(0.207)	(0.205)	(0.240)	(0.244)
January maximum temperature	0.086	0.083*	0.049	0.045	0.194***	0.192***
	(0.053)	(0.050)	(0.113)	(0.109)	(0.066)	(0.067)
July maximum temperature	-0.025	-0.029	0.008	0.004	-0.152	-0.152
	(0.091)	(0.090)	(0.077)	(0.078)	(0.094)	(0.093)
Log distance to nearest coastline	0.027	0.029	0.020	0.023	0.121	0.122
	(0.047)	(0.048)	(0.022)	(0.022)	(0.078)	(0.079)
Log distance to nearest big city	-0.041***	-0.042***	-0.036**	-0.037***	-0.051**	-0.052**
	(0.015)	(0.014)	(0.015)	(0.014)	(0.020)	(0.020)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	0.990	0.990	0.990	0.990	0.990	0.990
IV P value	0.000	0.000	0.000	0.000	0.000	0.000
IV Partial R2	0.68	0.67	0.68	0.67	0.68	0.67
First stage F statistic	48	47	48	47	48	47
Urban Areas	155	155	155	155	155	155

Notes : The table presents 2SLS estimates. Coefficients are all measured in standard deviations. Diversity is measured by a generalized fractionalization index. The "skilled" are the 15+ residents with at least a bachelor degree. Temperatures are in Celsius and distances in meters. A big city is a city with at least 300,000 residents. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases, Statistic Canada's Census 2006-2016 and boundaries files, Environment Canada's weather data.

3.7 Conclusion

Diverse cities are thought to be more stable and provide environments that lead to stronger economic growth. The results of the cross-section model estimation, based on a sample of 155 Canadian urban areas, highlight the role that manufacturing diversity, measured in terms of variety, has on local labor market. The results show that the relationship between manufacturing diversity and employment growth is positive and significant, especially for men employment, people without a university degree and people working in arts, entertainment and recreation services, professional services and construction services. Cities initially better endowed in terms of innovation observe a greater effect of manufacturing diversity on employment growth. Moreover, I find that manufacturing diversity helps cities maintain employment levels in the presence of a negative shock to local labor demand. This implies that regions may have to enhance their industrial diversity by attracting, opening or retaining more various firms in order to maintain high employment gains and ensure greater resilience to economic shocks.

3.8 Appendix to Chapter 3

This set of appendixes is organised as follows. Appendix 3.8.1 describes the data used in the analysis. Appendix 3.8.2 details the process followed to geocode the establishment database. Appendix 3.8.3 explains the decomposition of fractionalization index used in the analysis. Appendix 3.8.4 provides additional tables and figures. Appendix 3.9 displays additional results.

3.8.1 Data for regressions

Census data The Census data released by the Computing in the Humanities and Social Sciences (CHASS) data center at the University of Toronto contain a great deal of information on the socio-demographic characteristics of the residents as well as on the jobs thy occupy. We use them to construct several of our controls on top of our dependent variables.

The literature has shown that certain initial socio-economic characteristics of the population affect city-level population growth. Among them, the level of schooling—of human capital—of the population is strongly correlated with subsequent city growth (see, e.g., Glaeser et al., 1995; Moretti, 2004a). The proxy for the initial human capital is the share of residents holding at least a bachelor degree in 2001.I also include the share of manufacturing industry. Cities that have been concentrated in this industry have experienced a decline in employment due to the effects of deindustrialization in recent years. I also control for the unemployment rate

Table 3.7 presents descriptive statistics on the variables used in this study. The average population growth rate observed across Canadian urban areas is equal to 14.3%. In 2001, in Canadian urban areas, half of the population was part of the working age population defined as 20-54 year-old residents, 12% had a university degree on average, and 14.1% of employment was in manufacturing on average. In addition, 18% of the residents worked in educational, health and social assistance services, and 2% in cultural and recreational services. However, as the table illustrates, there is a great deal of variation across urban areas for all of these initial characteristics that are helpful for our estimations.

Table 3.7: Descriptive statistics, urban area variables.

Variable	Obs	Sample Mean	Std. Dev.	Minimum	Maximum
Growth rate					
Total Population	155	0.104	0.111	-0.089	0.649
Total Employment	155	0.050	0.108	-0.211	0.494
Total Unemployment	155	0.467	0.728	-0.367	3.642
Accomodation and food services	155	0.118	0.177	-0.284	0.785
Arts, entertainment and recreation services	155	0.195	0.454	-0.765	3.667
Education and health services	155	0.302	0.240	-0.236	1.056
Manufacturing industry	155	-0.145	0.238	-0.707	0.630
Professional services	155	0.212	0.152	-0.098	0.844
Trade and transport services	155	0.113	0.176	-0.333	0.704
	155	0.063	0.127	-0.240	0.624
Changes in shares					
Male to female ratio	155	-0.050	0.060	-0.272	0.077
Employment in manufacturing	155	-0.029	0.025	-0.110	0.022
People with university degree	155	0.036	0.018	-0.005	0.133
Diversity index					
Manufacturing index (simple)	155	0.926	0.056	0	0.988
Manufacturing index (distance)	155	0.912	0.055	0	0.974
Initial level (2006)					
(log) Initial employment	155	10.077	1.305	8.129	14.774
Patents per working age population	154	2.444	2.627	0	14.232
% Initial people with university degree	155	0.124	0.049	0.050	0.315
Labor force (industry)					
% Initial share of employment in manufacturing	155	0.123	0.071	0.022	0.341
Initial unemployment rate	155	6.716	2.966	2.252	22.362
Closure rate	155	0.057	0.045	0.000	0.237
Geographic variables					
Maximum January temperature (C)	155	7	3	-2	14
Maximum July temperature (C)	155	31	2	21	38
(log) Distance to nearest coast (m)	155	10.768	2.259	0	13.806
(log) Distance to nearest big urban area (m)	155	10.639	3.854	0	13.663

Notes: A big city is a city with at least 300,000 residents.

Geographic Data We control in our regression analysis for several relevant geographic characteristics that may influence city-level employment growth.

Distance Data: Proximity to the coast, which contributes to moderating extreme temperatures, is strongly positively correlated with population growth in the U.S. (see Rappaport and Sachs, 2003). We thus measure the distance between the centroid of each city and the nearest maritime coast. It has also been shown that cities that are close to the top metropolises in the urban hierarchy are more attractive to firms and workers (see Partridge et al., 2009). We thus calculate the distance separating each urban area from the largest urban area of at least 300,000 inhabitants.

