Deindustrialization and demographic change: Evidence from big plant closures and downsizing*

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Abstract

We estimate the causal effect of big manufacturing plant closures and downsizing on the socio-economic composition of Canadian cities between 2001 and 2021. Our instrumental variables estimates show that big manufacturing plant closures and downsizing—large local labor demand shocks—lead to less population growth and a shift in the demographic composition of cities towards an older population with less families. We find no other robust socio-demographic changes following big manufacturing plant closures. Exploiting heterogeneity across cities, we also find no robust evidence that initial city size and industrial diversity help to mitigate those negative effects. According to our results, the only factor, if anything, that may help make cities more resilient is the initial presence of cultural and recreational services.

Keywords: Big plant closures; downsizing; demographic change; manufacturing; city resilience.

JEL Classification: J10; R11; R12; R23.

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"The long view of urban resilience suggests that cities are far more vulnerable to economic and political dislocation than to earthquakes, wars and even pandemics. The most consequential catastrophes are those that fragment existing institutions and economies [...]." (Glaeser, 2022, p.4).

"In some regions of the country where the economy is not very diversified, the loss of manufacturing jobs can have particularly negative effects. In these regions, the closure of even a single plant, supplied by several companies, can weaken the economy." (Statistics Canada).

1 Introduction

How cities are affected by negative local labor demand shocks and what mitigates the effects of such shocks is an old and recurring question in regional and urban economics. While the negative shocks to the US automotive industry and the associated decline of Detroit have been an extreme case and, therefore, the most analyzed (Glaeser, 2012), the underlying dynamics play out at a smaller scale in many other places. Recently, a particular type of local labor demand shock—the exposure to changes in the international trading environment—has attracted substantial attention. Following the 'China shock' (Autor et al., 2013), numerous papers have investigated how local employment losses are shaped by cities' import exposure—which forces plants to either exit or to downsize their operations substantially. This analysis has a renewed sense of urgency in early 2025 following the indiscriminate adoption of substantial blanket tariffs by the second Trump administration. Canada, being one of the largest US trading partners, is likely to be significantly affected by these tariffs. Their effects will be felt differentially across places, based on their tariff exposure. While places such as Saint John, NB; Calgary, AB; or Winsor, ON, are strongly exposed to the tariffs, other places such as Sudbury, ON; Kamloops, BC; or Nanaimo, BC are less exposed.[1]

In this paper, we do not directly investigate how import exposure affects the economic performance of cities but rather look at how job losses due to the closure or downsizing of large manufacturing plants—eventually driven by import exposure—affect cities' population dynamics and demographic composition over the longer run. Do cities that experience more job losses due to big

[1]See, e.g., the ranking of Canadian cities' vulnerability to US tarifs by Stephen Tapp (2025). Source: https://businessdatalab.ca/publications/which-canadian-cities-are-most-exposed-to-trumps-tariffs/, last accessed on September 11, 2025.

plant closures or downsizing see their population grow less than less affected cities? How does the age structure of the population change? How do other socio-demographic characteristics—the sex ratio, the share of highly educated, the family structure—change? And what are the factors, if any, that can mitigate the negative effects of these closures?

To answer these questions, we leverage detailed establishment-level data from 2001 to 2021 and construct city-level measures of local labor demand shocks. We focus on big manufacturing plant closures since mass layoffs move many employees into unemployment at the same time, thereby reducing employment opportunities in the city in addition to affecting businesses that depend on the big plant's output. Big plants are also important employers in smaller localities, so that any negative shock to them is likely to have large local effects. To deal with the 'chicken-and-egg' question of whether jobs follow people or people follow jobs, we develop an IV strategy and construct an instrument for local labor demand shocks in Canada using a shift-share approach. Leveraging the 'China shock', we use US employment losses in manufacturing and 2001 city-level manufacturing composition in Canadian cities to instrument city-level plant closures and downsizing.

Our estimates show that larger job losses in big manufacturing plants in Canada between 2003 and 2019 cause lower total population growth over the 2001–2021 period. They affect mostly the working-age population and shift the age structure of cities towards older residents. We also find some evidence that the share of families decreases. There are, however, no significant effects on other socio-demographic outcomes such as the share of highly educated, the sex ratio, or the share of population with a migration background.

As to the heterogeneous effects across cities, we find no evidence that either initial size and industrial diversity, or the initial share of employment in educational, health, and social services, have any significant effect on a cities' demographic changes. According to our results, the only factor, if anything, that may help make cities more resilient is the initial presence of cultural and recreational services.

Our findings are important for two main reasons. First, governments invest substantial amounts to ward off big plant closures. In 2008–2009, e.g., the U.S. administration paid $50 billion to General Motors and Chrysler to prevent the closure of their plants. At the same time, the Canadian federal government paid $9.5 billion to General Motors to secure its business and thousands of jobs in Oshawa. Given the huge costs, understanding all potential gains of these subsidies is important.

Second, shrinking places that age do not offer an environment conducive to a future rebound of the place. Age-selective migration is a powerful driver of the geographic concentration of the elderly in some regions: it is the outcome of more mobile younger people leaving following negative local labor demand shocks. For example, in the German case, it has been documented that the eastern Länder have aged much more rapidly than the western following German reunification in 1990. One major reason was the progressive deindustrialization, where younger, more educated, and more female working-age individuals left for the west, leaving an elderly, more male, and less educated aging population behind (see, e.g., Uhlig 2008, Figure 16; and Rosenbaum-Feldbrügge et al. 2022). As stated before, the resulting socio-demographic tissue offers no favorable economic conditions, which partly explains why the eastern part of Germany (except for the special case of Berlin, which attracts migrants and investment) has failed to catch up with the west.

Our paper is related to the large literature on the local labor market effects of trade shocks (see, e.g., Autor et al. 2013 for the 'China shock'; Dauth et al. 2014 for the 'Eastern Europe shock'; Pierce and Schott 2020, for the 'China shock' and 'death by despair' in the US; Scheiring et al. 2023 for 'death by despair' in Eastern Europe). We extend this literature by looking at the effects of job losses on population and its composition over a relatively long time horizon.

It is futher related to the voluminous literature that looks at worker-level impacts of big plant closures and mass layoffs on individual outcomes (see, e.g., Ruhm 1991 for income; Eliason and Storrie 2006 for unemployment spells; Huttunen and Kellokumpu 2016 for fertility; or Sullivan and Von Wachter 2009 for mortality) and on local labor markets more generally (Gathmann et al. 2020; Jofre-Monseny et al. 2018). While the main focus of that literature is either on individuals or economic performance of the labor market, we examine the performance of cities in retaining specific segments of their population following a negative shock to their local labor market.

The remainder of the paper is structured as follows. We present our data in Section 2. Section 3 discusses the construction of the job-loss measures and presents descriptive statistics. Section 4 lays out the empirical specification and discusses identification problems and the instruments. Section 5 contains the main results. Finally, Section 6 concludes. We relegate details on the data and additional results to a set of appendices.

2 Data

2.1 Establishment-level data

Our data source for establishments are the *Scott's National All Business Directories*. They contain exhaustive information on manufacturing establishments operating in Canada (see Appendix A.1 for details on the Scott's data). We have access to those data for 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2017, and 2019. Each establishment reports: a unique identifier; information on its primary 6-digit North American Industry Classification (NAICS) code; its opening year; its number of employees; whether it is an exporter or a headquarter; and complete address information. We use the latter to geocode plants, which allows us to assign them to cities. Figure 1 illustrates the geographic granularity of our establishment-level data.

In what follows, we mainly use the years 2003 and 2019 as our start- and end points to construct measures of plant exit and job losses in manufacturing by city. In robustness checks, we also look at changes over shorter periods. The year 2001 will serve to construct controls for the cities' *initial levels* of manufacturing activity.

2.2 Cities

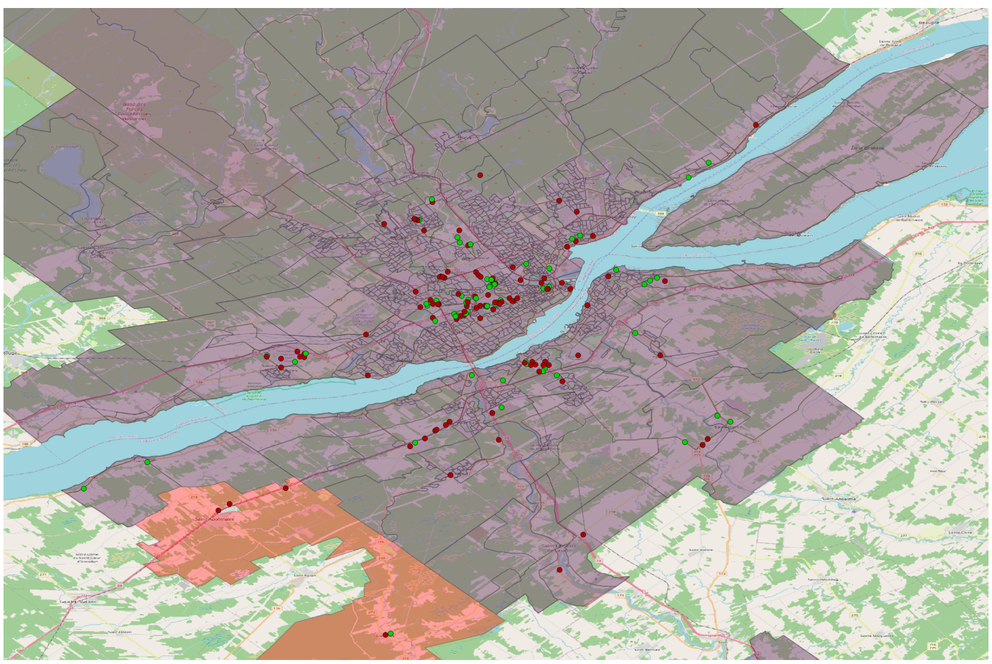
Our unit of analysis is a 'city' as defined by the *census metropolitan areas* (CMA) or *census agglomerations* (CA). In what follows, we refer to them as 'cities' for short. By construction, we may consider that a CMA corresponds to a local labor market, thus providing a suitable spatial unit for our analysis.[2] Because city boundaries change over time, aggregating census data to cities in a consistent way is challenging. We deal with this problem by first constructing the smallest stable spatial units

[2]The official definition of Statistics Canada is a follows: "A census metropolitan area (CMA) or a census agglomeration (CA) is formed by one or more adjacent municipalities centred on a population centre (known as the core). A CMA must have a total population of at least 100,000, based on data from the current Census of Population Program, of which 50,000 or more must live in the core based on adjusted data from the previous Census of Population Program. A CA must have a core population of at least 10,000 also based on data from the previous Census of Population Program. 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 data on place of work from the previous Census Program." Source: https://www12.statcan.gc.ca/census-recensement/2021/ref/dict/az/definition-eng.cfm?ID=geo009; last accessed, September 11, 2025.

at which census data are released for the 2001 to 2021 census waves. This is done by aggregating dissemination areas (DA) with the algorithm developed in Behrens et al. (2024). Since CMA definitions and boundaries change over time, we then construct a stable CMA geography by intersecting the 2016 CMA boundaries with our time-invariant stable dissemination areas. This intersection constitutes the (stable) geography of our cities that allows us to map them onto time-consistent census data from 2001 to 2021.

