Are clusters resilient? Evidence from Canadian textile industries

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Abstract

We investigate whether plants inside and outside geographic clusters differ in their resilience to adverse economic shocks. To this end, we develop a bottom-up procedure to delimit clusters using Canadian geo-coded plant-level data. Focussing on the textile and clothing industries and exploiting the dramatic changes faced by that sector between 2001 and 2013, we find no evidence that plants in clusters are more resilient than plants outside clusters: they are neither less likely to die nor more likely to adapt by switching their main line of business. However, conditional on switching, plants in urbanized clusters are more likely to transition to services.

Keywords: Geographic clusters; resilience; textile and clothing industries; Multifibre Arrangement; geo-coded data.

JEL Classifications: R12; F14

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"[...] perhaps the most discerning test of 'true' cluster dynamics is one that assesses the alleged cluster's resilience and robustness over time, in the face of severe shocks and dislocations. How has the region fared under such circumstances? How effectively have its firms and institutions adapted and evolved in response to such pressures for change?"(Wolfe & Gertler 2004, pp. 1085–1086).

1 Introduction

Developed countries have experienced major adverse shocks over the last two decades. The Great Recession, the 2008 trade collapse, and the surge of China are examples of negative disturbances that have affected many industries in those economies. One political response to these shocks is to put 'resilience' high on the policy agenda. This is echoed by recent speeches of global leaders like Christine Lagarde from the IMF who urges to "build a more resilient and inclusive global economy."[1]

A widely held view in policy circles is that economic clusters could foster this agenda. As there is an academic consensus that geographic clustering gives rise to productivity gains (see, e.g., Duranton & Puga 2004, Combes & Gobillon 2014), associating clusters with other positive outcomes — such as the 'resilience' of firms, industries, or regions — is tempting. However, we have very little empirical evidence to back such rather vague associations. To make progress on this topic, we investigate the resilience of plants in Canadian textile and clothing (T&C) clusters between 2001 and 2013. Previewing our key results, we find no evidence that plants in clusters are more resilient than plants outside clusters: they are neither less likely to die nor more likely to adapt by switching their main line of business. However, conditional on switching, plants in urbanized clusters are more likely to transition to services.

Evaluating the effect of geographic clustering on the resilience of plants faces two major difficulties. First, one needs an operational definition of clusters. Conceptually defined as *"a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities*

[1] Available online at `https://www.imf.org/en/News/Articles/2017/04/07/building-a-more-resilient-and-inclusive-global-economy-a-speech-by-christine-lagarde`, last accessed on July 14, 2017.

and complementarities" (Porter 1990, p.16), such clusters are more difficult to identify in practice as they rarely conform to existing industrial and administrative boundaries. Identifying clusters thus requires us to define meaningful geographic groupings of related activities, and to associate plants with these 'clusters' (see Delgado et al. 2016*b*, Behrens 2016). To tackle this problem, we use several measures of economic proximity between industries (e.g., input-output links, labor-force similarity) to delimit our textile and clothing sector, and then use detailed geocoded plant-level data to map the location and evolution of clusters in Canada using tools from spatial point-pattern analysis.

Second, one needs an operational definition of resilience. As emphasized by Pendall et al. (2010), Martin (2012), or Martin & Sunley (2015), resilience has become a buzzword in policy and academic circles. It may alternatively refer to the ability of a system to recover from, to absorb, or to adapt to a shock.[2] We propose an empirical framework to articulate these concepts and show how they relate to each other. In a nutshell, we consider that a resilient plant is one that remains active in its industry (referred to as 'strong resilience'), or at least, that survives by switching to another industry ('weak resilience').

Having delimited our geographic T&C clusters and conceptualized resilience, we then compare how clustered and unclustered plants resort to these different adjustment margins. We focus on the 2001—2013 period, when T&C industries experienced large adverse shocks. As a result of these shocks, the sector lost two thirds of its employees, half of its firms, while its imports from China surged by about 200%. Though these large and profound changes rapidly reshaped the Canadian T&C sector, we do not find evidence of a higher resilience of establishments in clusters in that period. On the contrary, we find that 'clustered' plants were about 2% more likely to die than plants located outside these clusters. While we do not observe systematic differences in the probability to switch to another industry, we do find that switching patterns are different for plants inside and outside clusters. Plants in clusters — partic-

[2] Martin & Sunley (2015) define three types of resilience. The 'engineering resilience' is a system's ability to absorb a shock without changing its structure, identity, and function. The 'ecological resilience' pertains to a system's velocity to retain the same equilibrium function, identity, and structure. The 'adaptive resilience' refers to a system's ability to resist external disturbances and disruptions by undergoing plastic changes in some aspects of its structure and components.

ularly in large urban clusters — were more likely to switch to services, while plants outside clusters were prone to switch to other manufacturing activities. These results are robust to alternative measures of exposition to clusters and several placebo tests. Besides, we control for a set of important plant-level characteristics in order to partially correct for the self-selection of plants into clusters. Last, we deal with the potential endogeneity of clusters' definition using detailed historical information on the location of T&C industries in the 19th century.

While the foregoing analysis offers important insights into the resilience of clusters, it does not pay explicit attention to the source and the nature of the economic shocks. Hence, we refine our analysis by looking at a large and well-identified industry shock: the removal of import quotas in January 2005 in the wake of the expiry of the Multifibre Arrangement (MFA). The magnitude of this industry-specific shock, combined with the fact that T&C industries were geographically strongly concentrated in 2001, provides an ideal laboratory for evaluating the interplay between resilience and geographic patterns in the presence of a large industry shock. Using our plant-level data, we find that the end of the MFA had a large adverse impact on the T&C sector: plants active in industries directly hit by the quota removal exited the sector at a faster rate than plants in less exposed industries. We further find that many of those plants did not die but, instead, switched to other activities. However, we still do not find evidence that plants in clusters were more resilient than plants outside clusters after this shock, and these results are robust to various specifications. In a nutshell, we fail to find evidence of a higher resilience of T&C clusters in general, and after the end of the MFA in particular.

Our contribution to the existing literature is twofold. First, we contribute to the studies on the resilience of clusters. Theoretically, some authors argue that clustering generates economic benefits, thereby enhancing firms' resilience to adverse shocks (e.g., Delgado et al. 2016*a*). However, a competing view is that clusters make firms more vulnerable to such shocks. As clusters mature, so goes the argument, they become a source of inertia by generating behavioral mimetism that makes plants less able to adapt (Pouder & John 1996, Martin & Sunley 2003, p.18). Besides, clusters may host firms that are more exposed to shocks. While small firms outside geographic clusters may specialize on niche products and cater to specific local demands, large firms in clusters may compete on more generic product segments in international markets (Holmes & Stevens 2014). The latter firms may well be more — rather than less — exposed and vulnerable to adverse economic shocks. The scarce empirical literature that examines this question includes Delgado et al. (2016*a*) who assess the role of clusters for the resilience of regional industries during the Great Recession in the U.S. They find that industries located in strong regional clusters experience higher employment growth during and after the recession. The authors interpret their findings as evidence of a lower vulnerability and a faster recovery of regional industries active in strong clusters. Turning to micro-level analyses, Martin et al. (2013) is the only contribution we know of that investigates whether firms in clusters resist better to economic shocks. The authors define resilience as the probability of exporters to stay active in foreign markets after the 2008 trade collapse. They show that exporters located near other exporters or targeted by cluster policies performed better than other firms under business-as-usual, but these cluster advantages vanished during the economic turmoil. Our results thus contribute to this debate by casting additional doubt on whether geographic clusters contribute to firms' resilience in times of major economic shocks.

Second, we contribute to the growing literature on the firm-level impact of increased Chinese competition in developed countries.[3] Consistent with Mion & Zhu (2013), we do not find a direct impact of Chinese competition on plants' survival. Instead, we find evidence that plants switch from T&C to other manufacturing industries and services. Transition to services is consistent with switching patterns observed in the U.S. (Bernard & Fort 2015) and Denmark (Bernard et al. 2017). Our finding is also in line with Breinlich et al. (2014) who document that UK firms switch to service provision as a response to increasing international competition. We find that these switching patterns are more pronounced for plants in urban clusters. Thus, 'where you cluster' matters for

[3] The end of the MFA is shown to have a deep impact on the *structure* and *composition* of the T&C industry in developed countries. Using Danish firm-level data, Utar (2012) shows that increasing competition from China following the quota removal led to a change in the workforce composition of Danish firms. Sales, value-added, intangible assets, and employment dropped in firms affected by this new source of competition. Bloom et al. (2016) shows that European firms exposed to increasing Chinese competition increased their volume of innovation. Finally, Martin & Mejean (2014) show that the quota removal on Chinese T&C exports led to a reallocation of activities in France from low- to high-quality firms.

adaptation.

The rest of the paper is organized as follows. Section 2 explains how we delineate the Canadian textile and clothing sector, and provides some historical context and aggregate facts on the dynamics of this industry. Section 3 shows how we construct and map our geographic clusters. In Section 4, we turn to the econometric analysis and present micro-level evidence on the resilience of textile plants in clusters. Finally, Section 5 concludes.

2 'Textile & Clothing' in Canada: context, definition, and facts

2.1 Historical context

This paper is about industry dynamics, trade protection, and geographic patterns. We first provide some historical context to show how those three components have shaped the Canadian textile landscape in place in the late 20th century.[4]

The origins of the Canadian textile industry date back to the 1820–1840 period, when wool and cotton were the two main fabrics of the country. The expansion of the textile industry during 19th century was triggered by several factors: (i) the growth of the internal market (the Canadian population almost doubled between 1870 and 1910); (ii) improvements in market access and political integration (expansion of the railroad system, proclamation of the Canadian Confederation); and (iii) strong import protection. Concerning the latter, despite support for free trade from many segments of the economy — especially the export-oriented staples industries like grains, ore, and lumber — Canada resorted to trade protection in manufactured goods early on. In particular, the country significantly increased import protection under the Macdonald national policy in 1879: tariffs almost doubled, reaching close to 30%. The story of the Canadian textile industry after that date is a classic one of import substituting industrialization. Many new large textile plants opened

[4]The following developments are largely based on Rouillard (1974), Mahon (1984) and McCullough (1992). A more detailed historical account of the material can be found in the online appendix W.

and industry output rose substantially until the 1890s in the cotton and wool industries, both protected by import tariffs.

The geography of the textile industry at the end of the 20th century largely took shape a hundred years earlier. Starting with wool, the location of the early industry was dictated by local market size, access to skilled labor, availability of raw materials, as well as proximity to hydraulic power. The wool industry was then made of numerous small family businesses, dispersed mainly across the province of Ontario. By contrast, the cotton industry was more geographically concentrated than wool. Also located in Ontario, but more importantly in Québec, it was a more capital intensive industry: its activity was automatically more concentrated geographically as it had larger plants. Because of its important capital and labor requirements, it was also more likely to be established in larger cities. In that respect, the province of Québec offered a geographically advantageous location. Access to railroads — Montréal being a national hub — allowed to import raw cotton from the U.S. and to dispatch finished products to geographically dispersed markets. Furthermore, the river system in Québec allowed to use cheap electric power which provided further incentives to locate in the Saint Lawrence valley between Québec city and Montréal. The latter city — being Canada's financial capital during that period — had finally a distinct advantage when it came to providing the large funds required to operate large cotton textile mills.