Weather Data: Climatic conditions, as proxied by temperatures, are also among the amenities identified in the literature as a determinant of the residential attractiveness of cities (see Glaeser et al., 2001; Rappaport, 2007). I use the monthly climate summaries from the Canadian Centre for Climate Services of Environment and Climate Change to measure, for each city, the average daily warmest temperatures attained in January and July from 2006 to 2016. [18]

Regions: Regional Development Agencies support manufacturers across Canada. [19] Specific regional public policies might also influence city-level population growth; we can think of Quebec, which has its own immigration policy, partly determined by its needs in terms of workforce. We thus build specific dummy variables for the Atlantic regions (New Brunswick, Newfoundland and Labrador, Nova Scotia, Prince Edward Island), the West (Alberta, British Columbia, Manitoba, Saskatchewan), Quebec and Ontario. [20]

Input output distance data I use input-output matrices to calculate this distance measure. One element of this matrix provides the share of industry i's inputs that come from industry j $intput_{ij}$ and the share of industry i's outputs that are sold to industry j $output_{ij}$. Then, I select the maximum share between $intput_{ij}$ and $output_{ij}$ for each ij. The data comes from the 4-digit NAICS average of the manufacturing industry in Canada over the years 1998 to 2010. I then transform it to one minus maximum share to represent the distance between i

18. These data are available from stations that produce daily data from 2006 to 2016.

19. These agencies are Atlantic Canada Opportunities Agency for Atlantic regions, Federal Economic Development Initiative and Federal Economic Development Agency for Ontario, Canada Economic Development for Quebec, and Western Economic Diversification Canada for Western region.

20. We do not use provincial dummies in our regressions because in some provinces, there are too few cities, such as in Atlantic Canada or in Manitoba and Saskatchewan, to allow for statistical inference based on within-province variations (see Table 3.14 in the Appendix).

and j.

3.8.2 Data processing

Geographical structure. Census Metropolitan Areas (CMA) and Census Agglomerations (CA) are the ideal spatial units in Canada for the analysis of local labor markets since their boundaries are delineated based on the commuting patterns of residents. Provinces are too coarse a spatial scale, whereas dissemination areas (census blocks) are too fine to analyze population dynamics following local labor market shocks, because an inventor could easily work in one dissemination area and reside in another. Since each dissemination area belongs to a given urban area (CMA/CA), I aggregate the Census data available at the level of dissemination areas at the urban area level.

I obtain census data at the urban area (CMA/CA) level for 135 urban areas in 1996, 145 in 2001, 148 in 2006, 151 in 2011 and 157 in 2016. The differences between years are explained by the fact that from a statistical point of view, an urban area can lose its census agglomeration status and disappear, or (re)gain it and (re)appear. Note for example that if the population of the core of a CA declines below 10,000, the CA is removed. However, once an urban area becomes a CMA, it remains a CMA even if its total population declines below 100,000 or if the population of its core falls below 50,000.

There are 164 unique urban areas in total (CMA/CA) between 1996 and 2016, of which 127 are present in the 5 census years, 11 in 3 census years, 11 in 2 census years, 8 in 2 census years, and 7 in a single census year. I overlay each urban area for every year it appears, and we take the envelope of the overlaid boundaries. Magog (present in 2001) has been added to Sherbrooke in 2006, so we merge them. Saint-Jean-sur-Richelieu (present in 2001, 2006, 2011) has been added to Montreal in 2016, so we merge them. We get 162 urban areas whose boundaries in terms of municipalities are stable over time. Indeed, in this study, we want to capture innovation variation that are related to city diversity level, not to changes in geographical boundaries.

I keep in the sample only those agglomerations that have at least 10,000 inhabitants on average over the whole 1996-2016 period and for which we have all the necessary information for the econometric analysis. I end up with 155 stable urban areas. I calculate 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 total population of the "stabilized" urban area as we measure it. On average, we can see in Table 3.8 that this ratio is equal to 0.96 over the period 1996-2016, which means that the demographics of stabilized urban areas are quite similar to the demographics of the original urban areas.

Table 3.8: Population ratio between the actual and the stabilized urban areas

	Year				
	1996	2001	2006	2011	2016
Minimum	0.254	0.535	0.320	0.407	0.323
Mean	0.929	0.943	0.958	0.958	0.964
Maximum	1	1	1	1	1
Std. error	0.121	0.091	0.089	0.095	0.098

The boundaries of "actual" urban areas are those defined by Statistics Canada in a given census year. The boundaries of "stabilized" urban areas are defined by the envelope of the boundaries observed across the various census years.

Geocoding process. The raw Scotts data provide some geographical coordinates for the establishments but after several checks, they do not seem extremely reliable. We thus geocode the dataset again.

The geocoding is a process through which an algorithm transforms an address into a pair of coordinates that can be positioned on a map of the surface of the earth. Throughout the process, in addition to the coordinates (longitude, latitude), the geocoder provides the actual addresses related to the coordinates of the points that it returns.

We first start by geolocating the Scotts Database on a postal code basis. To geolocate plants based on postal codes of the Scotts Database, we use latitude and longitude data of postal code centroids obtained from Statistics Canada's Postal Code Conversion Files (PCCF). The problem with zip code geolocation is that a zip code is relatively accurate for large cities, and more imperfect for small cities since the surface area of postal codes is larger in low-density places. We consider the geocoding of the Scott's database based on the postal codes to be "approximate". We thus also run geocoding processes based on the address of the establishments.

The Scott's database provides information on the company name and its full address (street number, street name, postal code, city and province). We use this information to geocode again the database in three ways. First, we use a commercial API on the Google Map server and we provide as input to the geocoder the full address line of each plant. Second, we used th same API of the Google Map server but we combine the company name with the full address line of the plant to generate the input for the geocoder. In this case, the geocoder is supposed to collect the exact location of the plant even if the plant has changed its location after the date on which the Scotts dataset was compiled. Third, we use an alternative API and the DMTI dataset which is an extensive database containing more than 15 million of feature points representing addresses in Canada. This private dataset records the location of addresses in Canada with their related geographic coordinates with a rooftop precision. From the DMTI, we construct an Address-Locator using ArcGIS tools and we geocode all the Scotts addresses via this alternative process.

We find that the geocoding of Google Maps is "rooftop", meaning that the plant is geocoded accurately down to the street address. The geocoding of DMTI is either "range interpolated", meaning that the plant is geocoded by interpolation of two precise points, or "rooftop".

In the end, we assign to each establishment the geographical coordinates that are the most precise among those that are available. First, when both the Google geocoding and the DMTI geocoding report the same coordinates, we retain these coordinates. If the returned coordinates differ, we first select the one based on the company name and the complete address line (Google 2) if available, otherwise we select the geocoding based on the complete address line only (Google 1), otherwise we select the DMTI geocoding, otherwise we maintain the postal code geocoding.

Following this procedure, nearly 88% of our data has a very precise location (rooftop accuracy). The rest is range interpolated or approximate accuracy (postal code geocoding). Table 3.9 shows the distribution of Canadian manufacturing plants according to the geocoding chosen between 2001 and 2017.

Table 3.9: Manufacturing plants data geocoding.

	Scott's 2001	Scott's 2003	Scott's 2005	Scott's 2007	Scott's 2009	Scott's 2011	Scott's 2013	Scott's 2017
Geocoding process								
Google 2 (Plant name & address)	33,744	33,080	32,198	31,240	30,521	29,529	25,972	23,746
Google 1 (Address)	11,350	11,115	10,661	10,033	9,466	8,904	7,242	6,204
DMTI (Address)	2,750	2,699	2,552	2,333	2,188	2,072	1,544	1,458
SCOTTS (PCCF)	6,500	5,890	5,153	4,682	4,474	4,119	3,343	2,727
Total Manufacturing plants	**54,344**	**52,784**	**50,564**	**48,288**	**46,649**	**44,624**	**38,101**	**34,135**
Geocoding Accuracy								
Rooftop	45,235	44,607	43,421	41,977	40,724	39,296	33,900	30,744
Range Interpolated	2,609	2,287	1,990	1,629	1,451	1,209	858	664
Postal Code	6,500	5,890	5,153	4,682	4,474	4,119	3,343	2,727
Total Manufacturing plants	**54,344**	**52,784**	**50,564**	**48,288**	**46,649**	**44,624**	**38,101**	**34,135**

The geocoding process was done by Postal Code Conversion Files (PCCF), Google's commercial API and DMTI spatial.