Our analysis includes most CMAs and CAs in Canada. We have a total of 145 cities with stable boundaries between 2001 to 2021. Figure 1 illustrates these stable spatial units for the CMA of Québec city. As shown, we can then readily aggregate our geocoded manufacturing establishments to the city level based on their geographic coordinates.

Figure 1: Quebec City CMA and big plant closures between 2003 and 2019.



Notes: This figure shows the geographic distribution of big manufacturing plant closures between 2003 and 2019 for the CMA of Québec City. Green dots indicate the geographic locations of big manufacturing plants in 2003 that were still active in 2019. Red dots indicate the geographic location of big manufacturing plants in 2003 that exited and were no longer active in 2019. The purple area shows the CMA as officially defined by the 2016 census geography. The stable spatial units we construct are outlined in the CMA. As shown, there is no perfect overlap. The orage zone corresponds to stable spatial units that intersect the CMA—and are hence considered part of it in our definition—but extend beyond the official CMA boundaries. We include those areas into our definition of the stable CMA.

2.3 Other data

We combine our establishment-level data with a variety of other data sources in our analysis. We briefly summarize the most important ones below.

First, we use census data (retrieved in pre-processed form from *Computing in the Humanities and Social Sciences*, CHASS at the University of Toronto) at the DA level, which we aggregate to our stable spatial units first and to cities afterwards as explained before. We use mainly total population and the socio-demographic composition in terms of gender, age, education, and occupations. We provide more details in Appendix A.2. We also use information on employment in broad industries (education, public services, arts and culture) for which the Scott's data is not exhaustive. This information will be used to examine the heterogeneous responses of cities to big plant closures and downsizing along a variety of dimensions.

Second, we retrieve US county business patterns (CBP) data to measure changes in the number of big plants and employment in US manufacturing industries (see Appendix A.3). As explained later, we use these data to construct instruments from the industry-level changes in the number of big plants and employment between 2003 and 2019 in the US.

Finally, we assemble data from miscellaneous sources to construct additional controls. We use weather data (the maximum July and minimum January temperatures) from the Canadian Centre for Climate Services of Environment and Climate Change; and various data constructed using GIS software (distance of each city from the US border, distance to the nearest big city etc.). Appendix A.4 provides details.

Descriptive statistics for the all of the variables we use in the subsequent analysis are summarized in Appendix Table B.1.

3 Manufacturing job losses between 2003 and 2019

3.1 Plant-closure rates and job losses

We construct measures of local labor demand shocks that are based on the literature on the effects of mass layoffs. Hence, in what follows, we focus on 'significant closures'.[3] The *manufacturing job-loss rate* in city c for plants with at least 50 employees in 2003 (collectively referred to as 'Job-loss rate') are defined as follows:

$$\text{Job-loss rate}_c = \frac{\text{\# empl. in plants (2003, exit and/or downsize +30\% by 2019)}}{\text{\# empl. in plants (2003)}} \tag{1}$$

It is the share of employment in big manufacturing plants in 2003 that is no longer present in 2019, either because the plant has exited or because the plant reports an at least 30% lower on-site employment in 2019 than in 2003. As alternative measures, used in robustness checks, we extend the definition (1) to the closures and downsizing for all big plants (including services and primary industries), and to include all manufacturing plants (i.e., also smaller plants with less than 50 employees in 2003).[4]

3.2 Some descriptive statistics

Table 1 summarizes the geographic structure of manufacturing in Canada in 2003 and 2019, respectively, and reports descriptive statistics related to the job-loss rate and big plant closures and downsizing. Appendix Table B.2 complements that information by providing the descriptives by manufacturing industry.

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

[4]While the Scott's database provides excellent coverage of the manufacturing sector, other sectors (mostly primary industries and services sectors) are more sparsely covered, especially outside the major cities. Hence, we do not include services in our main analysis. Our data also do not allow us to track mergers and acquisitions. While each establishment—corresponding to a location where business is carried out—has a unique identifier that does not change between 2003 and 2019, there are no firm identifiers allowing us to link plants to the owning firm or parent company. Although a textual description of the firm's legal name is provided, creating firm-level identifiers from there is likely to be complicated and error prone. We thus do not explicitly deal with mergers and acquisitions. This has no implication for our analysis since the plant identifier does not change even if ownership changes.

Table 1: Geography of manufacturing jobs and job losses.

	(1): 2003		(1): 2019		(3): Changes (50+)		
	#Plants	Avg. size	#Plants	Avg. size	#closed	Job-loss rate	Avg. size
Province-level breakdown							
Alberta	3,346	33.1	2,385	35.4	339	45.1%	147.5
British Columbia	5,451	26.8	3,100	30.1	454	42.9%	137.9
Manitoba	1,236	36.4	670	39.7	160	46.9%	132.0
New Brunswick	767	28.7	404	28.4	72	54.5%	166.5
Newfoundland and Labrador	321	26.3	197	30.2	20	34.0%	143.3
Nova Scotia	821	25.4	411	32.3	52	36.5%	146.6
Ontario	20,680	35.4	12,054	35.9	2,443	50.4%	151.2
Prince Edward Island	239	20.5	122	31.5	16	38.8%	119.2
Quebec	11,665	34.9	3,807	40.5	1,683	58.3%	141.1
Saskatchewan	866	26.5	519	29.3	62	40.9%	151.5
Others	0		15	12.7			
Total (All urban areas)	45,392	33.5	23,684	35.5	5,301	50.9%	146.1
Canada	52,770	33.4	27,049	35.5	6,125	51.1%	147.1
City-level breakdown (highest job-loss rates)							
Kitimat (BC)	8	95.4	5	44.0	2	94.4%	360.0
Prince Rupert (BC)	11	80.2	7	10.4	2	92.1%	406.0
La Tuque (QC)	15	75.5	2	247.5	3	91.8%	346.7
Grand Falls-Windsor (NL)	15	45.7	8	11.1	1	87.6%	600.0
Terrace (BC)	16	30.0	6	5.8	2	83.3%	200.0
City-level breakdown (lowest job-loss rates)							
Lacombe (AB)	47	15.4	39	24.9	1	6.9%	50.0
Yorkton (SK)	31	25.8	20	45.5	1	10.6%	85.0
Nelson (BC)	34	16.5	14	25.1	1	10.7%	60.0
Duncan (BC)	86	15.9	55	26.4	2	11.7%	80.0
Cold Lake (AB)	51	18.4	24	11.0	1	11.8%	110.0

Notes: Data from the Scott's National All Business Directories. The table is based on manufacturing plants (NAICS 31–33). Because of small numbers, the three territories (Northwest Territories, Nunavut, and Yukon) are not reported in the table but are included in the total. The average size is the number of employees divided by the number of plants. The job loss rate is related to large plant closures and downsizing in equation (1). The total line refers to the sample of plants in urban areas. The Canada line refers to the sample of plants including also all non-urban areas in Canada.

Table 1 shows that most manufacturing plants are located in the 'manufacturing belt' that runs through Québec and Ontario. Following the 'China shock' in 2001 (Autor et al., 2013), Table 1 shows that there has been a substantial deindustrialization process between 2003 and 2019. While there were 45,392 manufacturing establishments in 2003 in our data, only 23,684 remained in 2019, i.e., a decrease of 52.2%. A total of 4,412 big plants (50+ employees) operated in 2003 but closed by 2019. Another 889 big plants operated in 2003 but had laid off at least 30% of their workforce by 2019.

Overall, 44.71% of manufacturing jobs for firms active in 2003 disappeared by 2019 (from 1,520,220 to 840,432): almost every second job got displaced.[5]

Columns (1) and (2) show that while the number of plants that were active in 2003 was almost halved by 2019, the average size of continuing plants has slightly increased, from 33 employees in 2003 to 35 employees in 2019. This suggests some positive selection among survivors: more productive and larger plants are more likely to survive strong negative shocks (see, e.g., Bernard and Jensen, 2007) or to grow larger following globalization.

Column (3) in Table 1 reports the manufacturing job-loss rate between 2003 and 2019, due to the closure or downsizing of big plants. The average job-loss rate (weighted using 2003 industry plant shares) equals 50.9%. As shown, there is substantial heterogeneity in the distribution of manufacturing job losses across provinces and cities. Starting with provinces, the two big manufacturing provinces, Québec and Ontario, were the most severely hit by deindustrialization, whereas the Western provinces fared better. Even within provinces, there was substantial variation across cities. While some places like Kitimat (BC) experienced a huge decline in excess of 90%, other places such as Duncan (BC) saw only little change of barely 12%.[6] Clearly, big manufacturing plant closures have the largest effects in places with few large employers. We will exploit these large variations in manufacturing job losses in our subsequent analysis to understand how they affect the socio-demographic composition of cities.