A substantial geographic shift occurred between 1870 and 1900, driven by two forces. First, the 1882–1883 recession hit the textile industry hard. The cotton industry saw the formation of large enterprises that controlled many textile mills and manufactures. The consolidated industry colluded, and firms managed to weather the crisis relatively well. Such consolidation did not happen in the more fragmented wool industry, explaining its decline. Second, the different dynamics of wool and cotton was amplified after 1897 when trade protection was relaxed as the principle of the British preference was introduced. This led to a surge of imports of wool products which eroded further the industry. The decreasing importance of wool and the rise of cotton induced a shift in the geographic composition of the textile industry which shifted from Ontario to become mostly active in Québec's urban centers. The concentration of the cotton industry necessarily also drew other related segments of textile, clothing, and shoe industries in its wake, which already happened to be fairly concentrated in Montréal.[5]

Turning to the 20th century, the key development was the emergence and strong growth of man-made fabrics during the inter-war years. The silk and synthetics industry started operating in eastern Ontario and Québec and quickly became fairly concentrated, both in geographical and industrial terms. This concentration, when combined with the trade protection enforced in the wake of the Great Depression of 1929, cemented the geographic concentration of this industry. The textile industry prospered that way until 1951 (the date at which it recorded the highest employment level ever in Canada). After that date, decreasing protection, stagnating exports, and rising labor costs caused many bankruptcies and several mergers which reinforced industrial concentration. It is fair to say that the textile and clothing industry — which developed in a fairly protected environment since the 19th century — had difficulties adjusting to international competition in the face of lower protection. The outcome was the 1971 textile policy that aimed to wrestle some power and trade concessions from the staples industries. This was completed by the Multifibre Arrangement (MFA) in 1973, which was signed by Canada to limit textile imports from developing countries. Most of the MFA remained in place until the early 2000s, which is the starting point for our subsequent analysis.

2.2 Defining the sector

Our analysis is concerned with the resilience of T&C clusters. Going back to its definition, a cluster is *"a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities"* (Porter 1990, p.16). Though conceptually clear, the 'field' in the definition empirically rarely conforms to standard industrial classifications. Therefore, our first step consists in grouping textile- and clothing-related industries from the NAICS industrial classification into a coherent and broader

[5] While less is known about the history of the clothing industry, the evidence we have suggests that it started with a high level of concentration in larger cities, especially Montréal: "*By the mid-1850s, large-scale clothing manufacturing companies were typically located in Montréal with one factory employing eight hundred people* [...] *Sole-sewing machines made it efficient to concentrate shoe manufacturing in steam-driven factories. By the 1860s, there were five major shoe manufacturers located in Montréal that produced the majority of the footwear sold in Canada.*" (Balakrishnan & Eliasson 2007, p.271)

field that we refer to as the T&C sector. Similar to Delgado et al. (2016*b*), we use a mathematical cluster algorithm to group 4-digit industries according to their similarity along various dimensions of industrial relatedness. Let s_{ij} denote the similarity of industries i and j. We use five measures of s_{ij}: (i) the share of plants in industry i that report secondary activities in industry j; (ii) the strength of input-output links between industries i and j, based on national input-output tables; (iii) the similarity of industries i and j in terms of 553 occupational categories that they employ; (iv) the frequency with which patents in industry i cite patents originating in industry j; and (v) the extent of labor mobility across industries i and j. Details about the construction of those measures — which capture the relatedness ('commonalities and complementarities') of industries, a defining characteristic of geographic clusters — and the data underlying them are provided in Appendix A.1. Note that none of the aforementioned measures make use of geographic information. However, it is known that industrial relatedness, as proxied by (i)–(v), partly translates into geographic proximity (see Ellison et al. 2010, Behrens 2016, and Table 21 in the online appendix).

For each measure s_{ij}, the cluster algorithm partitions all 4-digit industries into groups such that industries are the most similar along s_{ij} within groups, and the most dissimilar along s_{ij} between groups. Table 1 summarizes the results of that procedure. As that table shows, the T&C sector is well delineated by NAICS 3131 to NAICS 3169. Roughly speaking, it encompasses all textile mills, apparel, cut-and-sew clothing, leather and hide, and footwear industries.[6] Observe that some other industries also tend to get as-

[6]Our T&C sector is close to that of Delgado et al. (2016*b*) in their 'Benchmark Cluster Definition': it encompasses their four clusters 'Apparel', 'Footwear', 'Leather and related products', and 'Textile manufacturing'. Note that we include the 'Leather and footwear' part in our definition of the T&C sector. As Table 1 shows, plants and firms engaged in textile manufacturing also tend to engage in footwear and leather-related activities ('Within-firm complementarities'). Note further that, although they use all industries in their analysis, the four textile-related clusters delimited by Delgado et al. (2016*b*) contain only manufacturing industries. Put differently, the T&C sector does not have extensive interactions with service or primary industries. Hence, the critique that our clusters 'abstract from the service industry' does not readily apply to our analysis. Furthermore, interviews with several Canadian apparel manufacturers revealed that 'associated institutions' do not seem to play a major role in textile industries: *"According to the respondents, the roles that associated institutions, such as government, trade associations and*

Table 1: T&C industry groupings, based on different similarity measures s_{ij} for 3,570 4-digit industry pairs.

	Groups into which the textile, apparel, footwear, and leather-related NAICS industries are partitioned			
Similarity measure s_{ij} used:	**Group 1**	**Group 2**	**Group 3**	**Residual groupings**
Within-firm complementarities	3141, **3379** Rugs and *furniture*	3131, 3149, 3133, 3132, 3159, **3231** Textile mills and *printing*	3151, 3161, 3162, 3169, 3152 Apparel and footwear	
Input-output linkages	**3116**, 3161, 3162, 3169 Footwear, leather, and *meat*	3131, 3132, 3133, 3141, 3149, 3151, 3152, 3159 Textiles mills, apparel and 'cut-and-sew'		
Occupational employment correlation	3131, 3132 Textile mills	3133, 3141, 3151, 3149, 3152, 3159, 3162 Textiles, apparel, and 'cut-and-sew'	3169 (a singleton cluster)	3161 (alone in one big cluster)
Patent citation flows	3161, 3162, 3169 Leather and footwear	3159, 3152 Cut-and-sew	3132 (a singleton cluster)	3131, 3133, 3149, 3141 (together in one big cluster)
Cross-industry labor mobility	3152, 3159, 3162 Cut-and-sew and footwear	3131, 3132, 3141, 3133, 3149, 3151, **3231** Textiles mills, rugs, hosiery and *printing*		3161, 3169 (together in one big cluster)

Notes: See Appendix A.1 for details on how we construct the different similarity measures. The clustering of industries is done using the Markov cluster algorithm (MCL) by Dongen (2000). The underlying graphs in the cluster algorithm are constructed with positive weights for all links with values above the median, and zero weights for all links below the median. Cutting off links at the median introduces more variability in the link weights, thereby making the graph less connected and allowing for sharper groupings. We run the algorithm on all 3,570 4-digit NAICS industry pairs, but we report only groups that contain industries related to textile and clothing in this table. Industries included in the T&C groups but which in the end are not included in our definition of the T&C sector (furniture, meat, printing) are italicized and their industry codes are reported in bold font.

sociated with the T&C sector, depending on which similarity metric is used. For example, some meat-related activities tend to enter into the 'footwear and leather' grouping when input-output relationships are considered, whereas some printing-related activities tend to enter the 'textile mills' grouping when within-firm complementarities or cross-industry labor mobility are considered. While these groupings make sense *a priori*, we exclude them because they only occur in a small subset of cases. However, we will see later that printing-related activities are indeed important for many textile plants, and that a substantial number of plants switched to printing as their main line of business in response to increased competition. Table 22 in online appendix S summarizes the aggregation of the T&C sector in terms of the underlying NAICS industries to produce time-consistent industry definitions. Eventually, our T&C sector comprises 11 4-digit industries, which are built from 22 6-digit industries.

2.3 Aggregate facts: industry dynamics

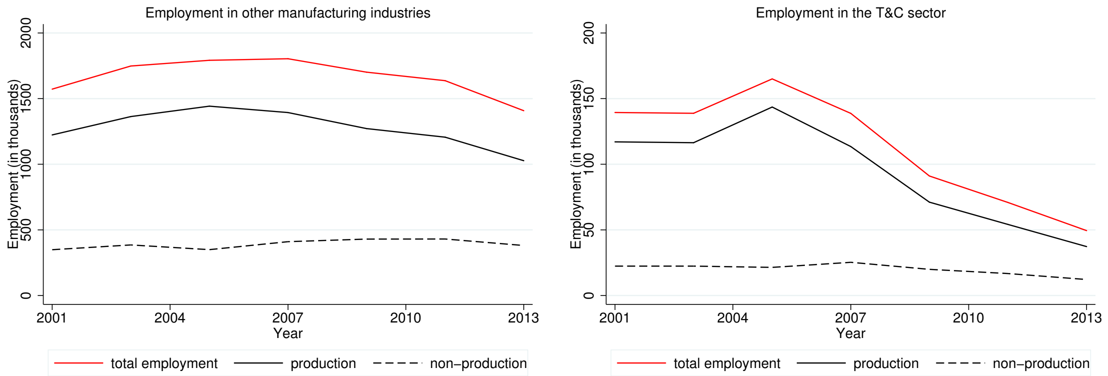
The late 1990s to late 2000s were a decade of profound change that significantly reshaped the T&C sector. Figure 1 depicts the evolution of employment in T&C and other manufacturing industries during that period, broken down by production and non-production jobs. The left panel shows that manufacturing employment has experienced a small increase from 2001 to 2007, followed by a decrease in the aftermath of the Great Recession. The evolution of T&C employment in the right panel is more marked and has a different time profile. More specifically, employment in this sector has declined sharply between 2005 and 2013, dropping from about 150,000 workers to a mere 50,000 workers. This decline has been mostly driven by production jobs as the number of non-production jobs remained relatively stable over our study period. Consequently, the share of non-production workers increased from less than 15% to almost 50% in the T&C sector.[7]

Table 2 shows that the fall in T&C employment was accompanied by a de-

educational institutions, play in this industry is quite limited." (Campaniaris et al. 2010, p.23).

[7] As noted in a 2004 report on changes in the Canadian apparel industry: "*Apparel executives intuitively are aware of the necessity to change* [...] *the industry intends to hire more than 3,000 white collar workers with expertise in areas such as logistics, sales and marketing. In implementing the required changes, the downsized apparel industry will shift from a blue collar to a white collar industry.*" (RichterConsulting 2004, p.3)

Figure 1: Employment trends in manufacturing and the T&C sector.



Notes: Our computations, based on the industry-level *Annual Survey of Manufacturers* dataset from Statistics Canada.

crease in the number of plants, which fell from 4,465 in 2001 to 2,057 in 2013. This decline has been markedly stronger in the T&C sector compared to the rest of the manufacturing industries so that the share of textile plants in Canada fell from 8.6% to 5.8% of manufacturing between 2001 and 2013. Table 2 summarizes the evolution of plant sizes, multiunit status, and export status over time. Contrary to the general trend of increasing plant sizes in manufacturing, the average plant size in the T&C sector has decreased over time. This suggests that textile plants may either have downsized (i.e., use the intensive margin) to adjust over our study period, or that large firms may have suffered more from changes in the economic environment: large firms producing standardized products are more exposed to increased import competition than smaller niche producers (Holmes & Stevens 2014). This explanation is consistent with the observed decrease in the share of multiunit plants — as can be seen from the last column of Table 2 — which fell more strongly in the T&C sector than in the remaining manufacturing industries. Last, Table 2 also reveals that the share of exporters increased in the T&C sector, which suggests that either exporters were better equipped to face competition from low-income countries or that more plants started exporting in the more globalized environment.