3.8.3 Index decomposition

In most of the empirical and theoretical literature on diversity, the fractionalization index is determined by the probability that two randomly selected members of a given group belong to different language groups. Greenberg (1956) proposed a so-called B-index, which takes into account the distances between the groups:

$$\mathrm{B} = 1 - \sum_{i=1}^{N} \sum_{j=1}^{N} \mathrm{s}_i \mathrm{s}_j w_{ij}$$

where s_i and s_j are the group shares comprising the entire sample, the sum of which is equal to 1, and w_{ij} refers to the similarity between the two groups.

We can decompose the B-index as follows:

$$\mathrm{B} = 1 - \sum_{i=1}^{N} \sum_{i=1}^{N} \mathrm{s}_i \mathrm{s}_i w_{ii} - \sum_{i=1}^{N} \sum_{j=1 \neq i}^{N} \mathrm{s}_i \mathrm{s}_j w_{ij}$$

$$B = 1 - \sum_{i=1}^{N} s_i{}^2 w_{ii} - \sum_{i=1}^{N} \sum_{j=1}^{N} s_i s_j w_{ij}$$

This index can be expressed in two ways:

Simple index: For each term that includes different groups i and j, the similarity term w_{ij} is equal to 0, so that the term vanishes. If i and $j$are identical, $w_{ij} = 0$, so that the term is s_i x s_i. Therefore, the simple index collects only the s_i x s_i terms; all others will be equal to 0. The index is then rewritten as follows:

$$\text{Simple index} = 1 - \sum_{i=1}^{N} s_i{}^2$$

which is the expression I use as the first measure of diversity in the estimates.

Distance-based index: For this index, we want to isolate only the component that takes into account distinct groups. Thus for each term that includes similar groups i and j, the similarity term $w_{ij} = 0$, so that this term disappears. If i and j are different, $w_{ij} \in [0, 1]$, so that only this term remains. Therefore, the index is written as follows:

$$\text{Distance index} = 1 - \sum_{i=1}^{N} \sum_{j=1}^{N} s_i s_j w_{ij}$$

By considering that $d_{ij} = 1 - w_{ij}$, it is easy to transform the index as follows:

$$\text{Distance index} = 1 - \sum_{i=1}^{N} \sum_{j=1}^{N} s_i s_j (1 - d_{ij})$$

$$\text{Distance index} = 1 - \sum_{i=1}^{N} \sum_{j=1}^{N} s_i s_j (1 - d_{ij})$$

With some algebra :

$$\text{Distance index} = 1 - \sum_{i=1}^{N} \mathrm{s}_i \sum_{j=1}^{N} \mathrm{s}_j + \sum_{i=1}^{N} \sum_{j=1}^{N} \mathrm{s}_i \mathrm{s}_j (1 - d_{ij})$$

with $\sum_{i=1}^{N} \mathrm{s}_i \sum_{j=1}^{N} \mathrm{s}_j = 1$:

$$\text{Distance index} = \sum_{i=1}^{N} \sum_{j=1}^{N} \mathrm{s}_i \mathrm{s}_j (1 - d_{ij})$$

which is the second measure of diversity used in the regression estimates.

3.8.4 Additional tables

Tables on data

Table 3.10: Comparing the Scott's National All database to the Annual Survey of Manufacturing (ASM).

	2001		2003		2005		2007		2009		2011	
Province	ASM	Scott's	ASM	Scott's	ASM	Scott's	ASM	Scott's	ASM	Scott's	ASM	Scott's
Alberta	4,843	3,935	4,882	3,650	7,750	3,482	8,091	3,723	7,852	3,597	7,003	3,477
British Columbia	7,085	6,212	6,933	5,923	11,942	5,400	12,179	5,267	11,605	5,031	11,552	4,946
Manitoba	1,465	1,654	1,481	1,556	2,307	1,489	2,351	1,405	2,323	1,280	1,918	1,302
New Brunswick	986	1,392	963	1,376	1,533	1,262	1,496	1,167	1,412	1,181	1,381	1,030
Newfoundland	525	576	522	578	706	544	738	517	657	482	660	432
Nova Scotia	1,097	1,677	1,106	1,576	1,944	1,506	1,904	1,354	1,817	1,312	1,760	1,184
Ontario	21,514	21,289	21,470	21,758	34,184	20,996	33,634	20,301	31,991	19,670	29,046	18,721
Prince Edward Island	233	328	211	303	299	327	369	309	358	282	342	260
Quebec	15,191	15,933	15,251	14,773	23,042	14,200	22,324	12,992	21,149	12,660	19,272	12,091
Saskatchewan	1,044	1,348	1,008	1,291	1,664	1,318	1,845	1,203	1,861	1,109	1,410	1,140
Territories		0		0		40		50		45		41
Canada	53,983	54,344	53,827	52,784	85,371	50,564	84,931	48,288	81,025	46,649	74,344	44,624
Cross-industry correlation	***0.973***		***0.972***		***0.945***		***0.935***		***0.932***		***0.881***	

Notes: Data are from the Scott's databases and Statistics Canada Annual Survey of Manufacturing (and Logging Industries) Table 16-10-0054-01 and Table 16-10-0038-01. The 2001 and 2003 ASMs report only employer plants with sales exceeding C$30,000 whereas the 2005 to 2009 ASMs report information for manufacturing plants (including logging industries, which is absent in the 2001 and 2003 ASMs) for all plants. The descriptive statistics reported as "cross-industry" in the bottom panel of the table are computed across all 3 digits manufacturing industries (NAICS 311–339).

Table 3.11: Comparing the Scott's National All database to the Canadian business counts (CBC).

	2001		2005		2009		2013		2017	
Province	CBC	Scott's	CBC	Scott's	CBC	Scott's	CBC	Scott's	CBC	Scott's
Alberta	5,843	3,935	5,416	3,482	5,351	3,597	4,882	3,144	4,095	2,891
British Columbia	8,797	6,212	8,261	5,400	7,697	5,031	6,933	4,148	5,984	3,966
Manitoba	1,883	1,654	1,741	1,489	1,605	1,280	1,481	1,108	1,049	1,061
New Brunswick	1,446	1,392	1,195	1,262	1,018	1,181	963	873	431	740
Newfoundland	757	576	629	544	508	482	522	364	244	320
Nova Scotia	1,832	1,677	1,483	1,506	1,225	1,312	1,106	970	666	816
Ontario	25,006	21,289	23,220	20,996	21,673	19,670	21,470	15,933	16,722	14,277
Prince Edward Island	354	328	292	327	256	282	211	199	114	154
Quebec	18,349	15,933	17,026	14,200	15,238	12,660	15,251	10,378	9,939	8,980
Saskatchewan	1,378	1,348	1,259	1,318	1,151	1,109	1,008	948	877	895
Territories		0		40		45		36		35
Canada	65,645	54,344	60,522	50,564	55,722	46,649	53,827	38,101	40,121	34,135
Cross-industry correlation	***0.908***		***0.939***		***0.937***		***0.931***		***0.773***	

Notes: Data are from Scott's National All databases and CBP (Table 33-10-0028-01 ,Table 33-10-0035-01). The descriptive statistics reported as "cross-industry" in the bottom panel of the table are computed across all 3 manufacturing digits industries (NAICS 311–339).