[5]This decline is roughly in line with magnitudes reported by Statistics Canada: "From 2004 to 2008, more than one in seven manufacturing jobs disappeared in Canada", i.e., 14% of manufacturing jobs in four years (Souce : Statistics Canada; https://www150.statcan.gc.ca/n1/pub/75-001-x/2009102/article/10788-eng.htm; last accessed September 9, 2025).

[6]"In the 1970s, Eurocan opened a pulp mill a few kilometres up the Kitimat River estuary, and in the 1980s, Methanex started producing and exporting methanol and ammonia from the waterfront. Neither stood the test of time. In 2005, Methanex announced it was shutting down, citing high gas prices. Five years later, Eurocan followed suit. With two of three major employers gone, Kitimat slipped into a period of economic decline." (Source : https://thenarwhal.ca/bc-kitimat-boom/; last accessed September 9, 2025).

4 Empirical specification

4.1 Estimation equation

We are interested in the effects of big manufacturing plant closures and downsizing on city-level growth rates of total population and of specific population subgroups. We estimate the following (long) differences model as our baseline:

$$\text{growth rate } y_c^{01-21} = \alpha \times \text{job loss rate}_c^{03-19} + \beta \times X_c^{01} + \gamma \times G_c + \varepsilon_c, \tag{2}$$

where y_c^{01-21} is the growth rate (measured using the the log difference) of the total population or of a specific population subgroup between 2001 and 2021 in city c; job loss rate$_c^{03-19}$ is one of our measure of labor demand shocks (1), and our primary variable of interest; and X_c^{01} is a vector of initial city-level controls measured in 2001 (which include population size, the share of highly educated, the share of manufacturing workers, the share of natural resource-related workers, and the employment rate). The vector G_c finally subsumes 'geographic' controls that may influence demographic change, namely the minimum January temperature, the distance to the nearest big city with more than 300K population, and the distance to the US border.

We estimate the model for several dependent demographic variables y to capture how the job-loss rate affects demographic changes and the demographic composition of cities. Our baseline results are for city-level changes in total population and in changes in the cities' age structures. We then further investigate how local labor demand shocks affect: the share of highly educated (having a university degree); the share of male; the share of male in manufacturing; the share of married, singles, and families with different numbers of children; and the share of population with a migration background.

The baseline estimates we report are for long changes that span two decades. Since demographic changes happen relatively slowly, one advantage of using long changes is that the estimates capture most of the effects of the labor demand shocks. However, the downside of the long time span is a restricted sample size (we have only 145 CMAs in our sample). We thus also estimate alternative models where we consider shorter time spans (2×10 years, or 4×5 years). Doing so increases sample size and allows to understand how quickly the adjustments occur. It has, however, the downside of capturing less well the changes that may unfold over a longer horizon.

As shown in (2), we look at the effects of gross job changes only. Put differently, we do not consider the difference between job losses and job creation, i.e., net job changes (churning). There are two reasons for that choice. First, there is a somewhat mechanical relationship between total population change and total employment change, the direction of which is unclear. Second, as explained in the next section, we will mostly run IV regressions, and our instrument should take care of the omitted job creation variable.

4.2 Identification concerns and IV

There are three main sources of potential endogeneity when estimating the effects of labor demand shocks on subsequent demographic outcomes. First, there is the usual 'chicken-and-egg' question of whether people follow jobs or jobs follow people. If the latter is true, or dominates the former, we may overestimate the negative impact of job losses on demographic outcomes. Second, whereas some manufacturing jobs are destroyed, others are created. Since we disregard entry in our analysis and look at job losses only, this may lead to an underestimation of the negative impact of job losses on demographic outcomes. Last, there may be other unobserved local shocks that simultaneously lead to manufacturing plant closures (or downsizing) and that may make workers, or specific subgroups thereof, leave the city.

To deal with reverse causality, as well as the potentially omitted job-creation variable, we use a shift-share Bartik instrument which we construct as follows:

$$IV_c = \sum_s \underbrace{\frac{\text{empl}_{c,s}^{01}}{\text{empl}_c^{01}}}_{\text{share}} \times \underbrace{\frac{\Delta \text{empl}_{US,s}^{03-19}}{\text{empl}_{US,s}^{03}}}_{\text{shift}} \tag{3}$$

The shares are the initial 2001 employment shares of each manufacturing industry s in city c. The shifts are constructed from the percentage changes in manufacturing employment for big plants (with more that 50 employees) in the US for the different manufacturing industries over the 2003 to 2019 period, using county business pattern data.

Our instrument will be relevant if the sectoral deindustrialization trajectories are similar in the US and Canada and driven by technological changes and shifts in the international division of labor following, e.g., the entry of China into the WTO in 2001. Our instrument will be valid if unobserved socio-demographic shocks, as well as labor demand and supply shocks in our cities, do not affect the growth rates of manufacturing industries in the US between 2003 and 2019. Validity also requires that, conditional on the controls we include (in particular the initial share of workers in the manufacturing and natural resources sector), the shares of the various 4-digit industries in the city's overall manufacturing employment in 2001 are exogenous. We discuss later placebo tests that corroborate this assumption.

In what follows, we construct two versions of the IV. The first is the continuous version as directly presented by (3). The second is a dichotomized version, where the shift is not the percentage change in US industry employment but rather a dummy variable taking value 1 for all US manufacturing industries where the employment growth is below the 35^{th} percentile, and 0 otherwise. This second instrument hence puts more weight on the industries that have been the most heavily affected by employment losses over our study period, while disregarding industries that have seen only few job losses.

5 Results

5.1 Job losses and demographic change

Table 2 shows our baseline results from estimating (2). The dependent variable is the (log) change in population (denoted by Δ). Column (1) reports OLS estimates of the univariate regression of the 2001–2021 city-level (log) population change on the job losses in big manufacturing plants from 2003 to 2019. The latter is measured using the manufacturing job-loss definition of (1) (including downsizing plants). As shown, there is a negative and statistically significant coefficient, thus suggesting that cities which lost more manufacturing jobs due to big plant closures and downsizing had also less population growth.

Columns (2) and (3) continue to report OLS estimates but add controls for initial conditions in 2001 (column (2)) and other geographical controls (column (3)). Regarding the initial conditions, cities that were larger in 2001 tended to have more population growth over the next two decades, which shows that there was no mean reversion in Canada between 2001 and 2021 and that city sizes progressively diverged. This is in line with results from many countries where large cities tend to grow even larger at the expense of small- and medium-sized cities. Note also that resource-based places, with a high initial share of employment in resource-based industries, tended to have less population growth. Places with a tight initial labor market (as captured by the labor-force participation rate in 2001) however tended to grow more between 2001 and 2021. Last, the geographic controls show that places with milder winters grew more, in line with the finding for the US by Glaeser and Shapiro (2003, p.150) who state that "January temperature is still the strongest positive predictor of MSA growth".

Column (4) still looks at the effects of job losses on total population but deals with potential reverse causality, omitted variables, and measurement error, by instrumenting our job-loss measure with the dichotomized version of the instrument (3). As shown by the Olea and Pflueger (2013) F-statistic and Figure 2 displaying the bin scatter plot of the first stage, this instrument is strong. The coefficient on job losses remains negative and highly significant, and there is a substantial decrease in its magnitude. The OLS estimates are thus biased upwards, consistent with the use of gross exit—thus disregarding entry—to measure job losses, as explained in Section 4.2.

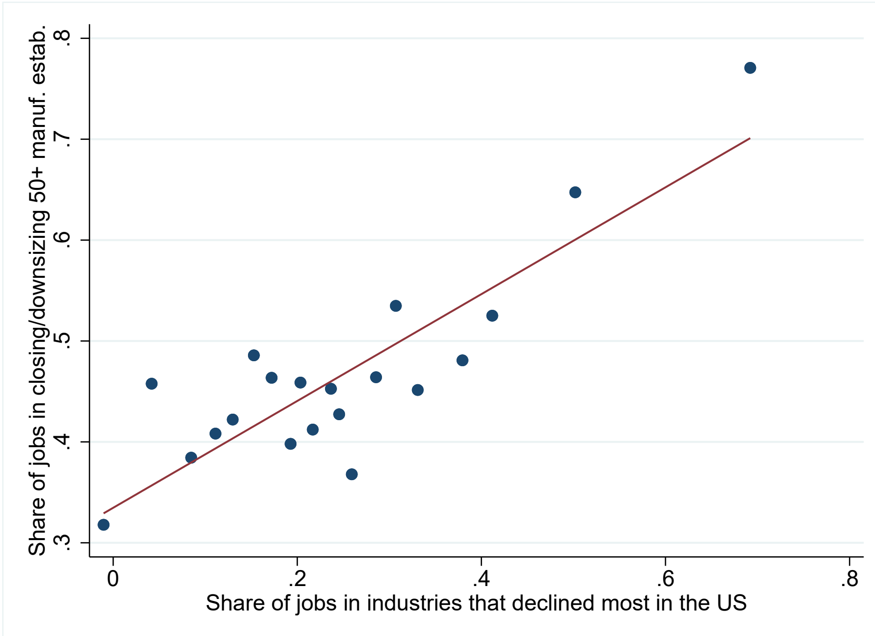
Table 2: Total population changes, 2001–2021.

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	IV[1]
Dependent variable:	Δ ln pop.	Δ ln pop.	Δ ln pop.	Δ ln pop.
Job losses in big plants	-0.189^a	-0.200^a	-0.187^a	-0.431^a
	(0.057)	(0.056)	(0.053)	(0.148)
ln population in 2001		0.033^c	0.025	0.041^b
		(0.015)	(0.022)	(0.020)
Share of population with at least a bachelor degree in 2001		-0.226	-0.383	-0.785^c
		(0.196)	(0.238)	(0.437)
Participation rate in 2001		0.896^b	0.972^a	1.026^a
		(0.305)	(0.274)	(0.210)
Share of manufacturing in overall employment in 2001		0.005	-0.148	0.106
		(0.228)	(0.256)	(0.265)
Share of natural resources in overall employment in 2001		-0.465^c	-0.442	-0.577^b
		(0.256)	(0.290)	(0.249)
January minimum temperature			0.002^a	0.002^a
			(0.001)	(0.000)
ln distance to nearest big urban areas (meters)			-0.002	0.000
			(0.005)	(0.003)
ln distance to nearest US border (meters)			-0.021	-0.018
			(0.028)	(0.024)
Observations	145	145	145	145
R-squared	0.074	0.302	0.331	
Montiel-Olea and Pflueger F-stat				44.85*

Notes: Huber-White robust standard errors in parentheses. [1]The IV results in this table use the dichotomized version of the Bartik instrument (3). *means that we reject the weak instrument hypothesis at a 10% significance level. Coefficients significant at: $^a p < 0.01$, $^b p < 0.05$, $^c p < 0.1$.