Table 3 summarizes plant exits in manufacturing and the T&C sector.[8] As

[8]Exit is particularly high between 2001 and 2003 — both for non-textile and for textile plants at 25% and 32%, respectively — whereas the total number of active plants remains almost constant. This large churning between 2001 and 2003 is partly explained by the switch in plant identifiers as *Scott's* changed them from 'Legacy' to 'Scott's ID'. Despite the use of

Table 2: Descriptive statistics for plants by year.

	Number of plants			% Exporter		Avg. plant size		% Multiunit	
Year	all	textile	% textile	textile	non-textile	textile	non-textile	textile	non-textile
2001	52,051	4,465	8.58	39.80	43.81	32.39	33.33	4.77	9.33
2003	51,893	4,386	8.45	41.43	45.06	31.54	33.96	4.58	8.99
2005	49,228	3,803	7.73	43.33	45.60	30.01	35.32	4.05	8.57
2007	46,272	3,170	6.85	45.55	45.95	28.13	36.21	3.82	8.22
2009	44,684	2,910	6.51	45.84	45.31	27.41	36.21	3.37	7.78
2011	42,219	2,696	6.39	45.51	45.48	25.81	35.59	2.74	7.65
2013	35,336	2,057	5.82	45.99	45.82	25.30	37.92	2.67	7.18

Notes: Our computations, based on the *Scott's National All* database (see Section 3.1 for a description). Textile plants are in NAICS industries 3131–3169. All industries are concorded to a stable classification. Plant size is measured by total employment. Plants indicate whether or not they are engaged in export activities (dummy variable). Multiunit is based on plants reporting the same legal name of the firm (see online appendix V for additional information). Average plant size is reported in terms of total plant employment.

can be seen from that table, there is substantial exit (and entry) over the period, and the magnitudes of our 2-year rates are broadly in line with what is know from other studies for the U.S. and Canada (Dunne et al. 1988). Furthermore, exit rates are systematically higher for T&C plants than for other plants. As in most studies, exit is defined from a 'national perspective': the plant leaves our Canadian database, but whether this is due to real exit, or to a relocation abroad, or to a change in name following a merger-and-acquisition cannot be ascertained using our dataset.[9] In all cases, Table 3 shows that the share of plant exits was higher in the T&C sector than in other manufacturing industries, and that this finding holds over our entire study period. Observe that the largest 'excess exit' in T&C occurred between 2005 and 2007.

While downsizing and exit are two possible responses to adverse economic shocks, changing business activity is another one.[10] Table 4 summarizes the

a concordance table, we have not been able to fully adjust for this change. We, therefore, conservatively exclude all changes at the plant level between 2001 and 2003 from our analysis. Since we define our clusters in the year 2001, this also puts some distance between our baseline year and the subsequent analysis, thereby mitigating simultaneity concerns regarding cluster definitions.

[9]Changes in ownership are not reported in the data. If two plants merge and both remain active, they will stay in the dataset and keep their identifiers. Note that if mergers lead to plant closures and a reallocation of resources across plants, one should observe an increase in exit together with an increase in employment in surviving plants. We do not find such pattern in our data.

[10]Historically, adaptation — a switch in activities — has always been important. For exam-

Table 3: Number of plants and plant exits by year.

	Other manufacturing plants				T&C plants			
	Active in $t-2$	# of exits	Share	Net change	Active in $t-2$	# of exits	Share	Net change
2003-2005	47,504	6,617	14%	-2,084	4,386	807	18%	-583
2005-2007	45,420	6,960	15%	-2,323	3,803	870	23%	-633
2007-2009	43,097	3,826	9%	-1,328	3,170	386	12%	-260
2009-2011	41,769	5,814	14%	-2,251	2,910	511	18%	-214
2011-2013	39,518	9,838	25%	-6,244	2,696	829	31%	-639

Notes: Our computations, based on the *Scott's National All* database (see Section 3.1 for a description). Net changes take into account entry. We define exit as a plant being out of the sample for at least four years, i.e., exit in year t is defined as a plant being out of the base in $t+2$ and $t+4$. Note that this condition is less stringent for exit between 2011 and 2013 since we do not observe plants in 2015. This right truncation may explain higher exit in 2011-2013.

Table 4: Change in primary sector of activity for T&C plants.

NAICS	Industry name	Number of switchers
Manufacturing industries:		
3231	Printing and related support activities	158
3399	Other Miscellaneous Manufacturing	55
3261	Plastic Product Manufacturing	30
3332	Industrial Machinery Manufacturing	24
—	All other manufacturing industries	110
Service industries:		
4141	Textile, clothing and footwear wholesaler-distributors	217
4189	Other miscellaneous wholesaler-distributors	55
4143	Home furnishings wholesaler-distributors	37
4191	Business-to-business electronic markets, and agents and brokers	26
—	All other service industries	117
Total number of T&C plants switching		377 + 452 = 829

Notes: We consider that a T&C plant switches industry between t and $t+2$ if it reports a primary NAICS code in the T&C sector in t, and a non-T&C primary NAICS code in $t+2$. The figures summarize industry switching between 2001 and 2013. Plants that exit are not considered as switchers, i.e., we only consider switching conditional on survival.

number of T&C plants that have changed their main line of business at some point between 2001 and 2013. We focus here on plants declaring a new primary activity outside the T&C sector, i.e., we disregard plants that switch their primary activity but remain in that sector. According to that definition, and taking 2001 as our base year, about 18.6% of textile plants changed their primary activity over our sample period.[11] Note further that many plants switched to

ple, during the 1882–1883 recession, when the textile industry suffered from excess capacity and more aggressive dumping from Great Britain and the U.S. (see Section 2.1), the industry realized that it had to diversify. Some firms became 'transformers', i.e., they processed textile (e.g., printing) without producing it (see McCullough 1992).

[11]Out of these 829 plants, one-fourth switched to 'Textile, clothing and footwear wholesaler-

the service industry. This is in line with general perceptions concerning some segments of the T&C sector: "*Based on the perceived importance of the primary activities, it appears that Canada's apparel supply is becoming more of a service industry.*" (Campaniaris et al. 2010, p.24).[12]

2.4 Aggregate facts: geographic patterns

As explained in Section 2.1, since the late 19th century, textile industries have been strongly concentrated geographically in Canada. We now show that the T&C sector: (i) remained among the most strongly localized sectors in 2001; (ii) was still substantially localized in 2013; yet (iii) experienced significant geographic deconcentration between those two years. To make those points, we exploit the microgeographic dimension of our data and measure the geographic concentration of industries using the distance-based K-densities pioneered by Duranton & Overman (2005, henceforth DO). Roughly speaking,

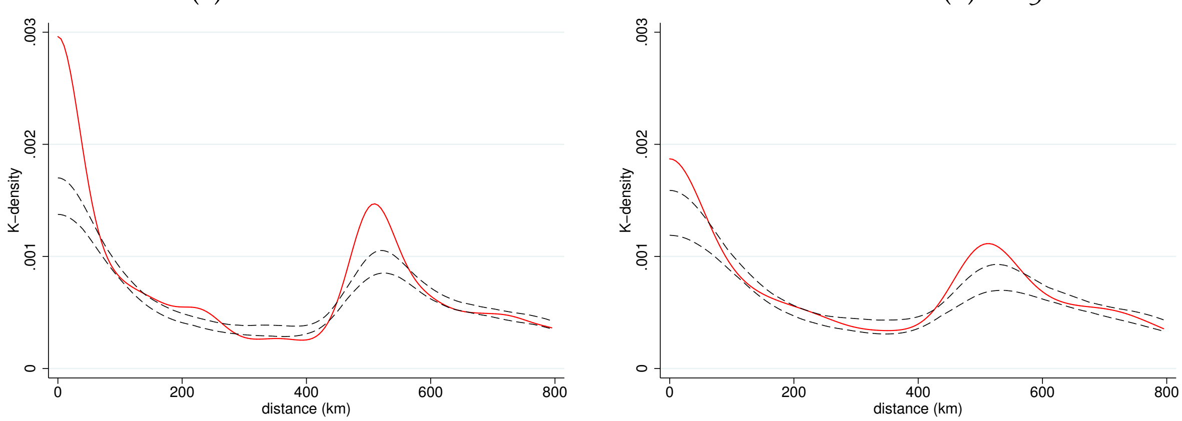
distributors' (NAICS 4141) and one-fifth switched to 'Printing and related support activities' (NAICS 3231). Interestingly, Delgado et al. (2016*b*) mention that they found a link between clothing and printing industries in the U.S. However, the absence of theoretical relations a priori between these two industries leads them to consider this association as an 'outlier' in their data. Our descriptive statistics on industry switching suggest that these industries may indeed be related, since a substantial fraction of textile firms that changed their activity as of 2001 changed it for printing activities. There is also a substantial fraction of T&C plants that report NAICS 3231 as a secondary activity. That share increased from 2.36% in 2001 to 6.60% in 2013. This suggests that there may be technological complementarities between textiles and printing, which would explain why printing is often a secondary activity of T&C plants and why they tend to switch into that activity. Actually, the links between textile manufacturing and printing are old and historically documented. For example, the first company that combined textile and printing in Canada — the Magog Textile and Printing Company — opened in 1884 (see Gaudreau 1995, for a full history).

[12]The Canadian textile industry is also widely engaged in product switching, product upgrading, and the development of product niches, which are adjustment margins that are hard to measure in a domestic context and, therefore, beyond the scope of our analysis. Recent anecdotal evidence illustrating those evolutions abound. As stated for example in a Québec business newspaper (our translation): "*Forget about cotton t-shirts: at the Expo Hightex 2009, the conferences were about 'nano-porous materials for drug transfers', 'preformed 3D textiles for aerospatial composites' or 'naturally flame-retardant cellulosic fibers'* [...] *Production is scaled back. The industry is oriented towards niche products with substantial value added and without aiming necessarily at large production runs.*" (Source: `http://affaires.lapresse.ca/economie/Québec/200910/16/01-912111-le-retour-du-textile-Québecois.php`, last accessed on June 13, 2017).

these measures looks at how close establishments are relative to each other by considering the distribution of bilateral distances between them. The idea is to apply sampling and bootstrap techniques to determine the distribution of bilateral distances between plants in an industry, and to compare it to a set of bilateral distances obtained from samples of randomly drawn plants. A technical description of that approach is provided in online appendix U.

Figure 2: Changes in the spatial concentration of the T&C sector between 2001 and 2013.

(a) 2001 (b) 2013



Notes: The figures report the K-densities (in solid red) and the 90% global confidence bands (in dashed black) for the T&C sector in 2001 and 2013, using plant counts. Distributions of distances that fall into this confidence band could be considered 'as good as random' and are, therefore, not considered to be either localized or dispersed.

Figure 2 summarizes the changes in the T&C K-densities between 2001 and 2013, based on plant counts (figures using employment-weighted K-densities are similar; see Figure 8 in online appendix S). As shown, the T&C sector was significantly localized in both years, with substantial excess agglomeration (compared to the rest of manufacturing) at very short distances, i.e., less than about 80 kilometers. These findings are consistent with many studies that have substantiated the existence of strong geographic concentration in the T&C sector, especially at fine geographic scales.[13] However, the strength of localization decreased substantially over the years, especially at extremely short

[13] See Duranton & Overman (2005) for the United Kingdom; Ellison et al. (2010) for the U.S.; Nakajima et al. (2012) for Japan; Barlet et al. (2013) for France; and Behrens & Bougna (2015) for Canada.