Table 3.12: Comparing the Scott's National All databases to the Labor Force Survey (LFS) by Cities (>100K).

	2001		2003		2005		2007		2009		2011		2013		2017	
Census Metropolitan Area	LFS	Scott's	LFS	Scott's	LFS	Scott's	LFS	Scott's	LFS	Scott's	LFS	Scott's	LFS	Scott's	LFS	Scott's
Abbotsford - Mission	10.6	6.7	9.9	6.7	9.9	7	10.4	6.7	8.5	6.3	7.5	5.8	8.2	4.9	9.7	5.1
Barrie	13.1	6.5	14.8	6.5	17.4	7.3	15.4	7.9	10.4	6.9	14.4	5.7	14.8	5.7	15.5	5.3
Brantford	15.8	9.6	17.4	10.2	17.7	15.2	15.8	14.1	14.5	13.4	13.6	10.8	13.8	10.5	14.4	9.5
Calgary	51.2	47.9	53.4	46.9	42.6	46.5	47.3	52	42.5	50	46.1	46.3	46.2	40.2	39	36.1
Edmonton	48.4	40.9	50.2	43.4	48.8	47.8	53.5	55.2	44.2	52.6	51.4	51.1	58.7	47.2	41.5	45.6
Gatineau	6.8	3.8	6.7	4.6	8	5	7.5	4.4	6.7	3.6	7	3.4	6.3	3	7	3.2
Greater Sudbury	3.6	3.6	4.3	4	4.4	4	3.7	3.7	3.5	3.6	3.9	3.5	3.3	3.4	3.1	3
Guelph	19.7	18	19.8	19.5	20.2	18.7	19.2	16.2	15.3	16.6	15.6	15.7	14.7	15.2	16.8	16.8
Halifax	11.5	11.1	10.8	12.1	9.9	10.9	12.5	12.2	11.8	12.9	11.4	12.7	10	10.6	10.5	8.7
Hamilton	73.7	37.4	76.2	38.5	69.2	39	58.1	37.5	51.1	35.3	49.3	34.4	46.6	31.8	49.8	29.3
Kelowna	6.5	5	7.8	5.4	6.4	6	8.3	5.9	6.6	5.4	6.3	5	4.4	5.9	5	4.7
Kingston	6.6	4.2	6	3.7	6.1	3.2	5.2	2.9	4.1	3	4.4	2.9	4	2.4	3.9	3.4
London	36	21.5	41.7	24	39.4	25.4	35.1	25.8	29.9	24.7	29.2	19.9	27.4	19.2	29.8	15.6
Moncton	6	5.2	5	6	4.4	6.1	4.3	5.6	5.9	6	5.4	5	4.6	5.2	4.2	4.1
Montreal	314.4	271.5	291.4	253.7	286.9	242	246.2	219.6	242.8	218.9	224.2	205.7	225.7	171.6	226	156.2
Oshawa	32.1	9.7	33.6	11	32.5	10.8	26.8	9.8	20.5	8.6	19.4	7.4	20.5	6.2	17.1	6.2
Ottawa	35.8	18.7	28.2	18.5	30.3	18.1	36	19.7	29.2	20.5	20.3	21.9	17	17.8	17.7	16.7
Peterborough	7.1	5	7.6	4.7	7.2	4.4	8.2	4.8	6	4.8	5.9	4.4	4.8	4.7	3.8	5.3
Quebec	32.4	29.5	33	29.6	40.7	34.9	39.3	34.4	32.3	34.8	32.2	32.4	28.4	32.1	32.1	28.4
Regina	5	6.5	5.5	5.9	6.4	6.1	6.5	6.8	7.5	6.3	6.8	7	7	5.4	8.3	5.5
Saguenay	11.2	7.5	10.2	7.5	10.6	8.3	11	8.6	9.1	8.8	8.6	9.2	9.3	6.8	7.8	6
Saint John	5.1	5.9	5.1	5.6	4.1	5.5	6	5.2	5.4	5.6	5.5	3.4	4.4	3.7	5.9	3.3
Saskatoon	10.1	11.8	9.2	12.5	11.8	11.2	11.3	10	11.1	9.7	9.1	10	11.4	8.8	8.8	8.4
Sherbrooke	19.7	16.7	23.1	15.7	17.6	14.8	14	11.6	12.4	11.9	13.3	11.8	11.9	10.9	14.8	11.1
St John's	3.5	6.8	3.4	5.9	3.9	5.4	5.2	6	4.4	6	3.8	5.7	5.1	6	3.7	4.5
St. Catharines - Niagara	32.4	22.1	30.5	21.8	26.9	20.7	25.6	18.7	20.6	16.6	21	15	21.8	12.8	21.6	12.6
Thunder Bay	7	3.6	6.7	3.7	5	3.7	4.4	3.4	2.9	2.8	2.9	3.5	4.2	2.5	3.2	2.1
Toronto	452.3	359.8	466.6	382.8	457.1	372	397.6	353.8	328.4	340.6	331.9	308.1	334.1	278.2	336.8	251.7
Trois-Rivieres	11.7	7.5	11	8.2	11.4	7.8	10.5	7.8	9.7	8.3	8.3	7.7	8.3	6.5	9.6	5.9
Vancouver	104.2	97.6	112.7	96.5	101.2	93	105.6	96.9	86.1	94.3	85.1	91.4	84.7	75.8	99.9	75.3
Victoria	6.3	5.3	8.5	6.1	7.7	5.7	6.7	5.7	6.2	5.9	5.9	5.7	5.8	5.4	7.2	4.8
Waterloo	63.2	42.6	63	46.1	63.7	46.8	59	43.6	49.8	40.9	49.3	35.9	52.3	30.3	51.3	30.5
Windsor	46.3	25.1	48.2	27.3	48	26.5	35.5	27.7	29.6	25.5	30.7	21.5	31.4	19	38.4	18.6
Winnipeg	50.5	37.9	47	38.2	45.7	38.4	48	35.6	40.5	33.1	37.5	33.6	41.3	29.7	42.8	25.2
Cross-employment correlation	***0.995***		***0.996***		***0.996***		***0.997***		***0.995***		***0.997***		***0.996***		***0.995***	

Notes: Distribution of Census Metropolitan Areas' employment (x1000) of manufacturing plants (NAICS 311–339). Data are from Scott's National All databases and Labor Force Survey Statistic Canada (Table 14-10-0098-01). The descriptive statistics reported as "cross-industry" in the bottom panel of the table are computed across all 3 digits industries.

Table 3.13: Breakdown of manufacturing plants by sector in Canada.