Zooming in on finer demographic changes, Table 3 reports results where the dependent variable is now the change in the share (denoted by Δ_s) of the age group. We break down the population

Figure 2: First-stage of the IV regression



Notes: This figure shows a bin scatter plot of the first-stage of the IV regression whose results appear in column (4) of Table 2. Both variables are computed over the period 2003-2019.

into three age bins: 0–19 years (young), 20–64 years (working age), and 65+ years (elderly) and use the population shares by age group as our dependent variables. As shown before, OLS estimates are biased upwards. Hence, in what follows we only report IV estimates.

Columns (1)–(4) of Table 3 show the results using our dichotomized instrument. Column (1) repeats the results from Table 2 as a reference point. Columns (2)–(4) show that the negative effects of job losses are concentrated on the working age population, with an offsetting positive effect on the elderly.[7] As expected, the working-age population is directly affected the most by negative local labor demand shocks. The coefficients of the initial-level controls in Table 3 largely mirror those in Table 2. In particular, the working age population tended to grow more in intially larger cities, whereas it tended to decline in places with larger initial shares of manufacturing employment and employment in resource-related industries.

[7]By construction, the shares sum to one so that our coefficient estimates for the three shares sum to zero. Since the effect on the young (0–19) is zero, the decrease in the share of working age population (20–64) maps into an equivalent increase in the share of the elderly (65+).

Table 3: Population changes by age group, 2001–2021, IV regressions.

	IV (dichotomized)				IV (continuous)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Δ ln pop.	Δ_s 0-19	Δ_s 20-64	Δ_s 65+	Δ ln pop.	Δ_s 0-19	Δ_s 20-64	Δ_s 65+
Job losses in big plants	-0.431^a	0.000	-0.045^c	0.046^b	-0.423^b	-0.028	-0.109^a	0.146^a
	(0.148)	(0.013)	(0.025)	(0.023)	(0.169)	(0.025)	(0.041)	(0.057)
ln population in 2001	0.041^b	0.003^b	0.008^a	-0.012^a	0.041	0.005^b	0.012^a	-0.019^a
	(0.020)	(0.001)	(0.002)	(0.002)	(0.025)	(0.002)	(0.003)	(0.004)
Share of population with at least a bachelor degree in 2001	-0.785^c	0.028	-0.354^a	0.344^a	-0.772	-0.019	-0.460^a	0.509^a
	(0.437)	(0.044)	(0.070)	(0.093)	(0.510)	(0.079)	(0.117)	(0.181)
Participation rate in 2001	1.026^a	-0.021	0.234^a	-0.287^a	1.024^a	-0.015	0.248^a	-0.309^a
	(0.210)	(0.018)	(0.040)	(0.038)	(0.215)	(0.029)	(0.072)	(0.090)
Share of manufacturing in overall employment in 2001	0.106	0.003	-0.124^b	0.129^b	0.098	0.033	-0.057	0.025
	(0.265)	(0.022)	(0.050)	(0.058)	(0.210)	(0.026)	(0.057)	(0.067)
Share of natural resources in overall employment in 2001	-0.577^b	0.063^c	-0.098^b	0.051	-0.573^b	0.048	-0.133	0.106
	(0.249)	(0.035)	(0.043)	(0.058)	(0.246)	(0.054)	(0.085)	(0.133)
January minimum temperature	0.002^a	-0.001^a	0.000	0.001	0.002^a	-0.001^a	0.000	0.001^c
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln distance to nearest big urban areas (meters)	0.000	0.000	-0.000	0.001^c	0.000	0.000	0.000	-0.000
	(0.003)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.001)	(0.001)
ln distance to nearest US border (meters)	-0.018	-0.003	-0.002	0.005	-0.018	-0.002	-0.001	0.004
	(0.024)	(0.002)	(0.003)	(0.004)	(0.022)	(0.002)	(0.003)	(0.004)
Observations	145	145	145	145	145	145	145	145
Montiel-Olea and Pflueger F-stat	44.85*	44.85*	44.85*	44.85*	8.041	8.041	8.041	8.041

Notes: Huber-White robust standard errors in parentheses. The regressions (1)–(4) use the dichotomized version of our IV, whereas the columns (5)–(8) use the continuous version of our IV. Δ_s denotes the change in shares. Geographic controls include 'January minimum temperature', 'log distance to nearest big urban areas (meters)', and 'ln distance to nearest US border (meters)'. Controls for the initial levels in 2001 include 'ln population', 'share of population with at least a bachelor degree', 'participation rate', 'share of manufacturing in overall employment', and 'share of natural resources in overall employment'. * means that we reject the weak instrument hypothesis at a 10% significance level. Coefficients significant at: $^a p < 0.01$, $^b p < 0.05$, $^c p < 0.1$.

Columns (5)–(8) of Table 3 show results from the same regressions where we use the continuous version of the Bartik instrument. As shown, although the continuous IV is a weaker instrument and has borderline significant F-statistics, our results are similar to those using the dichotomized IV: we see a decline in population that is essentially concentrated among the working-age population, accompanied by an offsetting increase in the share of the elderly. Although the point estimate for the young is negative, it is not statistically significant. Thus, the effect of manufacturing job losses due to big plant closures and downsizing are to reduce the share of the working age population and, thereby, to increase the share of the elderly.

Beyond total population and structure by age, we also run regressions using a number of other demographic characteristics as dependent variables (see Table C.3 in the Appendix). We find very few significant effects. It seems that big manufacturing plant closures and downsizing have no statistically discernible effect on: (i) the share of university graduates in the city's population; (ii) the sex ratio; (iii) the share of male workers in manufacturing; (iv) the share of married; (v) the share of single; (vi) and the share of migrants.[8] We do, however, find a strong negative effect on the share of families.

To summarize, our baseline results show that manufacturing job losses due to big plant closures and downsizing: (i) reduce population growth in places exposed to more such job losses; (ii) are concentrated among the working-age population; and (iii) lead to less growth in the share of families. Hence, cities subject to more such job losses see their total population decrease and their remaining population become older on average, with less families. Beyond those effects, we find no other significant changes in demographic characteristics related to closures.

5.2 Extensions and robustness

Until now, we have only looked at job losses occurring in big manufacturing plants. Table 4 extends our analysis to job losses in all manufacturing establishments (irrespective of their size; 'Job losses, all manufacturing establishments') and to job losses in all big plants (irrespective of their industry;

[8]Considering increasing Chinese import penetration in the US, Autor et al. (2019) find that the negative effects of the shock are more concentrated on young male workers. More Chinese import penetration had an impact on the share of young male residents, the local sex ratio, and the marriage rate. Different from the US, we do not find any effects on the sex ratio, the marriage rate, or males in manufacturing in Canada (see Table C.3).

'Job losses, big plants in all sectors'). As before, we just present IV estimates.[9]

Table 4 summarizes the results. Column (1) shows that there is a strong negative effect of manufacturing job losses on population growth. Job losses in big manufacturing plants and job losses in all manufacturing plants thus have a similar effect on local population changes. Our IV estimates in columns (2)–(4) are also of a similar magnitude than those in Table 3. However, they fail to achieve statistical significance because of the larger standard errors. Last, the sign and significance of the initial controls is also qualitatively identical between Table 3 and 4. In a nutshell, our results are robust irrespective of whether we look at job losses in large manufacturing plants or job losses in all manufacturing plants.[10] - Turning to the effects of overall job losses in large firms (manufacturing or not), column (5) shows that there is no statistically significant effect on total population growth: cities that experienced more job losses due to the closure or downsizing of big plants did not see a different evolution of total population, conditional on initial conditions and geographic controls. We think that one reason for this finding is that there is more turnover and replacement in the service industries than in manufacturing. Whereas most big manufacturing plant closures are not replaced by offsetting openings—since manufacturing is a declining sector over the period—many big plant closures in the services industry are probably replaced. The two reasons are that services is an expanding sector, and that capital is arguably less specific in the service industries and can be more easily redeployed than more specific manufacturing equipment.

We next investigate the robustness of our results to the chosen time horizon. Recall that the baseline analysis looks at long differences spanning two decades. This raises the question if our results also hold for shorter periods. As explained before, there is a trade-off between running the analysis over shorter periods—thereby increasing the number of observations but potentially not capturing the full impact of the closures if these need a longer time to materialize. Table 5 summarizes a series of estimations where instead of taking the long difference from 2001 to 2021

[9] We construct the corresponding US instruments to match the definition of our Canadian variables by using CBP data for: (i) changes in employment in manufacturing industries for all firms irrespective of their size; and (ii) changes in all industries for firms with more than 50 employees.

[10] Since job losses in big manufacturing plants constitute the lion's share of overall manufacturing job losses (accounting, on average across our cities, for 64% of the total; the median stands at 71%), this result is not too surprising. This is especially so since the largest job losses (in percentage) are for smaller places that seen a small number of large employers shut down or downsize substantially.

we take shorter differences over either 10 or 15 years.