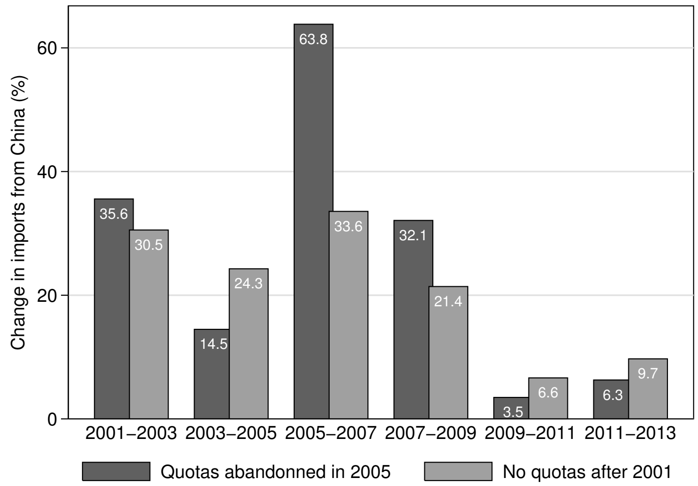
distances. Figure 2 thus suggests that plants in 'geographic clusters' — which are essentially defined by the concentration of plants and employment at short distances — may have been hit harder than more dispersed plants. We provide additional descriptive evidence for geographic concentration and changes therein in online appendix S (see Figure 10 for evidence of significantly more exit at short distances).

2.5 Aggregate facts: trade protection

The entry of China into the World Trade Organization (WTO) in 2001 and, more importantly, the end of the Multifibre Arrangement (MFA) on January 1st, 2005, profoundly altered the landscape of the T&C industry. Since 1973, the MFA regulated — via a quota system — how much textile and clothing products developing economies could export to developed countries. As described by Brambilla et al. (2010), quotas were removed in four phases in 1995, 1998, 2002, and 2005. Because China was not part of the WTO, quotas on Phases I, II, and III products were all relaxed in 2002. Phase IV — which we focus on in the remainder of the paper — relaxed the remaining quotas on Chinese exports (see Table 17 in Appendix B for a summary of the industries that were subject to active quotas until the end of 2004). This last wave of quota removal caused a dramatic increase in imports of formerly protected products from China and had the largest adverse impact on Canadian exports (Brambilla et al. 2010). As opposed to the U.S. or the European Union, who implemented safeguard measures to limit the growth of T&C imports from China until 2008, this policy was not impeded by subsequent import restrictions in Canada (Audet 2007, p.270).

Figure 3 shows that, as expected, sectors that had an active quota until December 31, 2004, experienced a much larger increase in imports than the remaining sectors in the wake of the MFA. Furthermore, this effect was especially strong between 2005 and 2007, i.e., when 'the floodgates opened'. For example, imports from China in the 'Hosiery and Sock Mills' industry (NAICS 315110) were multiplied by 24 between 2001 and 2013, and China's market share in Canadian imports in that industry jumped dramatically from 5 to 50%. Clearly, the textile industry experienced very substantial changes in its international trading environment over the study period.

Figure 3: Changes in T&C imports from China by quota status.



2.6 Preliminary analysis

As shown in Sections 2.3 and 2.4, the T&C sector was geographically strongly concentrated and subject to rapid change between 2001 and 2013. One reason for these rapid changes may have been the substantial modifications in trade protection after 2005, as explained in Section 2.5. How do changes in trade protection affect industry dynamics and how does it depend on the degree of geographic concentration? We will provide answers to that question in Section 4.3 using plant-level data and geographically delineated clusters. Before doing so, however, we take a preliminary look at the evidence for aggregate changes in textile industries. To this end, we regress industry-level measures of the number of plants, employment, and productivity on trade protection, geographic concentration, their interactions, and a set of controls including sector and year fixed effects. We measure trade protection by: (i) an MFA dummy that takes the value one as of 2005 — i.e., after the end of the Multifibre Arrangement — and zero otherwise; and (ii) a quota dummy that indicates whether the industry was protected by a quota until 2005 (see Table 17 in Appendix B). We measure geographic concentration by 'excess clustering', i.e., the difference between the measured level of concentration and the upper bound of the confidence band of the DO index (see online appendix U for details).

As shown by the first three columns of Table 5, the end of the MFA was associated with substantial exit of textile plants. The interaction terms show that

Table 5: Changes in the number of plants, employment, and productivity (T&C industries only).

	Number of plants			Industry employment			Industry productivity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post 2005 × Quota	-0.160^{a}		-0.073	-0.215^{c}		-0.082	0.140		0.048
	(0.046)		(0.052)	(0.120)		(0.126)	(0.117)		(0.171)
Post 2005 × Excess clustering		-0.009	0.000		-0.077^{a}	-0.068^{a}		0.014	0.006
		(0.011)	(0.007)		(0.021)	(0.021)		(0.013)	(0.012)
Post 2005 × Excess clustering × Quota			-0.055^{a}			-0.053			0.055
			(0.017)			(0.049)			(0.068)
Year = 2003 (with MFA)	-0.053	-0.055	-0.051	0.050	0.046	0.050	0.088	0.090	0.086
	(0.043)	(0.045)	(0.042)	(0.103)	(0.093)	(0.092)	(0.106)	(0.106)	(0.107)
Year = 2005	-0.086^{c}	-0.126^{a}	-0.083	0.300^{b}	0.322^{a}	0.368^{a}	-0.079	-0.052	-0.088
	(0.048)	(0.044)	(0.050)	(0.115)	(0.102)	(0.117)	(0.118)	(0.114)	(0.122)
Year = 2007 (post MFA)	-0.225^{a}	-0.268^{a}	-0.218^{a}	0.224^{c}	0.240^{b}	0.292^{b}	0.120	0.151	0.108
	(0.051)	(0.046)	(0.052)	(0.118)	(0.101)	(0.119)	(0.115)	(0.111)	(0.119)
Year = 2009	-0.296^{a}	-0.342^{a}	-0.289^{a}	-0.151	-0.138	-0.083	0.356^{a}	0.388^{a}	0.343^{a}
	(0.056)	(0.051)	(0.057)	(0.130)	(0.111)	(0.130)	(0.125)	(0.121)	(0.128)
Year = 2011	-0.358^{a}	-0.405^{a}	-0.350^{a}	-0.392^{a}	-0.381^{a}	-0.323^{b}	0.481^{a}	0.515^{a}	0.467^{a}
	(0.060)	(0.054)	(0.060)	(0.147)	(0.127)	(0.145)	(0.129)	(0.125)	(0.133)
Year = 2013	-0.551^{a}	-0.599^{a}	-0.541^{a}	-0.735^{a}	-0.726^{a}	-0.666^{a}	0.518^{a}	0.553^{a}	0.504^{a}
	(0.078)	(0.073)	(0.079)	(0.164)	(0.140)	(0.160)	(0.137)	(0.132)	(0.140)
Industry fixed effects	6-digit NAICS								
Additional controls	Export share of the industry to high-income countries								
Obs.	152	152	152	152	152	152	152	152	152
R^2	0.982	0.981	0.982	0.918	0.924	0.925	0.861	0.860	0.863

Notes: All variables are measured at the NAICS 6-digit level and in logs, except for the export share controls which are in levels. 'Industry productivity' is measured by the value added per worker. High-income countries are defined as countries whose GDP per capita is higher than 95% of U.S. GDP per capita (Bernard et al. 2006). 'Excess clustering' is an employment-weighted measure of excess agglomeration (at 25 kilometers distance) in 2001. It is given by the cumulative sum of the gap between the K-density and the upper bound of the confidence band. Since 'Excess clustering' is measured at the industry level, this variable is absorbed by the industry dummies. Huber-White robust standard errors in parentheses. ^{a} = significant at 1%, ^{b} = significant at 5%, ^{c} = significant at 10%.

this negative effect was even stronger in industries that were subject to a quota prior to 2005. The last term in column (3) shows that this result holds only for geographically concentrated industries. Hence, the aggregate evidence suggests that plants in agglomerated industries were not more resilient to the end of the MFA than plants in less spatially concentrated industries. This finding is corroborated by employment trends. Columns (5)–(6) of Table 5 show that the fall in employment was particularly strong after the end of the MFA in geographically concentrated T&C industries. Finally, columns (7)–(9) show that the end of the MFA was not associated with significant productivity gains — and that this result holds across T&C industries, agglomerated or not.

Our aggregate results uncover no evidence of a higher resilience of geographically more concentrated industries. On the contrary, they suggest that the geographic concentration of an industry matters for how hard it is hit by a shock: the stronger the overall concentration of an industry, the larger the negative effects on the number of plants and employees. However, this aggregate analysis is only suggestive. Indeed, all plants are not equally concentrated within industries: some plants belong to large geographic clusters, others to smaller but more specialized ones, whereas many plants are relatively isolated, i.e., do not belong to any cluster. The aggregate nature of the data also does not allow to disentangle plant death from industry switching, thus confounding various forms of resilience. The true test of the resilience of clusters is therefore the one that allows comparing, within a single industry, plants inside and outside clusters. This requires plant-level data and a more micro-geographic definition of clusters, which we now explain in detail.

3 T&C plants and geographic clusters

3.1 Data

Our primary data source is the *Scott's National All Business Directories Database*. This proprietary establishment-level database contains information on plants operating in Canada, with a very exhaustive coverage of the manufacturing sector. These data — which draw on the business register — are very similar to those of the *Annual Survey of Manufacturers* (ASM) Microdata Files and the *Canadian Business Patterns* (CBP) in terms of coverage and industry-level breakdown of plants and, therefore, provide a fairly accurate picture of the overall manufacturing structure in Canada over our study period. Our cleaned dataset contains 321,683 manufacturing plant-year observations from 2001 to 2013, in two-year intervals. For every establishment, we have information on its primary 6-digit NAICS code and up to four secondary 6-digit NAICS codes; its employment; its export status; up to 10 products produced; and its 6-digit postal code. We do not have firm identifiers for plants, but we create those using the legal name of the entity to which the plant belongs (see online appendix V for additional details on the procedure).

Because our dataset spans the 2001–2013 period, during which there are four different NAICS classifications (including NAICS 1997), we concord all 6-digit industries to 242 time-consistent industries using the crosswalks provided by Statistics Canada.[14] Table 22 in online appendix S shows which textile industries are aggregated to obtain our stable NAICS classification for T&C. We include all manufacturing plants (i.e., plants that report a manufacturing sector, NAICS 31–33, as their primary sector of activity) in our analysis and apply a 0.5% trimming from above on employment to get rid of some obvious coding mistakes in the data. We also drop a few plants for which we have partial information only.

We geocode plants by using latitude and longitude information of postal code centroids obtained from the Postal Code Conversion Files (PCCF). These files associate each postal code with different geographical classifications that are used for reporting census data. We match plant-level postal code information with geographic coordinates from the PCCF, using the postal code data for the next year in order to consider the fact that there is a six months delay in the updating of postal codes. Since postal codes have no one-to-one correspondence with the census geography, we match our postal codes using the Single Link Indicator of the PCCF in case of multiple matches. Note that postal codes are very fine-grained in Canada, especially in denser and more urban areas. There were, e.g., 818,907 unique postal codes postal as of May 2002, and 890,317 unique postal codes as of October 2010. Postal code centroids thus provide a fairly precise description of microgeographic location patterns. Al-

[14] We exclude two industries (NAICS 325110 'Petrochemical manufacturing', and 311830 'Tortilla manufacturing') from our analysis because they contain only a very small number of plants.

though they are somewhat less fine-grained in rural areas, those areas contain fewer plants. Figure 5 in online appendix S illustrates the granularity of our data.