NAICS4	Manufacturing sector	(1) Total plants	(2) Total employment	NAICS4	Manufacturing sector	(1) Total plants	(2) Total employment
3261	Plastic product	2361	102909	3272	Glass and glass product	460	12798
3231	Printing and related support activities	4242	83043	3333	Commercial and service industry machinery	347	12348
3323	Architectural and structural metals	2643	79440	3324	Boiler, tank and shipping container	256	12169
3332	Industrial machinery	3198	78813	3255	Paint, coating and adhesive	302	11727
3219	Other wood product	2880	78708	3313	Alumina and aluminum production and processing	110	11071
3211	Sawmills and wood preservation	827	54819	3359	Other electrical equipment and component	288	10847
3363	Motor vehicle parts	824	46960	3364	Aerospace product and parts	144	10599
3116	Meat product	752	42977	3322	Cutlery and hand tool	326	10469
3399	Other miscellaneous	3041	40906	3113	Sugar and confectionery product	234	10235
3222	Converted paper product	649	40499	3141	Textile furnishings mills	352	8973
3327	Machine shops, turned product, and screw, nut and bolt	2106	39512	3312	Steel product from purchased steel	101	8958
3152	Cut and sew clothing	1077	34016	3314	Non-ferrous metal (except aluminum) production and processing	131	8813
3117	Seafood product preparation and packaging	440	32938	3321	Forging and stamping	178	8772
3221	Pulp, paper and paperboard mills	158	32542	3112	Grain and oilseed milling	186	8695
3331	Agricultural, construction and mining machinery	746	32089	3132	Fabric mills	139	8045
3118	Bakeries and tortilla	965	31865	3253	Pesticide, fertilizer and other agricultural chemical	201	7981
3329	Other fabricated metal product	981	30797	3311	Iron and steel mills and ferro-alloy	242	7957
3273	Cement and concrete product	1073	29413	3351	Electric lighting equipment	194	7955
3335	Metalworking machinery	915	27371	3252	Resin, synthetic rubber, and artificial and synthetic fibres and filaments	103	6734
3119	Other food	565	25629	3341	Computer and peripheral equipment	182	6521
3371	Household and institutional furniture and kitchen cabinet	1237	24909	3336	Engine, turbine and power transmission equipment	238	6516
3372	Office furniture (including fixtures)	669	24162	3379	Other furniture-related product	216	6178
3339	Other general-purpose machinery	621	23508	3334	Ventilation, heating, air-conditioning and commercial refrigeration equipment	164	5384
3212	Veneer, plywood and engineered wood product	331	22544	3325	Hardware	106	5016
3345	Navigational, measuring, medical and control instruments	664	22466	3366	Ship and boat building	43	4467
3361	Motor vehicle	194	22451	3151	Clothing knitting mills	84	4405
3254	Pharmaceutical and medicine	239	20437	3262	Rubber product	88	4357
3353	Electrical equipment	482	20407	3326	Spring and wire product	120	4348
3115	Dairy product	275	20401	3346	Manufacturing and reproducing magnetic and optical media	130	4143
3344	Semiconductor and other electronic component	399	19895	3271	Clay product and refractory	167	3825
3241	Petroleum and coal product	307	19759	3133	Textile and fabric finishing and fabric coating	120	3481
3149	Other textile product mills	1087	19416	3162	Footwear	76	3182
3328	Coating, engraving, cold and heat treating and allied activities	696	18914	3274	Lime and gypsum product	54	2917
3121	Beverage	444	17834	3169	Other leather and allied product	162	2884
3114	Fruit and vegetable preserving	285	17343	3159	Clothing accessories and other clothing	114	2580
3315	Foundries	238	16456	3369	Other transportation equipment	60	2439
3362	Motor vehicle body and trailer	366	16107	3131	Fibre, yarn and thread mills	34	2384
3251	Basic chemical	319	14358	3352	Household appliance	69	2355
3259	Other chemical product	459	13828	3365	Railroad rolling stock	30	1920
3256	Soap, cleaning compound and toilet preparation	415	13466	3122	Tobacco	14	1847
3342	Communications equipment	281	12929	3343	Audio and video equipment	59	1387
				3161	Leather and hide tanning and finishing	27	447

Notes: Data from the Scott's National All Business Directories. The table is based on manufacturing plants (NAICS 3111–3399).

Table 3.14: Geographical breakdown of urban areas in Canada.

Region	Province	Total urban areas	Census metropolitan areas (CMA)	Census agglomeration CA	Minimum average population	Maximum average population
Western	Alberta	18	3	15	11,097	1,159,220
	British Columbia	26	4	22	13,609	2,214,755
	Manitoba	6	1	5	12,411	719,675
	Saskatchewan	10	2	8	10,074	254,852
		60	***10***	***50***	***10,074***	***2,214,755***
Atlantic	New Brunswick	7	2	5	15,080	132,529
	Newfoundland and Labrador	5	1	4	10,019	189,197
	Nova Scotia	5	1	4	25,933	379,159
	Prince Edward Island	2	0	2	16,355	64,537
		19	***4***	***15***	***10,019***	***379,159***
Ontario	Ontario	***46***	***16***	***30***	***10,791***	***5,316,603***
Quebec	Quebec	***30***	***6***	***24***	***12,205***	***3,820,933***
Canada		**155**	**36**	**119**	**10,019**	**5,316,603**

Notes : The table is based on census metropolitan agglomeration and census agglomeration information from Statistic Canada in 2006.

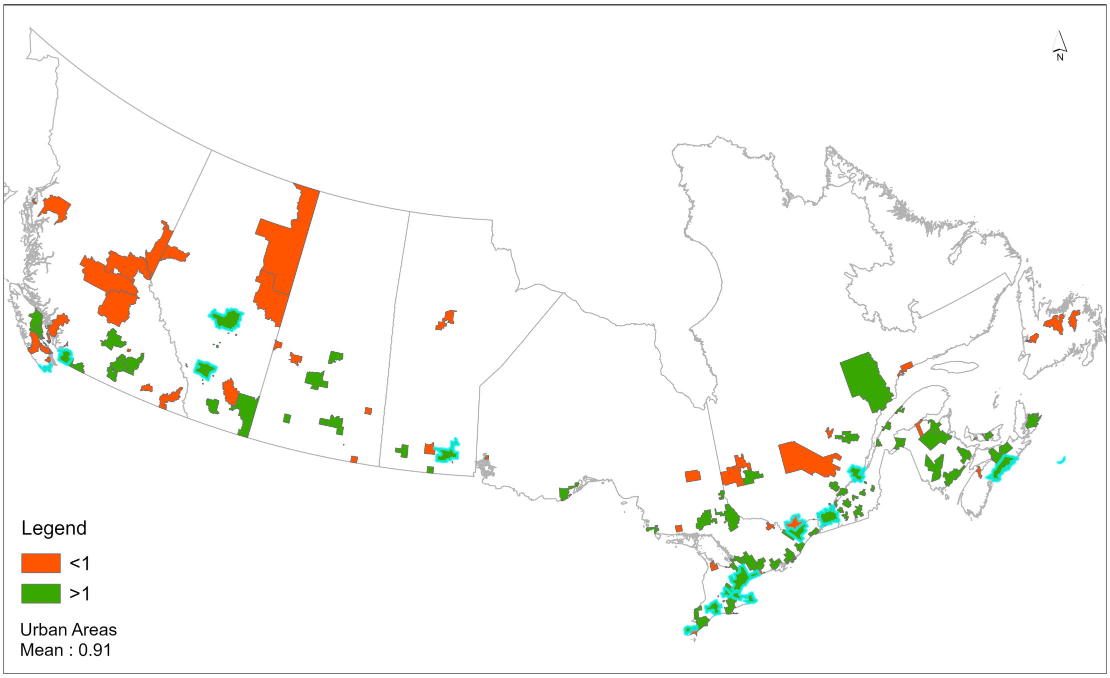
Table 3.15: Descriptive statistics of big manufacturing plants closed by NAICS 3-digit sectors.