Columns (1)–(4) of Table 5 show our results for the 15 years from 2001 to 2016, where we measure job losses using the Scott's data between 2003 and 2017. As shown, the results are largely in line with the baseline results in Table 2. Columns (5)–(8) of Table 5 present results for the two waves of decadal changes (2001–2011 and 2011–2021) pooled. To take out differences in levels, we include a cohort fixed effect into the regression. As shown, the results remain qualitatively similar, although the F-statistics of the instrument drop to very low levels. Since we have a weak instrument problem, we do neither further interpret these results nor report results for five-year changes.[11]

Finally, several recent contributions discuss the conditions under which shift-share instruments are valid and suggest procedures to verify if they can be safely used. Among the suggestions to check the validity of the instrument made by Borusyak et al. (2022)—concerning endogenous shares—and Goldsmith-Pinkham et al. (2020)—concerning endogenous shifts—are placebo tests where the dependent variable is replaced by pre-treatment outcomes (leaving the independent variables unchanged). In unreported regressions, we have thus reproduced the estimation of the impact of big plant closures and downsizing on population size and age composition where we have replaced the 2001–2021 population changes by those from1996–2001. The estimated coefficient on big plant closures and downsizing is close to zero and insignificant for all the outcomes except the share of 0–19-year-old (for which we find a significantly negative coefficient). We believe this confirms that our IV strategy is valid.

[11] Our instruments lose power because the dynamics of deindustrialization in the US and in Canada, though fundamentally similar, occurred at different points in time. While the US experienced large scale manufacturing job losses earlier, those in Canada came a bit later. Hence, our baseline regressions spanning two decades yield US instruments that have much more power in predicting changes in Canadian manufacturing industries than when we consider the two decades separately. We also ran the regressions by considering the whole panel structure of our data, focusing on the four five-year changes. Unsurprisingly, those regressions do not yield any significant results: the instrument is extremely weak. On top of that, changes in urban growth are also relatively slow, i.e., five years is likely too short a horizon to see demographic changes materialize.

Table 4: Job losses, all manufacturing plants or all industries (dichotomized IV).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ ln pop.	Δ_s 0-19	Δ_s 20-64	Δ_s 65+	Δ ln pop.	Δ_s 0-19	Δ_s 20-64	Δ_s 65+
Job losses, all manufacturing establishments	-0.533^a	-0.002	-0.052	0.052				
	(0.158)	(0.017)	(0.035)	(0.038)				
Job losses in big plants, all sectors					0.056	0.021	-0.059	0.042
					(0.262)	(0.021)	(0.047)	(0.049)
ln population in 2001	0.023	0.003^a	0.006^a	-0.011^a	0.012	0.003^b	0.007^a	-0.011^a
	(0.021)	(0.001)	(0.001)	(0.002)	(0.027)	(0.001)	(0.002)	(0.002)
Share of population with at least a bachelor degree in 2001	-0.742^c	0.025	-0.345^a	0.333^a	-0.060	0.033	-0.296^a	0.280^a
	(0.409)	(0.044)	(0.075)	(0.099)	(0.233)	(0.034)	(0.071)	(0.079)
Participation rate in 2001	1.006^a	-0.021	0.231^a	-0.284^a	0.915^a	-0.027	0.241^a	-0.289^a
	(0.206)	(0.018)	(0.037)	(0.037)	(0.352)	(0.020)	(0.051)	(0.044)
Share of manufacturing in overall employment in 2001	-0.078	0.004	-0.146^a	0.151^a	-0.392	-0.015	-0.118^b	0.140^b
	(0.279)	(0.020)	(0.038)	(0.049)	(0.254)	(0.021)	(0.047)	(0.057)
Share of natural resources in overall employment in 2001	-0.748^b	0.062	-0.113^a	0.066	-0.318	0.071^a	-0.095^c	0.042
	(0.325)	(0.039)	(0.036)	(0.050)	(0.371)	(0.026)	(0.049)	(0.059)
January minimum temperature	0.002^a	-0.001^a	0.000	0.001	0.002^a	-0.001^a	0.000	0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
ln distance to nearest big urban areas (meters)	-0.001	0.000	-0.001^b	0.001^a	-0.005	-0.000	-0.000	0.001
	(0.004)	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)	(0.001)	(0.000)
ln distance to nearest US border (meters)	-0.019	-0.003	-0.002	0.005	-0.024	-0.003	-0.003	0.005
	(0.024)	(0.002)	(0.003)	(0.004)	(0.029)	(0.002)	(0.003)	(0.004)
Observations	145	145	145	145	145	145	145	145
Montiel-Olea and Pflueger	31.45*	31.45*	31.45*	31.45*	38.91*	38.91*	38.91*	38.91*

Notes: Huber-White robust standard errors in parentheses. Δ_s denotes the change in shares. *means that we reject the weak instrument hypothesis at a 10% significance level. Coefficients significant at: $^a p < 0.01$, $^b p < 0.05$, $^c p < 0.1$.

Table 5: Job losses, all manufacturing plants or all industries (dichotomized IV).

	15 years: 2001–2016				10 years: 2001–2011, 2011–2021			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ ln pop.	Δ share 0-19	Δ share 20-64	Δ share 65+	Δ ln pop.	Δ share 0-19	Δ share 20-64	Δ share 65+
Job losses in big plants	-0.301^a	0.005	-0.039^b	0.024^c	-0.355	-0.036	-0.104^b	0.097^b
	(0.088)	(0.011)	(0.016)	(0.013)	(0.521)	(0.026)	(0.052)	(0.049)
ln population in base year	0.028	0.002^b	0.006^a	-0.008^a	0.020	0.003^a	0.006^a	-0.008^a
	(0.017)	(0.001)	(0.001)	(0.001)	(0.027)	(0.001)	(0.002)	(0.002)
Share of pop. with $\geq$ bachelor degree (base year)	-0.611^c	0.051	-0.292^a	0.220^a	-0.217	-0.042	-0.215^a	0.215^a
	(0.313)	(0.041)	(0.056)	(0.069)	(0.632)	(0.030)	(0.077)	(0.058)
Participation rate in base year	0.916^a	-0.017	0.205^a	-0.234^a	0.496^b	0.009	0.138^a	-0.175^a
	(0.185)	(0.015)	(0.028)	(0.029)	(0.229)	(0.015)	(0.051)	(0.045)
Share of manuf. in overall employment (base year)	-0.067	-0.010	-0.104^a	0.118^a	0.077	0.022	-0.028	0.027
	(0.167)	(0.017)	(0.040)	(0.045)	(0.215)	(0.017)	(0.036)	(0.036)
Share of natural res. in overall empl. (base year)	-0.218	0.055^c	-0.029	-0.004	-0.262	0.007	-0.083	0.053
	(0.199)	(0.033)	(0.032)	(0.038)	(0.250)	(0.023)	(0.059)	(0.052)
January minimum temperature	0.001	-0.001^a	-0.000	0.001^c	0.001^b	-0.000^a	0.000^c	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Ln Distance to nearest big urban areas (meters)	-0.002	0.000	-0.000	0.001	0.001	0.000	0.000	0.000
	(0.003)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)
Ln Distance to nearest US border (meters)	-0.010	-0.003	-0.002	0.005	-0.009	-0.001	-0.001	0.002
	(0.020)	(0.002)	(0.002)	(0.004)	(0.010)	(0.001)	(0.001)	(0.002)
Period 1 dummy					✓	✓	✓	✓
Observations	145	145	145	145	290	290	290	290
Montiel-Olea and Pflueger F-stat	63.56*	63.56*	63.56*	63.56*	4.441	4.441	4.441	4.441

Notes: Huber-White robust standard errors in parentheses. Δ_s denotes the change in shares. * means that we reject the weak instrument hypothesis at a 10% significance level. Coefficients significant at: $^a p < 0.01$, $^b p < 0.05$, $^c p < 0.1$.

5.3 Heterogeneous city effects and resilience

Negative economic shocks due to deindustrialization may reduce the provision of local public goods (see, e.g., Feler and Senses, 2017), thereby amplifying the direct effects of the shock. A related—yet different—question is whether cities with a larger initial provision of specific local public goods are better able to weather the adverse shocks. We thus now ask whether some cities did fare better than others and, if yes, along what dimensions they differed?

The voluminous literature on city growth and resilience (see Glaeser 2022 for a recent overview and survey) points to a number of characteristics that could make cities more resilient to adverse economic shocks. The usual factors used to explain resilience include population size, the initial composition of industries, the extent of industrial diversification, as well as the presence of educational public services and of arts, cultural, and recreational services.

We now revisit the question of resilience by slicing our data along various dimensions in which cities are heterogeneous. To do so, we run regressions where we interact our treatment (job losses in large manufacturing plants) with proxies for the above-mentioned factors in the year 2001. We do this one-by-one for each of the factors. Since population size, one of the main factors, is correlated with the other factors—e.g., larger cities are also more diversified—it is hard to separate the other factors from size. We hence also run regressions where we simultaneously include the different factors and population size to try to disentangle the effects.

Table C.2 in the Appendix shows results where we include all interaction terms for heterogeneity. We report OLS results only since it is not possible to estimate the model using IVs given the number of interations and the number of observations. The IV is weak, and applying it to a small sample with multiple interaction terms is asking a lot of the data. Table C.2 shows that the results are across the board insignificant: there is basically no interaction term that is significantly different from zero. The only effect we find is that the negative impacts of job losses seem smaller for the working-age population in cities that had a larger initial share of employment in arts, culture, and recreational services (see Table C.2 in the Appendix).

To summarize, we find no statistical evidence among the usual suspects for what makes some cities more resilient than others. While arts, cultural, and recreational services do seem to play some role, we do not want to read too much out of these results.

6 Conclusion

We estimate the causal effect of big manufacturing plant closures and downsizing on the socio-economic composition of Canadian cities between 2001 and 2021. Using US manufacturing data to instrument for job losses in Canada, we find robust evidence that big manufacturing plant closures and downsizing lead to less population growth and a shift in the demographic composition of cities towards an older population with less families. However, we find very little evidence that initial city size, industrial diversity, or the presence of public services, help to mitigate those negative effects. We find some weak evidence that specific amenities—related to initial employment in arts, culture, and recreational services—may mitigate some of the negative effects, but more work is needed to better understand what makes cities resilient following negative labor demand shocks to manufacturing plants.