3.2 Mapping clusters

We use our geocoded plant-level data to identify geographic clusters of T&C plants based on two criteria: specialization and size (see also Delgado et al. 2016*b*). Starting with specialization, we first compute for each T&C plant i, the number of *other* T&C plants and the number of non-T&C plants in a radius of 15 kilometers around plant i. Assume that there are n_i T&C plants and m_i non-T&C plants within that radius. Assume also that there are N T&C plants and M non-T&C plants in the total population of manufacturing plants. Then, the probability that there are more than n_i T&C plants among the $n_i + m_i$ plants around i can be computed from a cumulative distribution function (CDF) of a hypergeometric distribution. Assume that the value of the CDF is 0.9 for plant i. This means that there is only a 10% chance of observing more than n_i T&C plants around plant i, conditional on having $n_i + m_i$ plants in total around plant i and conditional on the overall share $N/(N + M)$ of T&C plants in the manufacturing population. We consider that such a case — with a p-value below 0.1 — represents 'clustering' of T&C plants around plant i, and we refer to such plants i as *focal plants*.[15] Turning next to size, we require that clusters have a minimum number of plant counts around the focal plants identified before. This criterion is required to exclude the case of areas with only few plants that happen to belong to the T&C sector. Such plants would always seem 'clustered' based on specialization alone, though it is hard to talk about clusters of very small numbers of plants. Hence, we impose a minimum requirement of 5 other T&C plants around focal plants in order to talk about clusters.

Using focal plants and our size thresholds, we define *big* clusters and *small*

[15]Our counterfactual corresponds to a 'random reshuffling' of plant types — T&C plants in our case — across all manufacturing sites. Contrary to the Duranton-Overman approach, based on permutations, we do not take into account the correlation between plants when computing their p-values, i.e., we assume that the draws are independent between plants. This is unlikely to induce substantial errors, since our samples are quite large, but it substantially alleviates the computational burden.

clusters as follows. Concerning big clusters, we take all focal plants (with p-values below 0.1) that have at least 25 other T&C plants around them. We then draw a 15 kilometers buffer around these focal plants and define the clusters as the unions of those buffers (see Buzard et al. 2015 for a similar approach called 'multi-scale core clustering'). Each disjoint set of the union corresponds to a separate geographic cluster. We similarly define small clusters using the focal plants with 5 or more other T&C plants around them (but less than 25). We then again draw 15 kilometers buffers around those focal plants and define the clusters as the unions of those buffers. Plants that are used to define big clusters are excluded from the construction of small clusters. In a last step, we associate all other manufacturing plants to the clusters as defined above.

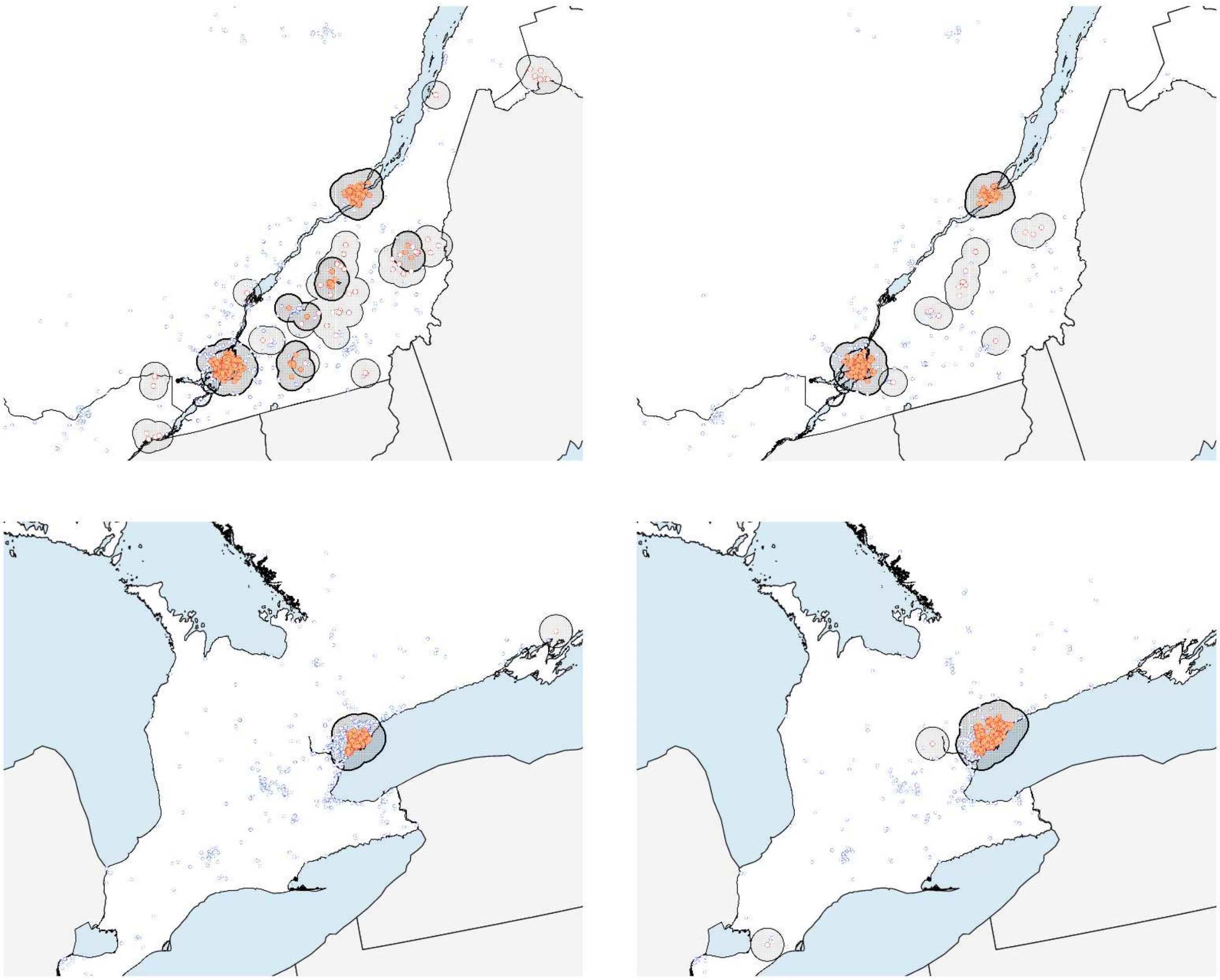
Figure 4 shows big and small clusters in Ontario and Québec in 2001 and 2013, respectively. Québec is the province with the highest share of employment in the T&C sector (53% in 2001, see Table 6), and both provinces account for more than 75% of total employment in that sector. As explained in Section 2.1, this pattern has a long history. The location of big clusters is depicted by the bold shaded areas, and big cluster focal plants are depicted by red orange-filled points. Small clusters are depicted by light shaded areas, and small cluster focal plants are depicted by red empty circles. Last, T&C plants that are not focal (i.e., with a p-value above 0.1) are depicted by blue empty circles. As mentioned before, although non-focal plants do not serve to define clusters, they may belong to a cluster if they are located less than 15 kilometers away from a focal plant. A visual inspection of Figure 4 shows that T&C clusters have been 'unweaving' — they progressively vanish over time — and only a few clusters still remain in 2013. Many clusters in Québec have disappeared between 2001 and 2013, and the two largest remaining clusters — around Montréal and Québec city — have decreased in size.

The substantial and rapid changes in the geography of clusters pose a problem when it comes to analyzing their impacts on plant-level outcomes. While clusters are inherently dynamic objects, their changing geographic boundaries complicate the econometric analysis (we return to that point later in more detail). To cope with that problem, we assign in what follows plants to clusters as defined by the clusters' geography in 2001.

Table 6 summarizes the allocation of plants to clusters for our different years. It shows that the T&C sector is strongly clustered as 64% of the textile

Figure 4: 'Unweaving' textile clusters in Québec (top panel) and Ontario (bottom panel).

(a) 2001. (b) 2013.



plants are either in a big or in a small cluster in 2001. This share remained stable until 2005 — despite a large drop in the total number of plants — and then declined to finally reach 58% in 2013. Looking at the evolution of plants in clusters reveals that the importance of small clusters declined at a quicker pace than that of big clusters. The number of plants in small clusters eventually dropped by 70%, against 58% in big clusters. By contrast, the total number of

Table 6: Allocation of T&C plants to textile clusters.

Year	Number of plants	Constant cluster definitions, based on 2001 delimitations In big clusters	In small clusters	Not in clusters	Share clustered	Share of Canadian T&C empl. in Québec
2001	4,465	2,667	196	1,602	64.12%	53.41%
2003	4,386	2,622	181	1,583	63.91%	51.34%
2005	3,803	2,252	153	1,398	63.24%	52.60%
2007	3,170	1,842	109	1,219	61.55%	48.31%
2009	2,910	1,671	100	1.139	60.86%	47.33%
2011	2,696	1,521	85	1,090	59.57%	46.72%
2013	2,057	1,130	59	868	57.80%	45.82%

Notes: We report the allocation of T&C plants to clusters, where clusters are defined based on their 2001 delimitations (i.e., we do not report results based on the contemporaneous delimitation of clusters as given by the spatial structure in the current year *t*). The last column reports the share of T&C employment located in Québec (all plants, including those not in clusters).

plants in the T&C sector declined by 'only' 54% between 2001 and 2013. Again, the empirical evidence suggests that plants in clusters exited more than more isolated plants (see also Figure 10 in online appendix S).

3.3 Dissecting clusters

To better understand how and why clusters have fared differently between 2001 and 2013, we need to understand their heterogeneity. Clusters indeed come in a variety of sizes and compositions, and they serve different functions for the sector. Our cluster mapping procedure in Section 3.2 allows us to delimit 9 big and 15 small T&C clusters in Canada in 2001. Table 7 lists these 24 clusters. In 2001, there were on average 2,465 plants (both T&C and non-T&C) in the nine big clusters, compared to 89 plants in the fifteen small clusters. The remaining 28,531 plants were not in T&C clusters. Big clusters had, on average, 296 T&C plants, compared to 13 in the small clusters. However, small clusters were more specialized, with an average share of T&C plants of 14.8%, compared to 12% in the big clusters and 5.6% for the rest of Canada.

We can further dissect the different T&C clusters by looking both at the characteristics of their T&C plants and their broader industrial composition. As Table 7 shows, the average plant size in small clusters is about 49 workers, whereas that in big clusters is about 34 workers. Plants outside clusters are smaller, with an average size of about 28 workers. As can be seen from the bottom panel of Table 7, big clusters are very heterogeneous too. Some clusters have large average plant size — e.g., the 'Saint-Georges-Beauceville' cluster —

Table 7: Allocation of T&C plants to textile clusters and cluster characteristics in 2001.

	T&C plants		**Plant-level structure**			**Inputs and labor**		**Non T&C plants**	
	Number	Employment	Avg. size	% Multiunit	% Exporter	Input share	Labor corr.	Plants	Employment
Cluster types:									
Big clusters (9)	2,667	90,316	33.86	3.75%	44.32%	0.34%	0.18	19,520	647,906
Small clusters (15)	196	9,557	48.76	9.69%	29.08%	1.86%	0.20	1,132	33,868
Outside clusters	1,602	44,771	27.95	5.87%	33.58%	1.08%	0.17	26,929	904,059
Big cluster details:									
Montréal, QC	1,316	45,266	34.40	3.50%	44.38%	0.21%	0.20	6,093	210,259
Toronto, ON	676	20,701	30.66	4%	45.19%	0.14%	0.16	7,668	262,522
Vancouver, BC	279	7,433	26.74	2.87%	46.40%	0.22%	0.16	2,722	75,126
Québec City, QC	129	2,836	21.98	0.78%	24.81%	0.68%	0.16	1,047	28,480
Winnipeg, MN	125	5,597	44.78	3.2%	56%	1.06%	0.20	955	31,978
Granby, QC	40	3,274	81.85	17.5%	57.5%	2.07%	0.19	365	14,664
Victoriaville-Plessisville, QC	39	1,562	40.05	12.82%	17.95%	1.91%	0.19	234	8,247
Drummondville, QC	33	1,247	37.73	3.03%	42.42%	1.19%	0.16	275	10,036
Saint-Georges-Beauceville, QC	30	2,400	80	3.33%	56.67%	1.27%	0.19	161	6,594

Notes: See online appendix S for details on how we construct the 'input share' and 'labor correlation' measures. 'Avg. size' measures the average employment in T&C plants. '% Exporter' refers to the share of plants that report exporting (to any destination). '% Multiunit' refers to the share of multiunit plants, where the latter are based on plants having the same legal firm name using the procedure explained in the online Appendix V.

whereas others have small average plant size — e.g., the Québec city cluster.[16] The variation in average plant size is even larger for the small clusters, with some of them having very small plants (about 5 to 25 employees), while others have quite big plants (about 85 to 100 employees).