NAICS3	Manufacturing sector	(1) Closure rate closed in initial plants	(3) Avg. # jobs of closed big plants
321	Wood product	17.0%	196.3
313	Chemical	11.9%	157.7
331	Primary metal	10.5%	187.7
336	Transportation equipment	9.8%	202.8
314	Textile product mills	9.0%	116.9
326	Plastics and rubber products	8.3%	136.6
316	Leather and allied product	7.8%	138.8
311	Food	7.6%	154.3
324	Petroleum and coal product	7.5%	140.9
334	Computer and electronic product	7.0%	140.2
323	Printing and related support actv.	6.5%	222.9
335	Electrical equipment, appliance	5.6%	160.6
333	Machinery	5.0%	125.9
313	Textile mills	4.7%	116.6
337	Furniture and related product	4.6%	110.9
327	Non-metallic mineral product	4.0%	131.4
332	Fabricated metal product	4.0%	119.4
315	Clothing	3.8%	106.7
322	Paper	3.5%	141.5
312	Beverage and tobacco product	3.5%	136.3
339	Miscellaneous	2.2%	125.0
	All sectors	**5.9%**	**143.3**

Notes: "Big plants" refer to 50+ establishments from 2003 that disappeared in 2017. The data are from Scott's National All Business Directories.

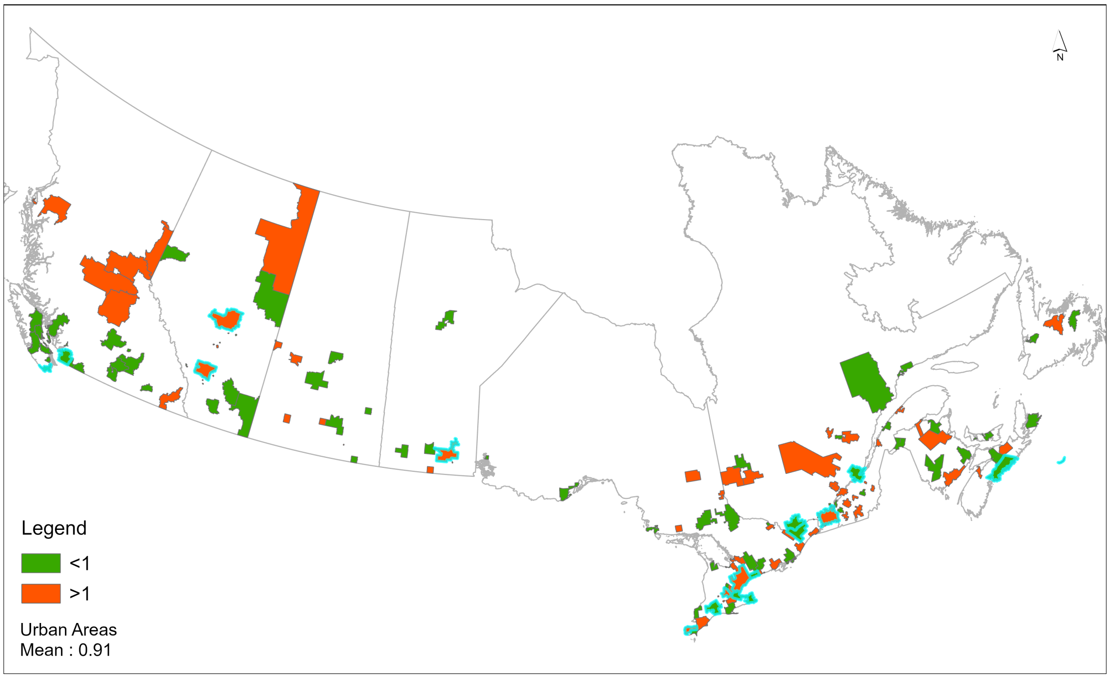
Figures on data

Figure 3.3: Relative manufacturing diversity with input-output flows based distances



Notes: Manufacturing diversity are measured relatively to the urban area average. A value of 1 on the map means that the urban area's growth rate is the same as all urban areas mean. Cyan contours outline cities with population of at least 300,000.

Figure 3.4: Big manufacturing plant closures in Canadian urban areas



Notes: Cyan contours outline cities with population of at least 300,000.

3.9 Additional results

Table 3.16: Placebo Test : Manufacturing diversity and local growth in Canadian cities

Dependent variable y: Growth of	Total Population		Total Employment		Total Unemployment	
	IV(1) Simple index	IV(2) Distance index	IV(3) Simple index	IV(4) Distance index	IV(5) Simple index	IV(6) Distance index
Manufacturing diversity	0.109		0.169		0.002	
	(0.118)		(0.157)		(0.012)	
Manufacturing diversity (input/output distance)		0.103		0.163		0.011
		(0.114)		(0.152)		(0.013)
Ln Total initial employment	-0.177***	-0.174***	-0.150**	-0.146**		
	(0.058)	(0.057)	(0.067)	(0.065)		
Share of 15+ with a university degree	0.035	0.033	-0.040	-0.042	-0.106	-0.107
	(0.042)	(0.042)	(0.046)	(0.046)	(0.131)	(0.130)
Share of manufacturing employment	-0.121***	-0.116***	-0.136***	-0.129***	-0.077	-0.077
	(0.022)	(0.022)	(0.038)	(0.042)	(0.065)	(0.066)
Unemployment rate	-0.387*	-0.386*	-0.431*	-0.428*	-0.113	-0.112
	(0.218)	(0.219)	(0.245)	(0.245)	(0.209)	(0.210)
January maximum temperature	0.285***	0.286***	0.256***	0.256***	-0.079	-0.081
	(0.049)	(0.049)	(0.061)	(0.061)	(0.147)	(0.146)
July maximum temperature	-0.067	-0.068	-0.086	-0.088	-0.074	-0.075
	(0.066)	(0.064)	(0.061)	(0.060)	(0.145)	(0.145)
Log distance to nearest coastline	0.058	0.058	0.068	0.069	0.037	0.037
	(0.056)	(0.055)	(0.064)	(0.064)	(0.048)	(0.048)
Log distance to nearest big city	-0.046***	-0.046***	-0.045***	-0.044***	-0.072***	-0.072***
	(0.011)	(0.011)	(0.008)	(0.008)	(0.020)	(0.020)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	0.890	0.890	0.890	0.890	0.852	0.852
IV P value	0.000	0.000	0.000	0.000	0.000	0.000
IV Partial R2	0.64	0.63	0.64	0.63	0.68	0.67
First stage F statistic	35	34	35	34	37	36
Urban Areas	155	155	155	155	155	155

Notes : The table presents OLS and 2SLS estimates. Coefficients are all measured in standard deviations. Diversity is measured by a generalized fractionalization index. The "skilled" are the 15+ residents with at least a bachelor degree. Temperatures are in Celsius and distances in meters. A big city is a city with at least 300,000 residents. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases, Statistic Canada's Census 1996-2016 and boundaries files, Environment Canada's weather data.