Our results suggest that the recent trade frictions between Canada and the US—which are likely to lead to big manufacturing plant closures and downsizing—may adversely affect the most exposed cities cities by reducing their population growth and shifting the age structure towards an older population. Neither is particularly helpful in view of a future rebound, as shown by the German experience in the eastern Länder following reunification in 1990 (e.g., Uhlig 2008).

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Appendix material

This set of appendices is organized as follows. Appendix A describes our data and provides descriptive statistics. Appendix B provides additional descriptive statistics and figures for the job loss variables we compute. Appendix C shows additional results.

Appendix A Data

A.1 Representativeness of the Scott's data

While the Scott's database is fairly exhaustive, it is not a census of manufacturing plants. Yet, it arguably constitutes the best alternative to restricted-access datasets such as Statistics Canada's Annual Survey of Manufacturers or the Business Register. Tables S.1 and S.2 in online Appendix S provide a comparison between the Scott's database and other Statistics Canada databases containing establishments (Annual Survey of Manufacturers; Canadian Business Register; and Labor Force Survey). In contrast to the Annual Survey of Manufacturers, the Scott's database provides more information on smaller plants. In contrast to the Business Register, it tracks plants and information about them over 16 years. In all cases, we see that the Scott's data provides good coverage that is on par with the other data sources.

We also computed the correlations between sectoral or provincial establishment counts and employment in the Scott's Data and the aforementioned Statistics Canada datasets. They are high (about 0.95 on average), thus showing that our data provide a fairly accurate picture of the overall manufacturing structure in terms of industrial composition, the number of plants, and employment.

A.2 Census data

We use Canadian census data from the years 2001, 2006, 2011, 2016, and 2021, as released by the Computing in the Humanities and Social Sciences (CHASS) data center at the University of Toronto. These data provide rich information on the socio-demographic characteristics of residents and their employment profiles. We use them to construct both dependent and control variables throughout the analysis.

Table B.1 summarizes the key variables used in the analysis. On average, Canadian urban areas experienced a population growth of 14.6% over the 20-year period, with substantial heterogeneity across cities. Family structures also shifted, with a notable decrease in families with multiple children. The share of residents with at least a bachelor's degree averaged 14% in 2001 (ranging from 4.9% to 42.4%), serving as our proxy for initial human capital. Prior research shows that human capital is a strong predictor of urban growth, as cities with higher educational attainment attract innovative firms and benefit from knowledge spillovers (see, e.g., Glaeser et al., 1995; Moretti, 2004). The average activity rate was 63.8%, reflecting labor market tightness, which is positively associated with urban resilience (see, e.g., Bound and Holzer, 2000). Manufacturing employment accounted for 11.1% of jobs on average, with some cities showing complete absence of manufacturing activity. The share of male workers in manufacturing was 78.2%, highlighting gender segmentation in industrial employment. Natural resource dependence, proxied by the share of employment in resource industries, averaged 5.9%. Cities with higher resource dependence tend to be more vulnerable to economic shocks and exhibit slower structural transformation (see Scheiring et al., 2023).

These figures highlight substantial variation in demographic, educational, and economic characteristics, which are essential for the empirical estimations.

A.3 County Business Pattern data

To construct our instrumental variables (IVs), we rely on the U.S. County Business Patterns (CBP) data from 2003 to 2019. These data provide detailed information on employment and establishment counts by industry and county. We compute the job losses rate of large manufacturing plants (with 50+ employees) in the U.S. by industry to build shift-share Bartik-style instruments. The identifying assumption is that industry-specific employment trends in the U.S. are exogenous to local shocks in Canadian cities. This approach allows us to isolate plausibly exogenous variation in Canadian manufacturing job losses driven by global industry trends rather than local conditions

A.4 Other geographic data

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

First, we construct distances of cities to various geographic features and other cities. 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 coastline. It has also been shown that cities that are close large cities in the urban hierarchy are more attractive to firms and workers (see Partridge et al., 2009). We thus calculate the distance of each urban area to the closest big city, where the latter is defined as a city of at least 300,000 inhabitants. Last, given the importance of trade with the US, we compute for each city the distance to the nearest segment of the US border.

We next leverage climate 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.[12]

Appendix B Descriptives for the job-loss rate

This appendix contains additional descriptive statistics for our job-loss rates. While Table 1 in the main text summarizes the geographic dimension of the job losses, Table B.2 illustrates their sectoral dimension. We exploit this variation across industries when constructing our instruments to capture cities' potential exposure to job losses. As shown, the total manufacturing job-loss rate constructed using our measure is 50.9% for the whole of Canada. This means that 51 out of 100 manufacturing jobs in large plants (50+ employees) present in 2003 were no longer existent in 2019, many to be not replaced.

[12] These data are available from stations that produce daily data from 2001 to 2016.

Table B.1: Descriptive statistics, urban area variables.

Variable	Obs	Mean	Std. dev.	Minimum	Maximum
Dependent variables					
Change in share of 0-19 people (10-year intervals)	435	-0.014	0.015	-0.056	0.026
Change in share of 0-19 people (15-year interval)	290	-0.021	0.015	-0.068	0.012
Change in share of 0-19 people (20-year interval)	145	-0.032	0.015	-0.069	0.002
Change in share of 20-64 people (10-year intervals)	435	-0.026	0.019	-0.076	0.048
Change in share of 20-64 people (15-year interval)	290	-0.039	0.023	-0.105	0.031
Change in share of 20-64 people (20-year interval)	145	-0.050	0.027	-0.113	0.001
Change in share of families with 1 kid (15-year interval)	145	0.036	0.030	-0.032	0.108
Change in share of families with 2 kids (15-year interval)	145	-0.020	0.020	-0.074	0.024
Change in share of families with 3 kids or more (15-year interval)	145	-0.016	0.022	-0.080	0.040
Change in share of families with kids (20-year interval)	145	-0.078	0.040	-0.200	-0.002
Change in share of lone families with kids (20-year interval)	145	0.054	0.033	-0.028	0.171
Change in share of male people (20-year interval)	145	0.003	0.006	-0.016	0.025
Change in share of married people (20-year interval)	145	0.277	0.019	0.221	0.337
Change in share of migrants (20-year interval)	145	0.025	0.038	-0.052	0.131
Change in share of people aged 65 and over (10-year intervals)	435	0.041	0.023	-0.029	0.104
Change in share of people aged 65 and over (15-year interval)	290	0.062	0.031	-0.028	0.137
Change in share of people aged 65 and over (20-year interval)	145	0.081	0.036	-0.009	0.165
Change in share of pop. with at least a bachelor degree (20-year interval)	145	0.065	0.029	0.017	0.180
Change in total population (10-year intervals)	435	0.074	0.083	-0.210	0.350
Change in total population (15-year interval)	290	0.111	0.119	-0.235	0.515
Change in total population (20-year interval)	145	0.146	0.154	-0.222	0.699
Job losses variables					
Job losses in big plants (5-year intervals)	580	0.187	0.166	0.000	0.917
Job losses in big plants (5-year intervals)	290	0.310	0.197	0.000	0.944
Job losses in big plants (15-year interval)	725	0.404	0.216	0.000	0.944
Job losses in big plants (20-year interval)	725	0.465	0.221	0.000	0.944
Other dependent variables					
(log) total population	725	11.006	1.265	8.831	15.640
Share of people with university degree	725	0.146	0.060	0.049	0.424
Activity rate	725	0.638	0.069	0.353	0.850
Share of manufacturing employment	725	0.111	0.074	0.000	0.443
Share of male in manufacturing employment	289	0.782	0.079	0.517	1.000
Share of natural ressources employment	725	0.059	0.058	0.000	0.333
January minimum temperature	725	-25.263	9.480	-40.700	0.000
(log) distance to nearest big urban areas	725	10.747	3.883	0.000	14.168
(log) distance to nearest US border	725	11.907	0.937	9.623	13.948

Notes: A big urban area is a city with at least 300,000 residents. Mean is the sample mean.

Table B.2: Sectoral dimension of job losses (Part 1 of 2).

NAICS4	Manufacturing sector	Significant closures	
		Job loss rate	Avg. size
3111	Animal Food	38.8%	162.7
3112	Grain and Oilseed Milling	44.2%	139.3
3113	Sugar and Confectionery Product	39.1%	203.3
3114	Fruit and Vegetable Preserving and Specialty Food	60.0%	172.6
3115	Dairy Product	54.0%	159.4
3116	Animal Slaughtering and Processing	49.9%	155.6
3117	Seafood Product Preparation and Packaging	53.8%	159.8
3118	Bakeries and Tortilla	44.2%	141.8
3119	Other Food	52.6%	139.0
3121	Beverage	40.1%	172.2
3122	Tobacco	81.2%	292.0
3131	Fiber, Yarn, and Thread Mills	88.7%	175.3
3132	Fabric Mills	78.8%	179.6
3133	Textile and Fabric Finishing and Fabric Coating Mills	64.4%	155.1
3141	Textile Furnishings Mills	55.3%	116.8
3149	Other Textile Product Mills	52.6%	127.3
3151	Apparel Knitting Mills	82.7%	169.9
3152	Cut and Sew Apparel	61.0%	131.4
3159	Apparel Accessories and Other Apparel	51.1%	82.2
3161	Leather and Hide Tanning and Finishing	73.4%	104.4
3162	Footwear	68.5%	157.9
3169	Other Leather and Allied Product	46.6%	127.0
3211	Sawmills and Wood Preservation	62.4%	179.1
3212	Veneer, Plywood, and Engineered Wood Product	55.9%	151.4
3219	Other Wood Product	46.2%	124.5
3221	Pulp, Paper, and Paperboard Mills	89.0%	346.5
3222	Converted Paper Product	56.9%	141.6
3231	Printing and Related Support Activities	43.5%	126.3
3241	Petroleum and Coal Products	49.6%	193.5
3251	Basic Chemical	57.3%	138.5
3252	Resin, Synthetic Rubber, and Artificial and Synthetic Fibers and Filaments	69.7%	150.4
3253	Pesticide, Fertilizer, and Other Agricultural Chemical	37.0%	120.4
3254	Pharmaceutical and Medicine	56.7%	187.6
3255	Paint, Coating, and Adhesive	46.9%	129.5
3256	Soap, Cleaning Compound, and Toilet Preparation	47.6%	129.2
3259	Other Chemical Product and Preparation	42.6%	107.8
3261	Plastics Product	52.2%	130.7
3262	Rubber Product	56.6%	201.9
3271	Clay Product and Refractory	49.6%	96.6
3272	Glass and Glass Product	63.6%	182.0
3273	Cement and Concrete Product	33.0%	116.7
3274	Lime and Gypsum Product	74.2%	174.5

Table B.3: Sectoral dimension of job losses (Part 2 of 2).