Table 7 further shows that cluster composition is also very heterogeneous. Small clusters host more plants that belong to multiunit firms, whereas big clusters host more standalone plants. Yet, plants in small clusters are less export-oriented than plants in the big clusters. Finally, we also provide summary measures of how strong input-output links are on average across plants in the clusters, and on how similar the plants are on average in terms of the types of workers they hire (see the online appendix S for details on how we construct those measures using industry-level data and microgeographic location patterns). As Table 7 shows, small clusters are more specialized in the sense that plants there are close to other plants with whom they potentially have strong input-output relationships, and are also close to plants that hire more similar types of workers. These strong links and similarity may make these plants more vulnerable to adverse shocks.

4 Empirical analysis

We now use our plant-level data and geographic clusters to investigate whether or not plants in clusters are more resilient to adverse economic shocks than plants outside clusters. To begin with, we first define what we mean by resilience and look at some of its dimensions.

4.1 Resilience: Empirical framework

Any empirical analysis on resilience must ask two questions: What is resilience (concept) and who is resilient (object)? Let us start with the question 'What is

[16]This partly reflects the different specializations of the clusters. In the 'Saint-Georges-Beauceville' cluster, 16 out of 30 plants belong to 'Cut and Sew Clothing Manufacturing' (NAICS 3152; see Table 22 in online appendix S). Historically, the Beauce region in Québec was home to the 'jeaners', i.e., the jeans-producing and transforming industry that ran large plants. Conversely, although Québec city also had 47 plants in 'Cut and Sew Clothing Manufacturing', it also had a large share of plants in footwear and leather manufacturing.

resilience'? Following Martin & Sunley (2015, pp. 3–7), we can define a variety of types of resilience: (i) engineering resilience, defined as *"a system's ability to absorb a shock without changing its structure, identity and function"*; (ii) ecological resilience, defined as *"how fast a system that has been displaced from equilibrium by a disturbance or shock returns to that equilibrium while undergoing change so as to still retain essentially the same function, structure, and identity"*; and (iii) adaptative resilience, defined as the ability to *"resist external and internal disturbances and disruptions if necessary by undergoing plastic change in some aspects of its structure and components"*. In what follows, we refer to (i) and (ii) as 'strong resilience' and to (iii) as 'weak resilience'. Let us next ask 'Who is resilient'? Is it plants? Industries? Regions? Clearly, the answer to that question largely determines the analysis. For example, assume that plants in industry i and region r get hit by shocks. If they die, we can surely say that there is no resilience (neither at the plant level, nor at the industry or region level). If they, on the contrary, stay and continue with business-as-usual, then the plant (and industry and region) is resilient (strong resilience). However, if plants switch from industry i to industry j, or move from region r to region s, then there is resilience at the level of the plants, but not for the industry or the region (weak resilience).

To fix ideas on how to operationalize the concepts of strong and weak resilience described above, consider a plant that operates in the T&C sector and faces either idiosyncratic or industry-wide shocks. The plant can either: (i) stay in the T&C sector ('stay'); or (ii) exit from the T&C sector ('exit'). Exit can further take one of the following forms: plant death ('die'); or switching out of textile manufacturing into some other manufacturing or service activity ('switch'). A plant that stays exhibits a strong form of resilience, since it absorbs the shock without changing its structure, identity, and function. A plant that exits without dying exhibits a weak form of resilience since it has to change in order to adapt to the disturbance. Finally, a plant that dies is not resilient.

Let $P(\cdot)$ denote the probability of an event, and let $P_X(\cdot)$ denote the probability of that event conditional on a set of covariates X. Let $C = 1$ if the plant belongs to a cluster, and $C = 0$ otherwise. Let $\Delta P_X(\text{die})$ denote the difference in the probability of death between a 'clustered' plant and a plant outside of the cluster, conditional on X. This probability premium of death for a plant in a cluster can be written as:[17]

$$\begin{aligned} \Delta P_X(\text{die}) &\equiv P_X(\text{die}, C=1) - P_X(\text{die}, C=0) \\ &= \beta \Delta P_X(\text{exit}) - \alpha \Delta P_X(\text{switch}|\text{exit}), \end{aligned} \quad (1)$$

with $\alpha \equiv P_X(\text{exit}, C=1) > 0$ and $\beta \equiv P_X(\text{die}|\text{exit}, C=0) > 0$. Equation (1) shows that the difference in the probability of death between 'clustered' and 'unclustered' plants rises with the probability of exiting from the T&C sector and, conditional on this exit, decreases with the probability to switch into another industry. In a nutshell, the three terms in equation (1) are linked to our three concepts of interest: (i) $\Delta P_X(\text{die})$ is related to the absence of resilience; (ii) $\Delta P_X(\text{exit})$ is related to strong resilience; and (iii) $\Delta P_X(\text{switch}|\text{exit})$ is related to weak resilience. The subsequent presentation of our empirical results is thus organized along these lines. We examine whether plants in cluster are more resilient or not in a broad way, as captured by $\Delta P_X(\text{die})$, and what is the effect of the 'engineering resilience' — the ability to stay active in the industry, $\Delta P_X(\text{exit})$ — and the 'adaptive resilience' — the ability to switch activity when exiting, $\Delta P_X(\text{switch}|\text{exit})$.

4.2 The resilience of T&C clusters

As explained above, we are interested in several adjustment margins to gauge how resilient plants are to adverse shocks: plant death; exit from textile manufacturing; and 'adaptation', measured as a plant's ability to change its main line of business, conditional on exit.[18]

[17] To derive this formula, we use the following: (i) exit is due to either plant death or switching, i.e., $P_X(\text{switch}|\text{exit}) + P_X(\text{die}|\text{exit}) = 1$; (ii) the conditional probability $P_X(\text{die} \cap \text{exit}) = P_X(\text{die}|\text{exit}) \times P_X(\text{exit})$; and (iii) $P_X(\text{die} \cap \text{exit}) = P_X(\text{die})$, since a plant necessarily exits if it dies.

[18] We also analyze downsizing, as measured by employment changes, conditional on staying in the T&C sector. Since we find almost no interesting effects for the latter, we relegate the results for this outcome to Appendix B (see Table 18). Observe that the aggregate analysis in Section 2.6 shows that employment in textile industries fell after the end of the MFA. As a result, this effect seems to be mainly driven by the extensive margin (exit) rather than by the intensive margin (downsizing). The aggregate analysis does not allow to disentangle these two effects.

4.2.1 Baseline results

We start by estimating the following econometric model:

$$y_{jpt} = \beta_0' X_{jt} + \beta_1 CL_j^{01} + \gamma_{pt} + \epsilon_{jpt}, \tag{2}$$

where y_{jpt} alternatively refers to our three dimensions of resilience of a plant j, located in province p at time t. We regress these variables on a number of time-varying plant characteristics X_{jt}, including employment, a dummy variable indicating whether the plant exports or not, a dummy variable indicating whether the plant belongs to a multiunit firm or not, and a measure of the plant's 'industry breadth', defined as the number of non-T&C industries declared by the plant as secondary activities. We also include a binary variable CL_j^{01} that takes value one if the plant belongs to a geographic cluster, and zero otherwise. Our coefficient of interest is β_1. We have no prior on whether it is positive of negative, since theory is inconclusive as to whether or not clusters make plants more resilient (see the online Appendix T for a simple model that makes this point formally).

As explained in Section 3.2, clusters change over time, and their geographic extent is endogenous to plants' survival and location choices. Hence, to minimize endogeneity concerns, we use constant cluster definitions based on 2001 data. We estimate (2) for 2003–2013 using either a linear probability model (LPM) or a probit model, and we include province-year fixed effects γ_{pt} in all estimations. Last, we restrict our sample to plants that were present in 2003, i.e., we do not consider entry and (eventually) subsequent exit of new plants. Though the results are basically the same, we believe this is a cleaner exercise. Finally, ϵ_{jpt} is the error term.

Table 8 summarizes our baseline results. In column (1), we estimate model (2) for plant death, i.e., our indicator y_{jpt} ('die') equals one if the plant ceases to exist between year t and $t+4$, and zero if it is still active in $t+4$. Observe first that plant characteristics matter substantially: large plants, exporters, and stand-alone plants have a lower probability to die (see Bernard et al. 2007, for similar results). Besides, the industrial breadth of a plant — the extent of its cross-sectoral diversification — is also negatively correlated with this outcome. Hence, plants that have additional non-T&C activities have a lower probability of death. Finally, our main coefficient of interest — the cluster variable — in

Table 8: Dimensions of resilience of T&C sector plants (LPM).

	Die	Exit	Switch | Exit	Services | Switch
	(1)	(2)	(3)	(4)
Employment	-0.018^{a}	-0.019^{a}	0.014^{b}	0.004
	(0.002)	(0.003)	(0.005)	(0.014)
Exporter	-0.038^{a}	-0.041^{a}	0.029^{c}	0.122^{a}
	(0.007)	(0.007)	(0.017)	(0.037)
Multiunit	0.062^{a}	0.059^{a}	-0.067^{c}	-0.082
	(0.017)	(0.018)	(0.035)	(0.089)
Industry breadth	-0.067^{a}	0.019^{b}	0.318^{a}	-0.090^{a}
	(0.006)	(0.007)	(0.018)	(0.033)
Cluster	0.016^{b}	0.020^{b}	-0.006	0.137^{a}
	(0.007)	(0.008)	(0.017)	(0.041)
Fixed effects		Province-year		
Obs.	14,707	14,707	3,166	831
R^2	0.033	0.048	0.220	0.200

Notes: Huber-White robust standard errors in parenthesis. ^{a} = significant at 1%, ^{b} = significant at 5%, ^{c} = significant at 10%.

column (1) shows that plants belonging to a cluster are more likely to die than other plants. This suggests that T&C plants that belong to a cluster do not perform better than more isolated ones in terms of ceasing operations. They even have a lower resilience than unclustered plants. We hence conclude that plants in clusters do not display strong resilience compared to plants outside clusters.

In columns (2) and (3), we examine whether this higher probability of death in clusters is driven by a higher probability of exiting from the T&C sector in those clusters, or by a lower probability of adaptation conditional on exit. Our results show that the first effect prevails. Conditional on plant characteristics, plants in clusters exit more, but are not more likely to change their primary activity conditional on exit. We hence conclude that plants in clusters do not display weak resilience compared to plants outside clusters: clusters do not seem to make plants in the T&C sector more likely to survive by adapting their main line of business (conditional on their individual characteristics and on exit). Quantitatively, we find that clustered plants are on average 2% more likely to die and to exit the T&C sector than isolated plants. Furthermore, plants in clusters that exit the T&C sector are as likely to switch to another industry than more isolated plants.