Table 3.17: Alternative IV : Manufacturing diversity and local growth in Canadian cities

Dependent variable y: Growth of	Total Population		Total Employment		Total Unemployment	
	IV(1) Simple index	IV(2) Distance index	IV(3) Simple index	IV(4) Distance index	IV(5) Simple index	IV(6) Distance index
Manufacturing diversity	0.182**		0.131***		0.015	
	(0.071)		(0.035)		(0.036)	
Manufacturing diversity (input/output distance)		0.182**		0.136***		0.011
		(0.074)		(0.037)		(0.038)
Ln Total initial employment	-0.177*	-0.176*	-0.150*	-0.151*	-0.135**	-0.134**
	(0.101)	(0.103)	(0.077)	(0.079)	(0.057)	(0.057)
Share of 15+ with a university degree	0.163	0.161	0.250**	0.249**	-0.143	-0.143
	(0.126)	(0.127)	(0.120)	(0.122)	(0.088)	(0.089)
Share of manufacturing employment	-0.105***	-0.098***	-0.148***	-0.144***	-0.195**	-0.194**
	(0.034)	(0.031)	(0.039)	(0.039)	(0.083)	(0.082)
Unemployment rate	-0.370	-0.366	-0.137	-0.133	-0.518*	-0.518*
	(0.228)	(0.229)	(0.222)	(0.223)	(0.271)	(0.271)
January maximum temperature	0.101*	0.100*	0.063	0.061	0.198***	0.199***
	(0.054)	(0.051)	(0.116)	(0.113)	(0.064)	(0.064)
July maximum temperature	-0.015	-0.017	0.019	0.017	-0.148*	-0.148*
	(0.081)	(0.080)	(0.067)	(0.067)	(0.087)	(0.087)
Log distance to nearest coastline	0.024	0.025	0.019	0.020	0.122	0.122
	(0.047)	(0.047)	(0.018)	(0.019)	(0.077)	(0.077)
Log distance to nearest big city	-0.036**	-0.036**	-0.031**	-0.031**	-0.049**	-0.049**
	(0.015)	(0.015)	(0.016)	(0.015)	(0.024)	(0.024)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	0.739	0.739	0.739	0.739	0.739	0.739
IV P value	0.000	0.000	0.000	0.000	0.000	0.000
IV Partial R2	0.50	0.47	0.50	0.47	0.50	0.47
First stage F statistic	27	25	27	25	27	25
Urban Areas	155	155	155	155	155	155

Notes: The table presents 2SLS estimates. Coefficients are all measured in standard deviations. Diversity is measured by a generalized fractionalization index. The "skilled" are the 15+ residents with at least a bachelor degree. Temperatures are in Celsius and distances in meters. A big city is a city with at least 300,000 residents. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases, Statistic Canada's Census 2006-2016 and boundaries files, Environment Canada's weather data.

Table 3.18: Manufacturing diversity and employment by industry in Canadian cities

Dependent variable y: Growth of	Manufacturing industry	Construction services	Arts, entertainment and recreation services	Professional services	Trade and transport services	Education and health services	Accomodation and food services
	IV(1) Distance index	IV(2) Distance index	IV(3) Distance index	IV(4) Distance index	IV(5) Distance index	IV(6) Distance index	IV(7) Distance index
Manufacturing diversity (input/output distance)	0.142**	0.232***	0.282***	0.154**	-0.055	0.076	-0.029
	(0.062)	(0.027)	(0.042)	(0.076)	(0.067)	(0.094)	(0.051)
Ln Total initial employment	-0.006	0.004	-0.267***	-0.133*	-0.085***	-0.129***	-0.033
	(0.082)	(0.065)	(0.024)	(0.077)	(0.029)	(0.029)	(0.083)
Share of 15+ with a university degree	0.036	0.108***	0.184*	-0.028	0.132	-0.058	0.068
	(0.044)	(0.040)	(0.109)	(0.236)	(0.089)	(0.138)	(0.122)
Share of manufacturing employment	-0.045	0.182**	-0.022	0.010	0.003	-0.132	-0.034
	(0.145)	(0.080)	(0.026)	(0.109)	(0.107)	(0.099)	(0.098)
Unemployment rate	-0.459*	0.111	-0.180	-0.317**	-0.314	-0.289***	-0.133
	(0.240)	(0.207)	(0.116)	(0.148)	(0.200)	(0.097)	(0.279)
January maximum temperature	-0.068	-0.295**	0.172**	0.003	0.191***	0.125***	0.067
	(0.127)	(0.141)	(0.078)	(0.053)	(0.035)	(0.044)	(0.116)
July maximum temperature	0.025	-0.159*	-0.112	-0.025	0.031	0.070	0.184***
	(0.047)	(0.096)	(0.089)	(0.039)	(0.057)	(0.053)	(0.029)
Log distance to nearest coastline	0.037**	0.063	0.011	-0.021	0.015	0.011	-0.011
	(0.016)	(0.040)	(0.016)	(0.013)	(0.029)	(0.036)	(0.037)
Log distance to nearest big city	0.013	-0.002	-0.039***	-0.041**	-0.025*	-0.015**	-0.035
	(0.016)	(0.010)	(0.013)	(0.020)	(0.015)	(0.007)	(0.023)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV estimate	0.890	0.890	0.890	0.890	0.890	0.890	0.890
IV P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IV Partial R2	0.63	0.63	0.63	0.63	0.63	0.63	0.63
First stage F statistic	34	34	34	34	34	34	34
Urban Areas	155	155	155	155	155	155	155

Notes : The table presents 2SLS estimates. Coefficients are all measured in standard deviations. Diversity is measured by a fractionalization index with input-ouput distance between sectors. The "skilled" are the 15+ residents with at least a bachelor degree. Temperatures are in Celsius and distances in meters. A big city is a city with at least 300,000 residents. Standard errors in parentheses are clustered at the level of big Canadian regions. Significance levels 0.10 * 0.05 ** 0.01 ***. Data are from Canadian patent database digitized by the CD Howe Institute, Scott's National All databases, Statistic Canada's Census 2006-2016 and boundaries files, Environment Canada's weather data.

CONCLUSION

Cette thèse propose trois chapitres relatifs à la croissance des villes. Elle vise à répondre aux questions suivantes : Quelles sont les principales causes de croissances dans les villes et quels sont les facteurs de résilience des villes durant des chocs économiques ? Le premier chapitre examine l'effet des fermetures de grandes usines manufacturières sur les changements sociodémographiques dans les zones urbaines entre 2001 et 2016. Le deuxième chapitre examine la diversité culturelle et industrielle comme déterminants du niveau d'innovation locale, un moteur important de la croissance économique urbaine, entre 2006 et 2016. Enfin, le troisième chapitre analyse la diversité industrielle comme source de croissance de l'emploi et de résilience dans les villes entre 2006 et 2016.