NAICS4	Manufacturing sector	Significant closures	
		Job loss rate	Avg. size
3279	Other Nonmetallic Mineral Product	48.2%	119.4
3311	Iron and Steel Mills and Ferroalloy	53.9%	187.5
3312	Steel Product from Purchased Steel	56.5%	192.8
3313	Alumina and Aluminum Production and Processing	67.0%	222.4
3314	Nonferrous Metal (except Aluminum) Production and Processing	54.7%	181.0
3315	Foundries	68.4%	196.3
3321	Forging and Stamping	66.2%	159.0
3322	Cutlery and Handtool	45.1%	155.6
3323	Architectural and Structural Metals	35.4%	121.2
3324	Boiler, Tank, and Shipping Container	60.0%	123.5
3325	Hardware	63.6%	201.3
3326	Spring and Wire Product	58.8%	146.2
3327	Machine Shops; Turned Product; and Screw, Nut, and Bolt	32.1%	110.1
3328	Coating, Engraving, Heat Treating, and Allied Activities	41.1%	99.5
3329	Other Fabricated Metal Product	45.7%	132.8
3331	Agriculture, Construction, and Mining Machinery	49.4%	128.1
3332	Industrial Machinery	41.5%	117.2
3333	Commercial and Service Industry Machinery	47.8%	170.3
3334	Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment	38.0%	103.9
3335	Metalworking Machinery	40.4%	112.4
3336	Engine, Turbine, and Power Transmission Equipment	39.1%	137.1
3339	Other General Purpose Machinery	42.4%	112.2
3341	Computer and Peripheral Equipment	49.6%	112.6
3342	Communications Equipment	65.6%	197.6
3343	Audio and Video Equipment	58.3%	113.1
3344	Semiconductor and Other Electronic Component	65.9%	182.8
3345	Navigational, Measuring, Electromedical, and Control Instruments	41.4%	157.1
3346	and Reproducing Magnetic and Optical Media	50.8%	137.9
3351	Electric Lighting Equipment	52.2%	171.6
3352	Household Appliance	66.9%	170.0
3353	Electrical Equipment	43.8%	152.8
3359	Other Electrical Equipment and Component	57.8%	144.4
3361	Motor Vehicle	58.1%	215.6
3362	Motor Vehicle Body and Trailer	48.4%	142.3
3363	Motor Vehicle Parts	69.4%	227.1
3364	Aerospace Product and Parts	67.2%	249.0
3365	Railroad Rolling Stock	59.3%	107.8
3366	Ship and Boat Building	40.3%	152.0
3369	Other Transportation Equipment	79.2%	200.6
3371	Household and Institutional Furniture and Kitchen Cabinet	44.4%	157.4
3372	Office Furniture (including Fixtures)	45.9%	128.2
3379	Other Furniture Related Product	42.9%	113.6
3399	Other Miscellaneous	43.0%	132.1
	All manufacturing sectors	50.9%	146.1

Appendix C   Additional tables and results

Table C.1: Other demographic outcomes.

	(1) Δ_s univ.	(2) Δ_s male	(3) Δ_s male/mfg	(4) Δ_s married	(5) Δ_s families	(6) Δ_s lone	(7) Δ_s 1-kid	(8) Δ_s 2-kids	(9) Δ_s 3-kids	(10) Δ_s migrants
Job losses in big plants	-0.019	0.005	-0.083	-0.002	-0.100^a	-0.015	-0.054	0.022^c	0.032	-0.019
	(0.014)	(0.006)	(0.086)	(0.010)	(0.035)	(0.015)	(0.039)	(0.013)	(0.034)	(0.015)
ln population in 2001.	0.001	0.001^b	0.004	-0.004^c	0.014^a	-0.003	-0.003	0.003^a	-0.000	0.006^a
	(0.002)	(0.001)	(0.010)	(0.002)	(0.004)	(0.004)	(0.002)	(0.001)	(0.002)	(0.002)
Share of population with at least a bachelor degree in 2001	0.143^b	-0.019	-0.107	0.120^b	-0.536^a	-0.154^c	-0.209^c	0.090	0.119^c	0.074
	(0.068)	(0.019)	(0.290)	(0.058)	(0.136)	(0.090)	(0.110)	(0.064)	(0.071)	(0.050)
Participation rate in 2001	0.151^a	-0.010	-0.112	0.036	0.253^a	-0.193^a	0.046	0.060	-0.106^b	0.218^a
	(0.016)	(0.012)	(0.113)	(0.053)	(0.087)	(0.045)	(0.073)	(0.042)	(0.042)	(0.027)
Share of manufacturing in overall employment in 2001	-0.081^b	-0.019^a	-0.052	0.035^b	-0.110	0.090^b	-0.030	0.004	0.027	-0.081^c
	(0.032)	(0.006)	(0.113)	(0.017)	(0.085)	(0.044)	(0.039)	(0.026)	(0.032)	(0.042)
Share of natural resources in overall employment in 2001	-0.169^a	-0.025^a	0.029	0.088^b	-0.075	0.067	-0.084	-0.012	0.096^a	0.015
	(0.045)	(0.008)	(0.177)	(0.042)	(0.052)	(0.044)	(0.056)	(0.044)	(0.020)	(0.028)
January minimum temperature	0.001^a	-0.000^a	-0.002^a	0.000^a	-0.000	-0.001	0.001^b	-0.000	-0.001^a	-0.001^a
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln distance to nearest big urban areas (meters)	-0.001^a	0.000^c	0.001	0.000	-0.002^a	-0.001	0.000	0.001	-0.001	-0.001^c
	(0.000)	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
ln distance to nearest US border (meters)	0.000	-0.001^a	-0.014^c	-0.001	-0.007^a	0.005	0.001	0.002	-0.004^b	-0.002
	(0.003)	(0.000)	(0.007)	(0.003)	(0.003)	(0.005)	(0.003)	(0.002)	(0.001)	(0.004)
Observations	145	145	144	145	145	145	145	145	145	145
Montiel-Olea and Pflueger F-stat	44.85*	44.85*	45.08*	44.85*	44.85*	44.85*	36.39*	36.39*	36.39*	44.85*

Notes: Δ_s denotes the change in shares. Huber-White robust standard errors in parentheses. [1]The IV results we present in this table use the dichotomized version of the Bartik instrument (3).
*means that we reject the weak instrument hypothesis at a 10% significance level. Coefficients significant at: $^a p < 0.01$, $^b p < 0.05$, $^c p < 0.1$.

Table C.2: Heterogeneous effects across cities.

	(1) Δ ln pop.	(2) Δ_s 0-19	(3) Δ_s 20-64	(4) Δ_s 65+
Job losses in big plants	0.345	0.246^{b}	0.171	-0.441
	(0.911)	(0.089)	(0.197)	(0.252)
Job losses in big plants $\times$ ln population in 2001	-0.029	-0.003	-0.012	0.017
	(0.065)	(0.003)	(0.010)	(0.015)
Job losses in big plants $\times$ share of manufacturing 2001	-0.479	-0.127	0.069	0.163
	(1.480)	(0.136)	(0.137)	(0.160)
Job losses in big plants $\times$ share of arts in 2001	-2.188	0.138	1.043^{a}	-1.133^{b}
	(2.171)	(0.284)	(0.311)	(0.390)
Job losses in big plants $\times$ ln sectoral diversity in 2001	-0.064	-0.082^{b}	-0.041	0.118
	(0.319)	(0.033)	(0.063)	(0.089)
ln population in 2001	0.037	0.006^{a}	0.012^{b}	-0.020^{b}
	(0.045)	(0.002)	(0.005)	(0.008)
Share of population with at least a bachelor degree in 2001	-0.313	-0.012	-0.317^{a}	0.319^{a}
	(0.338)	(0.029)	(0.087)	(0.095)
Participation rate in 2001	0.955^{a}	-0.007	0.232^{a}	-0.295^{a}
	(0.293)	(0.024)	(0.034)	(0.033)
Share of manufacturing in overall employment in 2001	0.291	-0.030	-0.182^{b}	0.172^{b}
	(0.398)	(0.036)	(0.067)	(0.073)
Share of natural resources in overall employment in 2001	-0.314	0.032	-0.092^{c}	0.061
	(0.408)	(0.029)	(0.051)	(0.064)
Share of arts and recreation in overall employment in 2001	2.903^{b}	-0.299	-0.341	0.576^{c}
	(1.260)	(0.186)	(0.274)	(0.303)
ln sectoral diversity in 2001	0.071	0.008	0.023	-0.023
	(0.107)	(0.012)	(0.033)	(0.046)
January minimum temperature	0.001	-0.001^{a}	0.000	0.001
	(0.001)	(0.000)	(0.000)	(0.001)
ln distance to nearest big urban areas (meters)	-0.002	0.000	-0.001^{b}	0.001^{b}
	(0.006)	(0.000)	(0.000)	(0.000)
ln distance to nearest US border (meters)	-0.019	-0.003^{c}	-0.003	0.006
	(0.029)	(0.002)	(0.003)	(0.004)
Observations	145	145	145	145
R-squared	0.352	0.362	0.463	0.514

Notes: Δ_s denotes the change in shares. Huber-White robust standard errors in parentheses. Sectoral diversity is measured using the inverse of the Hirschman-Herfindahl index of employment share concentration in 2001. [1]The IV results we present in this table use the dichotomized version of the Bartik instrument (3). Coefficients significant at: $^{a}p < 0.01$, $^{b}p < 0.05$, $^{c}p < 0.1$.