As previously shown in Table 4, about half of the switching plants changed for service industries, while the other half switched to a different (non-T&C)

manufacturing activity. Hence, in column (4) of Table 8, we further investigate whether there are systematic differences in the switching behavior inside and outside clusters, i.e., we look at the determinants of switching into services conditional on switching. The estimation on these 'switchers' shows that plants in clusters are 13.7% more likely to switch into services than unclustered plants. Put differently, isolated plants are — everything else equal — more likely to switch into another manufacturing industry but less likely to make the transition into the service industry. This suggests that, conditional on switching, clusters facilitate transitions from blue collar to white collar activities.

4.2.2 Robustness

We next perform a number of robustness checks. First, we replicate the previous estimations using a probit model. To ease the interpretation of the coefficients, we report the marginal effects of the explanatory variables at the mean. The results displayed in Table 9 are very similar — both qualitatively and quantitatively — to those of the LPM but offer the advantage to keep the predicted values within the unit interval. For instance, they show that plants belonging to a cluster are on average 1.6% more likely to die than non-clustered plants. As before, this lower resilience is driven by a higher probability of exiting the T&C sector. Finally, we still find that, conditional on switching, plants in clusters are 15.5% more likely to switch into services than unclustered plants.

Table 9: Dimensions of resilience of T&C sector plants (probit).

	Die	Exit	Switch | Exit	Services | Switch
	(1)	(2)	(3)	(4)
Employment	-0.018^{a}	-0.019^{a}	0.016^{b}	0.005
	(0.002)	(0.003)	(0.006)	(0.016)
Exporter	-0.038^{a}	-0.042^{a}	0.035^{c}	0.148^{a}
	(0.007)	(0.007)	(0.019)	(0.042)
Multiunit	0.069^{a}	0.065^{a}	-0.069^{c}	-0.106
	(0.019)	(0.020)	(0.036)	(0.108)
Industry breadth	-0.076^{a}	0.015^{b}	0.300^{a}	-0.115^{a}
	(0.007)	(0.007)	(0.018)	(0.039)
Cluster	0.016^{b}	0.020^{b}	0.002	0.155^{a}
	(0.007)	(0.008)	(0.019)	(0.045)
Fixed effects		Province-year		
Obs.	14,707	14,707	3,123	784
R^2	0.040	0.045	0.184	0.125

Notes: Huber-White robust standard errors in parenthesis. ^{a} = significant at 1%, ^{b} = significant at 5%, ^{c} = significant at 10%.

Until now, our measure of clustering is a dummy variable that takes value one if the plant belongs to a cluster and zero otherwise. One might argue that a plant located at the 'border' of a cluster could still benefit from its positive externalities or, conversely, might suffer from increased competition in factor and product markets. We hence now use a continuous measure of exposure to clusters by computing for each plant its distance to the centroid of the closest cluster. Consequently, we introduce variations within unclustered plants, between those which are relatively close to a cluster and the ones that are truly isolated. Similarly, we introduce variations within clusters between centrally located plants and those which are at the cluster fringe. Our results, summarized in Table 10, are remarkably similar to those using the dummy variable. Eventually they show that, as distance to the centroid of a cluster rises by 1%, plants are 0.7% less likely to die and 1% less likely to exit. Besides, they are not statistically more or less likely to adapt conditional on exit. Finally, we still find a higher probability of switching into services conditional on switching as a plant gets closer to a cluster.

Table 10: Continuous exposure of plants to T&C clusters (LPM).

	Die	Exit	Switch | Exit	Services | Switch
	(1)	(2)	(3)	(4)
Employment	-0.019^a	-0.020^a	0.013^b	0.002
	(0.002)	(0.003)	(0.005)	(0.014)
Exporter	-0.038^a	-0.041^a	0.029^c	0.118^a
	(0.007)	(0.007)	(0.017)	(0.037)
Multiunit	0.062^a	0.060^a	-0.066^c	-0.083
	(0.017)	(0.018)	(0.036)	(0.088)
Industry breadth	-0.066^a	0.020^a	0.319^a	-0.083^b
	(0.006)	(0.007)	(0.018)	(0.033)
Distance to cluster	-0.007^a	-0.010^a	-0.001	-0.051^a
	(0.002)	(0.003)	(0.006)	(0.014)
Fixed effects			Province-year	
Obs.	14,707	14,707	3,166	831
R^2	0.034	0.048	0.22	0.203

Notes: Huber-White robust standard errors in parenthesis. ^{a} = significant at 1%, ^{b} = significant at 5%, ^{c} = significant at 10%.

We next verify that our results are not spurious. Since there are more plants in clusters than outside clusters, the probability to have more plants that exit in clusters could be systematically higher, even if exit was random. To verify this, we run placebo regressions where we randomly reshuffle the exit indicator across T&C plants. With 200 replications, the cluster dummy is not statistically different from zero at the 10% level using the empirical distribution of the estimated coefficients to define the confidence intervals. We redo the same exercise with a random reshuffling of the cluster dummies. All plant-level covariates ('employment', 'exporter', 'multiunit', 'industry breadth') remain very stable and are basically identical to the estimates reported in Table 8, whereas the cluster dummy is again insignificant at the 10% level. These results show that exit is not mechanically higher in clusters because they contain by definition more T&C plants.

Table 11: Dimensions of resilience of T&C sector plants (LPM, no individual controls).

	Die	Exit	Switch | Exit	Services | Switch
	(1)	(2)	(3)	(4)
Cluster	0.015^b	0.007	-0.040^b	0.163^a
	(0.007)	(0.008)	(0.018)	(0.041)
Fixed effects			Province-year	
Obs.	14,707	14,707	3,166	831
R^2	0.016	0.039	0.114	0.180

Notes: Huber-White robust standard errors in parenthesis. ^{a} = significant at 1%, ^{b} = significant at 5%, ^{c} = significant at 10%.

One may wonder whether firms self-select into clusters. Eventually, plants with different characteristics can sort differently across space. For instance, low- or high-performing plants can disproportionately sort into clusters. To understand how plants' different characteristics inside and outside clusters can affect our results, we replicate our baseline estimates in Table 11 without plant-level controls. As can be seen, the results on plant death in column (1) and on switching to services conditional on switching in column (4) remain unchanged. However, the results in columns (2) and (3) are different. Without plant-level controls, the higher probability of death in clusters is explained by a lower probability of switching conditional on exit, while it is due to more exit when individual controls are included. Comparing the results with and without controls suggests that plants inside and outside clusters differ along their individual characteristics including employment, export status, multiunit status, and plant diversification. Because these characteristics are correlated with the plant outcomes we examine and affect the results, we conclude that it is important to control for selection in our analysis. Of course, we acknowledge that our list of controls is not exhaustive. However, we do believe that they are highly correlated with most of the theoretical characteristics that may influence a plant's location choice — on top of them, performance — and the various outcomes we consider.

Last, one may worry that clusters delineated in 2001 are the result of recent anticipations of individual plants. For instance, plants anticipating their switching to services could choose to locate near city centers. Observed clusters would thus be implied by individual plants' decisions regarding their transition. To deal with these endogeneity issues, we use historical information on clusters. More specifically, Table 12 reports results where we instrument for the presence of a plant in a cluster using information on the spatial distribution of T&C industries in 1871. As explained in Section 2.1, the T&C sector was historically strongly concentrated in Québec and Ontario. The presence of these historical clusters may have persisted over time as they offered local skilled labor and dedicated infrastructures (e.g. proximity to hydraulic energy). Hence, we instrument our cluster dummy by computing, for each plant, its distance to historical census districts, weighted by the T&C employment share of each district in the 1871 Census.[19] The instrument thus reflects how close the plant is from historical T&C jobs. If there is persistence in the location patterns of plants, the instrument helps to predict the location of T&C clusters without being affected by contemporaneous considerations on plants' resilience. As Table 12 shows, our baseline results are robust to this instrumentation strategy. The first stage shows that distance to 1871 T&C employment strongly predicts the presence of a plant in a 2001 cluster. Once instrumented, the coefficients of the baseline regressions are very similar, and precisely measured.

4.2.3 Further results: cluster size and the determinants of switching

As shown in Table 7 of Section 3.3, clusters differ substantially by size and composition. We now refine our results by splitting clusters along size. To this end, we use two distinct cluster dummies, one for the *big* clusters and one for the *small* clusters. In terms of magnitude, Table 13 shows that there are

[19] Details on the 1871 Canadian Census are provided in Appendix A.2. Our instrument is constructed as: $Dist1871_p = \sum_d w_d log(dist_{pd})$, with w_d the share of district d in 1871 T&C employment, and $dist_{pd}$ the distance between plant p and district d. There are 194 such districts. The districts are relatively precise around cities in the provinces of Québec and Ontario, but large in western territories. This reflects the distribution of the population at the time. See Figures 11 and 12 in the Supplemental Appendix W for an illustration of our historic data.

Table 12: Dimensions of resilience of T&C sector plants (IV regressions).

	Die	Exit	Switch | Exit	Services | Switch
	(1)	(2)	(3)	(4)
			Second stage	
Cluster	0.057^a	0.081^a	0.018	0.249^a
	(0.015)	(0.017)	(0.035)	(0.086)
			First stage. Dependent variable: Cluster dummy	
Dist. 1871 T&C employment (log)	-0.764^a	-0.764^a	-0.803^a	-0.784^a
	(0.011)	(0.011)	(0.026)	(0.047)
Plant-level controls			Included	
Fixed effects			Province-year	
Obs.	14,586	14,586	3,136	823
R^2	0.031	0.044	0.220	0.192
F-test	4,243	4,243	949	215

Notes: Huber-White robust standard errors in parenthesis. ^{a} = significant at 1%, ^{b} = significant at 5%, ^{c} = significant at 10%. Cragg-Donald Wald F-statistic. Plant-level controls are included but not reported. The excluded instrument is the average distance of the plant to 1871 Census districts, weighted by the 1871 T&C employment of the districts.

no large differences in plant death and exit between big and small clusters. If anything, the effect for plant death is statistically stronger and more precisely estimated for big clusters than for small ones — which is insignificant in column (1). Similarly, both coefficients in the third estimation (on 'adaptation') are insignificant. As shown by column (4), there is however a large difference between clusters of different sizes in switching to services conditional on switching. Indeed, the positive effect of clusters appears only for big clusters, while there is no effect for small ones. This suggests that big clusters — which are mostly associated with larger urban areas — make it easier for plants to transition into services.

Table 14 summarizes some results on the determinants of switching. In these estimations, we consider all potential (non-T&C) manufacturing industries into which a T&C establishment located in a cluster — either a big or a small — can switch. Therefore, there are as many observations per plant as there are manufacturing industries in the cluster, with only one for which the dependent variable takes value one instead of zero. We then regress these dummy variables on the local size of each industry, measured as the total employment or the number of plants of that industry in the cluster.[20] Positive coefficients mean that a plant has a higher propensity to switch into indus-

[20]We focus on switching to other (non-T&C) manufacturing industries as we do not have detailed information on plant counts and employment for service industries in the cluster.

Table 13: Dimensions of resilience of T&C sector plants by cluster size (LPM).