J'ai identifié quatres clés de la croissance démographique des villes des économies développées. Premièrement, les pertes d'emplois dues aux fermetures de grandes usines et aux licenciements massifs ont un effet négatif sur la croissance de la population dans les zones urbaines du Canada entre 2001 et 2016. Cet effet est concentré sur les résidents plus jeunes (en âge de travailler). La part des familles et des couples dans la population locale augmente dans les villes où les pertes d'emploi sont les plus élevées, ce qui montre qu'ils sont moins mobiles que les personnes seules. À l'inverse, la part des immigrés diminue, conformément au fait bien documenté que les immigrés sont plus mobiles et que leurs décisions de localisation sont davantage motivées par les opportunités d'emploi. Certaines caractéristiques initiales de la ville, telles que l'offre de services publics (éducation, santé et services sociaux), ainsi que les commodités de consommation (arts et services récréatifs), contribuent à atténuer l'effet négatif des fermetures d'usines sur les changements démographiques ultérieurs pour certaines catégories de population.

Deuxièmement, une composition ethnique plus diverse de la population, et une composition sectorielle plus diverse des usines manufacturières, conduisent à des niveaux plus élevés d'activité d'innovation dans les zones urbaines canadiennes entre 2006 et 2016. Les effets de la diversité ethnique sur l'innovation passent principalement par les différences entre les groupes ethniques qui assurent un mélange d'idées et de compétences propice à l'innovation. Pour la diversité manufacturière, ce sont les différentes usines qui composent l'industrie manufacturière qui assurent un niveau d'innovation plus élevé que la présence de l'industrie manufacturière dans la ville. Je montre également que la diversité ethnique a des effets plus forts sur l'innovation locale que la diversité manufacturière. Troisièmement, la diversité industrielle et la croissance de l'emploi sont positives et significatives, en particulier pour l'emploi des hommes, et dans les services d'art, de divertissement et de loisirs, les services professionnels et les services de construction. Deplus, je constate que la diversité industrielle aide les villes à maintenir le niveau d'emploi en présence d'un choc négatif sur la demande de main-d'oeuvre locale.

L'implication de ces résultats est que les investissements dans l'éducation, la santé et les services sociaux, ou dans les services culturels et récréatifs pourraient avoir des effets à long terme en favorisant la capacité des villes à retenir leurs résidents les plus mobiles en cas de mauvais chocs. Une autre implication de ces résultats est que les investissements qui favorisent un écosystème diversifié de personnes et d'entreprises, ne partageant pas nécessairement des similitudes apparentes, contribueront à soutenir la croissance économique des villes tirée par l'innovation et le progrès technologique. Enfin, cela implique que les régions doivent continuellement investir dans une variété d'industries qui leur sont associées afin de maintenir des gains d'emploi élevés et d'assurer une plus grande résilience aux chocs économiques.

Les nuances de l'innovation, de la diversité et les spécificités du système urbain canadien éclairent vos résultats. Au cours de la dernière décennie, le flux de brevets canadiens dans tous les secteurs techniques n'a cessé de diminuer.[21] Ainsi, tout en ne produisant qu'environ 1% des brevets mondiaux, le Canada est un exportateur net de brevets, notamment dans les domaines du génie électrique, des télécommunications et des communications numériques. En plus de ne pas réussir à conserver ses brevets localement, le Canada a du mal à transformer ses inventions (souvent mesurées par le nombre de brevets) en innovations. Il existe également une hétérogénéité considérable dans le brevetage entre les provinces, l'Ontario étant en tête. Le nombre de brevets est également beaucoup plus élevé dans les grandes villes comme Toronto, Montréal, Vancouver, Ottawa et Calgary. Le Canada est à la traîne de ses pairs en matière d'innovation depuis des décennies. Ainsi, une analyse de la capacité d'innovation du Canada basée sur les brevets devrait tenir compte de leur distribution non uniforme dans l'espace (notre analyse inclut des effets fixes de province et tient compte de la taille des villes), ainsi que de leur transformation imparfaite en innovation effective.

La population canadienne est de plus en plus diversifiée et cette diversité semble se concentrer dans les plus grandes villes telles que Toronto, Vancouver ou Montréal. La concentration des choix de localisation des immigrants s'apparente aux tendances générales de la croissance urbaine au Canada (e.g. Polèse and Shearmur, 2006). En effet, le Canada est marqué par une diminution de la population dans de nombreuses régions à l'extérieur des grandes villes et par une concentration croissante de l'emploi dans les grandes villes (e.g. Beckstead and Brown, 2003; Shearmur and Polèse, 2007). La nature hautement métropolitaine de l'immigration récente et la nature variée de cette immigration font que les plus grandes villes du Canada sont à la fois de plus en plus diversifiées et de plus en plus différentes du reste du Canada. Des études montrent que les migrants augmentent la diversité de la société (e.g. Collier, 2013), et bien que tous les immigrants ne soient pas ethniquement différents de la population autochtone, l'hétérogénéité ethnique dans la société moderne est largement déter-

21. voir CCA, 2018, Competing in a Global Innovation Economy : L'état actuel de la R&D au Canada

minée par la marée montante de l'immigration. Cela fait du Canada un cas intéressant de diversité à analyser, en intégrant à l'analyse la forte diversité observée dans les grandes villes.

Cette thèse apporte trois contributions à la littérature économique. Premièrement, elle ajoute à la littérature sur la recherche du marché du travail local, une analyse de la relation entre les fermetures d'usines et les changements démographiques au niveau local. Les fermetures d'usines et les licenciements massifs peuvent remodeler la composition démographique des villes en déplaçant des populations plus mobiles, ce qui peut à son tour affecter les perspectives de croissance de ces villes. Elle ajoute également à cette littérature que la diversité technologique est associée à la croissance de l'emploi, en particulier pour l'emploi des femmes, et dans les services d'art, de divertissement et de loisirs, les services professionnels et les services de commerce et de transport. Deuxièmement, elle ajoute à la littérature récente sur la résilience des économies locales, certaines caractéristiques au niveau de la ville telles que la présence de services d'éducation et de santé, ainsi que les équipements artistiques et récréatif, ou d'une industrie locale plus diverse, contribuent à la résilience face à des chocs locaux. Enfin, l'étude ajoute des éléments à la littérature sur la diversité régionale en montrant que la diversité culturelle et industrielle sont simultanément un moteur important de la croissance urbaine.

En revanche, certains moteurs potentiels de la croissance des villes restent encore à explorer, comme les effets des administrations municipales, des politiques locales et des finances publiques. Ensuite, les moteurs de la croissance urbaine peuvent se substituer les uns aux autres ou, peut-être, se compléter. La compréhension des relations entre les moteurs de la croissance urbaine présente un intérêt académique, mais elle pourrait également être très pertinente pour la conception de stratégies de croissance urbaine. Enfin, malgré la croissance des villes, toute la population ne bénéficie pas de cette croissance, en plus de devoir supporter les effets de la congestion et de la pollution. Il conviendrait de présenter davantage de données empiriques sur les effets de la croissance économique sur le bien-être des populations locales et sur la manière dont les politiques pourraient être orientées pour que les personnes peu qualifiées ou peu productives, par exemple, bénéficient de cette croissance.

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