Table C.3: Results by age, OLS estimations.

	(1)	(2)	(3)	(4)
	Δ ln pop.	Δ_s 0-19	Δ_s 0-64	Δ_s 65+
Job losses in big plants 0319	-0.187^{a}	0.003	-0.015	0.009
	(0.053)	(0.005)	(0.010)	(0.011)
ln population in 2001	0.025	0.003^{b}	0.006^{a}	-0.010^{a}
	(0.022)	(0.001)	(0.001)	(0.002)
Share of population with at least a bachelor degree in 2001	-0.383	0.032	-0.305^{a}	0.283^{a}
	(0.238)	(0.035)	(0.071)	(0.088)
Participation rate in 2001	0.972^{a}	-0.022	0.227^{a}	-0.279^{a}
	(0.274)	(0.018)	(0.038)	(0.036)
Share of manufacturing in overall employment in 2001	-0.148	0.001	-0.155^{a}	0.168^{b}
	(0.256)	(0.023)	(0.048)	(0.061)
Share of natural resources in overall employment in 2001	-0.442	0.065^{c}	-0.081^{b}	0.031
	(0.290)	(0.033)	(0.036)	(0.044)
January minimum temperature	0.002^{a}	-0.001^{a}	0.000	0.001
	(0.001)	(0.000)	(0.000)	(0.000)
ln distance to nearest big urban areas (meters)	-0.002	0.000	-0.001^{c}	0.001^{a}
	(0.005)	(0.000)	(0.000)	(0.000)
ln distance to nearest US border (meters)	-0.021	-0.003	-0.003	0.005
	(0.028)	(0.002)	(0.003)	(0.004)
Observations	145	145	145	145
R-squared	0.331	0.289	0.423	0.477

Notes: Δ_s denotes the change in shares. Huber-White robust standard errors in parentheses. Coefficients significant at: $^{a}p < 0.01$, $^{b}p < 0.05$, $^{c}p < 0.1$.

Supplementary Appendix Material for :

"Deindustrialization and demographic change: Evidence from big plant closures and downsizing"

Appendix S Comparing the Scott's data to other datasources.

Table S.1: Comparing the Scott's National All database to the ASM database.

Scott's National All database and the Annual Survey of Manufacturing (ASM)

	2003		2005		2007		2009		2011	
Province	ASM	Scott's	ASM	Scott's	ASM	Scott's	ASM	Scott's	ASM	Scott's
Alberta	4,882	3,649	7,750	3,453	8,091	3,702	7,852	3,579	7,003	3,454
British Columbia	6,933	5,921	11,942	5,373	12,179	5,230	11,605	4,992	11,552	4,898
Manitoba	1,481	1,555	2,307	1,480	2,351	1,394	2,323	1,262	1,918	1,279
New Brunswick	963	1,376	1,533	1,259	1,496	1,158	1,412	1,173	1,381	1,019
Newfoundland	522	578	706	539	738	508	657	472	660	418
Nova Scotia	1,106	1,576	1,944	1,495	1,904	1,337	1,817	1,296	1,760	1,163
Ontario	21,470	21,753	34,184	20,965	33,634	20,260	31,991	19,636	29,046	18,689
Prince Edward Island	211	303	299	327	369	307	358	281	342	258
Quebec	15,251	14,768	23,042	14,165	22,324	12,907	21,149	12,566	19,272	11,969
Saskatchewan	1,008	1,291	1,664	1,305	1,845	1,190	1,861	1,093	1,410	1,125
Canada	53,827	52,770	85,371	50,401	84,931	48,043	81,025	46,395	74,344	44,313
Cross-industry correlation	***0.91***		***0.87***		***0.85***		***0.85***		***0.85***	

Notes: Data are from the Scott's databases, 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. Because of small numbers, the three territories (Northwest Territories, Nunavut, and Yukon) are not reported in the table but are included in the total. The descriptive statistics reported as "cross-industry" in the bottom panel of the table are computed across all 4 digits manufacturing industries (NAICS 3111–3399).

Table S.2: Comparing the Scott's National All databases to the Labor Force Survey (LFS) by Cities (>100K).

	2003		2005		2007		2009		2011		2013		2017		2019	
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	9.9	6.8	9.9	7.2	10.4	6.6	8.5	6.3	7.5	5.8	8.2	4.9	9.7	5.1	9.9	5.1
Barrie	14.8	6.6	17.4	7.4	15.4	8.1	10.4	6.8	14.4	6.0	14.8	5.9	15.5	5.8	13.3	5.4
Brantford	17.4	14.7	17.7	15.2	15.8	14.1	14.5	13.4	13.6	10.8	13.8	10.4	14.4	9.4	14.7	8.9
Calgary	53.4	47.6	42.6	46.0	47.3	52.0	42.5	50.6	46.1	47.3	46.2	41.4	39.0	35.5	46.4	31.3
Edmonton	50.2	43.4	48.8	47.8	53.5	56.5	44.2	53.1	51.4	51.3	58.7	47.0	41.5	44.5	50.9	38.1
Greater Sudbury	4.3	4.0	4.4	3.9	3.7	3.6	3.5	3.6	3.9	3.4	3.3	3.7	3.1	2.9	2.8	2.6
Guelph	19.8	25.7	20.2	24.1	19.2	21.9	15.3	21.6	15.6	20.0	14.7	19.7	16.8	19.9	18.8	19.5
Halifax	10.8	12.5	9.9	11.3	12.5	12.3	11.8	13.1	11.4	12.8	10.0	10.8	10.5	8.6	10.9	8.7
Hamilton	76.2	38.6	69.2	39.1	58.1	37.0	51.1	35.3	49.3	34.4	46.6	31.2	49.8	28.3	50.2	26.7
Kelowna	7.8	5.4	6.4	5.9	8.3	5.8	6.6	5.3	6.3	4.9	4.4	5.9	5.0	4.7	5.2	3.9
Kingston	6.0	3.7	6.1	3.1	5.2	2.9	4.1	2.9	4.4	2.9	4.0	2.4	3.9	3.3	4.3	2.8
London	41.7	24.4	39.4	25.4	35.1	25.9	29.9	24.6	29.2	19.9	27.4	19.1	29.8	15.8	34.3	15.2
Moncton	5.0	7.7	4.4	7.7	4.3	6.8	5.9	7.4	5.4	5.9	4.6	6.2	4.2	5.0	4.9	3.9
Montreal	291.4	250.5	286.9	238.4	246.2	215.9	242.8	215.3	224.2	202.9	225.7	169.4	226.0	143.6	237.8	84.4
Oshawa	33.6	11.0	32.5	10.8	26.8	9.8	20.5	8.6	19.4	7.4	20.5	6.2	17.1	6.1	17.0	5.2
Ottawa-Gatineau	34.9	27.2	38.3	26.8	43.5	27.6	35.9	27.3	27.3	27.4	23.3	23.6	24.7	22.0	21.8	17.9
Peterborough	7.6	4.8	7.2	4.6	8.2	4.8	6.0	4.8	5.9	4.4	4.8	4.8	3.8	5.2	4.4	4.7
Quebec	33.0	32.6	40.7	35.7	39.3	35.3	32.3	35.5	32.2	32.4	28.4	32.7	32.1	26.2	32.0	17.6
Regina	5.5	5.9	6.4	6.7	6.5	6.3	7.5	6.3	6.8	7.0	7.0	5.5	8.3	5.4	7.4	4.6
Saguenay	10.2	7.5	10.6	8.4	11.0	8.5	9.1	8.8	8.6	9.2	9.3	6.8	7.8	5.8	8.9	1.9
Saint John	5.1	5.6	4.1	5.5	6.0	5.1	5.4	5.6	5.5	2.8	4.4	3.8	5.9	2.6	5.1	2.7
Saskatoon	9.2	12.5	11.8	11.1	11.3	9.9	11.1	9.5	9.1	9.9	11.4	8.6	8.8	8.3	11.0	8.0
Sherbrooke	23.1	17.3	17.6	16.4	14.0	12.8	12.4	12.9	13.3	12.5	11.9	11.6	14.8	11.7	15.0	5.8
St John's	3.4	5.9	3.9	5.4	5.2	5.9	4.4	5.9	3.8	5.5	5.1	5.9	3.7	4.3	3.4	4.4
St. Catharines - Niagara	30.5	21.9	26.9	20.6	25.6	18.7	20.6	17.1	21.0	15.0	21.8	13.1	21.6	12.2	18.5	11.5
Thunder Bay	6.7	4.1	5.0	4.2	4.4	4.1	2.9	3.1	2.9	3.5	4.2	2.5	3.2	2.1	2.9	2.1
Toronto	466.6	383.1	457.1	372.3	397.6	352.2	328.4	340.9	331.9	307.3	334.1	277.7	336.8	245.2	328.4	220.3
Trois-Rivieres	11.0	8.9	11.4	8.8	10.5	8.5	9.7	8.2	8.3	7.6	8.3	6.5	9.6	5.8	9.0	3.6
Vancouver	112.7	96.8	101.2	92.5	105.6	97.5	86.1	94.8	85.1	91.7	84.7	76.2	99.9	74.2	96.2	61.9
Victoria	8.5	5.8	7.7	5.8	6.7	5.6	6.2	5.9	5.9	5.8	5.8	5.2	7.2	4.7	5.9	4.2
Waterloo	63.0	47.3	63.7	47.7	59.0	45.0	49.8	42.1	49.3	36.9	52.3	31.1	51.3	30.5	51.1	27.3
Windsor	48.2	27.5	48.0	26.5	35.5	27.8	29.6	25.5	30.7	21.5	31.4	19.6	38.4	18.4	36.0	15.3
Winnipeg	47.0	39.9	45.7	40.4	48.0	37.4	40.5	35.1	37.5	35.9	41.3	32.0	42.8	26.3	43.4	22.2
Cross-employment correlation	***0.99***		***0.99***		***0.99***		***0.99***		***0.99***		***0.99***		***0.99***		***0.96***	

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.