	Die	Exit	Switch | Exit	Services | Switch
	(1)	(2)	(3)	(4)
Employment	-0.018^{a}	-0.019^{a}	0.013^{b}	0.003
	(0.002)	(0.003)	(0.005)	(0.014)
Exporter	-0.038^{a}	-0.040^{a}	0.030^{c}	0.120^{a}
	(0.007)	(0.007)	(0.017)	(0.037)
Multiunit	0.061^{a}	0.058^{a}	-0.069^{c}	-0.070
	(0.017)	(0.018)	(0.036)	(0.089)
Industry breadth	-0.067^{a}	0.019^{b}	0.318^{a}	-0.089^{a}
	(0.006)	(0.007)	(0.018)	(0.033)
Small cluster	0.021	0.038^{b}	0.028	-0.035
	(0.016)	(0.018)	(0.035)	(0.084)
Big cluster	0.016^{b}	0.019^{b}	-0.009	0.157^{a}
	(0.007)	(0.008)	(0.017)	(0.042)
Fixed effects			Province-year	
Obs.	14,707	14,707	3,166	831
R^2	0.033	0.048	0.221	0.206

Notes: Huber-White robust standard errors in parenthesis. ^{a} = significant at 1%, ^{b} = significant at 5%, ^{c} = significant at 10%.

tries which are already large in the cluster. In addition, switching might be facilitated by prior experience. Eventually, 50% of plants switching to another manufacturing activity (187 out of 377) changed to an industry they had already been active in. Therefore, we also include as an additional variable an indicator that takes value one if the plant switches its main line of business into a sector that it already reported as being a secondary activity, and zero otherwise.

Table 14 shows that the coefficients on all variables are positive and highly significant. In words, plants that adapt tend to switch into activities they have prior experience with ('Has as secondary industry'). Furthermore, plants also tend to switch into sectors which have a larger local base in the cluster (either in terms of employment, 'Cluster employment NAICS', or in terms of plant counts, 'Cluster plant-count NAICS'). The latter effect holds even conditional on prior experience which, as expected, is a stronger predictor of switching.

4.3 Resilience after the end of the MFA

The foregoing analysis offers important insights into the resilience of clusters. However, it does not pay explicit attention to the source and the nature of the economic shocks. In order to convincingly evaluate how plants react in the

Table 14: External and internal causes of switching, conditional on switching (LPM).

Dep. variable: Industry indicator	(1)	(2)	(3)	(4)
Cluster employment by NAICS	0.001[a]		0.001[a]	
	(0.000)		(0.000)	
Cluster plant-count by NAICS		0.004[a]		0.002[a]
		(0.000)		(0.000)
Has as secondary industry			0.281[a]	0.279[a]
			(0.027)	(0.027)
Plant-level controls		Included		
Fixed effects		Province-year		
Obs.	40,414	40,414	40,414	40,414
R^2	0.002	0.006	0.132	0.134

Notes: Sample restricted to the plants that switch primary industry among the T&C plants to another (non-T&C) manufacturing industry, in either big or small clusters. There are as many observations per plant as there are manufacturing industries in the cluster. The dependent variable equals 1 for the industry into which the plant switches, and 0 otherwise. 'Cluster employment by NAICS' if the level of employment of the industry in the cluster. 'Cluster plant-count by NAICS' is the count of establishments in the industry in the cluster. 'Has as secondary industry' equals 1 if the plant reports being active in that industry as secondary line of business in the base year. Huber-White robust standard errors. [a] = significant at 1%, [b] = significant at 5%, [c] = significant at 10%.

presence of a specific shock, we need the latter to be exogenous to the clusters. Given that clusters are rather small and host subsets of strongly interconnected industries, idiosyncratic shocks to establishments may simultaneously drive firm-level outcomes and cluster dynamics, thereby complicating identification. On top of being exogenous, the shock should be large in magnitude and specific to the clustered industries.[21] With this in mind, we refine our identification strategy by exploiting the end of the MFA as an industry-wide shock to Canadian T&C firms. As explained in Section 2.5, starting from 2005 we observe a surge in imports from China for goods in industries that were previously protected by an active quota until the end of 2004. Since having an active quota in 2004 is a good predictor of the magnitude of the sectoral trade shock (see Figure 3), we will use a 'quota dummy' as a proxy for the increase in import exposure. Contrary to trade flows, this variable is much less likely to suffer from potential endogeneity biases. Industries with an active quota in

[21]Large macroeconomic shocks — such as the Great Recession or the trade collapse — are probably too diffuse to allow for clean identification, and are not well suited to tease out the effects of that shock and its interaction with the geographic structure of the industry (Martin et al. 2013, Delgado et al. 2016*a*).

2004 should display a stronger reaction since they experienced a more severe treatment. By contrast, we do not expect any specific change in imports from China for unprotected goods or for products protected by quotas that were not binding.

Before proceeding, it is worth pointing out that the end of the MFA was anticipated. In the words of Harrigan & Barrows (2009, p.282), the end of the MFA was a "[...] *large, sudden, fully anticipated, easily measured, and statistically exogenous change in trade policy.*" This raises the question of potential anticipation effects that may blur the treatment as firms already adjusted prior to the shock. However, we do not think that extensive pre-shock adjustements are important in our case. Indeed, the Apparel Human Resource Council of Canada commissioned a study in 2004 to evaluate potential adverse consequences of the end of the MFA (see RichterConsulting 2004). A survey of senior executives of Canadian apparel manufacturers and contractors revealed that, although "*[m]ost executives are aware of the pending free trade agreements and most believe that there will be major ramifications resulting there from* [...] *a startling 83% of companies do not have a clear strategic plan to deal with these changes.*"[22] Also, should anticipation effects have been important, we should not have seen the spike in exit after 2005. Last, would anticipations have interacted with geographic patterns, we instrument the contemporaneous presence in a cluster by historical information on geographic concentration.

4.3.1 Main results

To investigate the consequences of the loss in trade protection, we now recast equation (2) as follows:

$$\begin{aligned} y_{jpt} \;=\; & \beta_0' X_{jt} + \beta_1 CL^{01}_{jt} + \beta_2\, Quota_{i(j)} + \beta_3\, Post2005_t \times CL^{01}_{jt} \\ & + \beta_4\, Post2005_t \times Quota_{i(j)} + \beta_5\, Quota_{i(j)} \times CL^{01}_{jt} \\ & + \beta_6\, Post2005_t \times Quota_{i(j)} \times CL^{01}_{jt} + \gamma_{pt} + \epsilon_{jpt} \qquad (3) \end{aligned}$$

where $Post2005_t$ is a dummy variable that takes value one for the period after the end of the MFA, and zero otherwise; and $Quota_{i(j)}$ is our measure of trade

[22]For that survey, 109 questionnaires were completed in September and October 2003. The firms that were surveyed represented approximately 25% of the workforce in the apparel industry. About 93% of the respondents operated in urban areas, with 66% manufacturers and 34% contractors. See RichterConsulting (2004).

exposure which indicates whether plant j belongs to an industry i that was subject to quota restrictions until 2005. Our coefficient of interest is β_6, which measures whether plants in clusters that operated in quota-constrained T&C segments were affected differently after the end of the MFA.

Table 15: Dimensions of resilience of T&C sector plants after the end of MFA (LPM).

	Die	Exit	Switch | Exit	Services | Switch
	(1)	(2)	(3)	(4)
Employment	-0.020^a	-0.021^a	0.014^a	-0.004
	(0.003)	(0.003)	(0.005)	(0.013)
Exporter	-0.038^a	-0.041^a	0.029^c	0.097^a
	(0.007)	(0.007)	(0.017)	(0.035)
Multiunit	0.065^a	0.062^a	-0.074^b	-0.043
	(0.017)	(0.018)	(0.036)	(0.084)
Industry breadth	-0.061^a	0.026^a	0.315^a	-0.037
	(0.006)	(0.008)	(0.018)	(0.034)
Quota	0.036	-0.001	-0.161^a	0.435^a
	(0.022)	(0.024)	(0.052)	(0.150)
Post2005$\times$ Quota	0.019	0.067^b	0.161^a	-0.180
	(0.027)	(0.029)	(0.061)	(0.168)
Cluster	0.019	0.012	-0.034	0.102
	(0.015)	(0.017)	(0.042)	(0.073)
Cluster$\times$Post2005	-0.004	0.008	0.030	0.014
	(0.018)	(0.020)	(0.047)	(0.091)
Quota$\times$Cluster	0.001	0.017	0.041	0.076
	(0.026)	(0.029)	(0.061)	(0.165)
Post2005$\times$Quota$\times$Cluster	-0.028	-0.040	-0.005	-0.110
	(0.032)	(0.035)	(0.072)	(0.188)
Fixed effects	Province-year			
Obs.	14,707	14,707	3,166	831
R^2	0.035	0.050	0.228	0.263

Notes: Huber-White robust standard errors in parenthesis. ^{a} = significant at 1%, ^{b} = significant at 5%, ^{c} = significant at 10%. 'Post2005' is included but absorbed by the province-year fixed effects.

As Table 15 shows, there are no systematic differences in plant deaths depending on the initial protection of the industry, and this pattern holds before and after the end of the MFA. However, establishments belonging to sectors in which quotas were active under the MFA were more likely to exit the T&C industry and to switch into other industries after 2005. This suggests that the pattern we see in the aggregate regressions in Table 5 is driven by the fact that many firms exited from quota-protected industries and switched into non-T&C industries. In addition, the results in the last column show that plants in protected industries disproportionately switched to services, even if we do not see more action after the quota removal in 2005. While these patterns are robust, we do not observe any difference in the response of plants located inside and outside of clusters. This confirms our main finding that establishments in clusters are not more resilient than establishments outside of clusters.

4.3.2 Robustness

We performed a variety of robustness checks for our treatment regression (3), which we succinctly summarize in what follows. First, we ran the version without the plant-level controls to assess the importance of selection effects. The results are very similar to those in the baseline case and we, therefore, do not reproduce them here.

Second, one may be worried about the financial crisis and the trade collapse of 2008. Indeed, our post-MFA period may be contaminated by this large shock which affected economic activity overall in a variety of ways. We hence replicated our results for the period before 2008, only. Table 19 in Appendix B shows that this does not change our main conclusions.

Third, we also replicated our results using the continuous exposure measure to clusters. Table 20 in Appendix B shows that there are some marginally significant effects of clusters on resilience, which are qualitatively in line with what we find in the baseline case. However, there are no effects of the interaction of the distance variable with the treatment, and if anything there are marginally more deaths and exits in clusters. Again, we find that plants in clusters are not more resilient than plants outside clusters, neither in a strong nor in a weak sense.

Finally, one might be worried about the endogeneity of our clusters based on 2001 definitions. As explained above, endogeneity could arise if clusters are the consequence of plants' expectations regarding their resilience (death, industry switching). We thus instrument the cluster variable (and its interactions with our trade policy dummies) with the distance to 1871 T&C employment. Table 16 displays the results. The instrumented specification delivers similar results: the end of the MFA has affected more strongly the most exposed sectors, but plants inside and outside clusters did not adjust differently following this shock.

Table 16: Dimensions of resilience of T&C sector plants after the end of MFA (IV regressions).

	Die	Exit	Switch | Exit	Services | Switch
	(1)	(2)	(3)	(4)
Employment	-0.021[a]	-0.022[a]	0.015[a]	-0.004
	(0.003)	(0.003)	(0.005)	(0.013)
Exporter	-0.042[a]	-0.045[a]	0.029[c]	0.099[a]
	(0.007)	(0.007)	(0.017)	(0.036)
Multiunit	0.064[a]	0.064[a]	-0.065[c]	-0.068
	(0.017)	(0.019)	(0.036)	(0.084)
Industry breadth	-0.057[a]	0.032[a]	0.317[a]	-0.025
	(0.006)	(0.008)	(0.018)	(0.036)
Quota	0.036	-0.001	-0.161[a]	0.435[a]
	(0.022)	(0.024)	(0.052)	(0.150)
Post2005× Quota	0.103	0.164[b]	0.152	-0.382
	(0.070)	(0.077)	(0.175)	(0.255)
Cluster	0.111[a]	0.132[a]	-0.046	0.507[a]
	(0.035)	(0.040)	(0.089)	(0.117)
Cluster×Post2005	-0.022	-0.033	0.008	-0.439[a]
	(0.042)	(0.048)	(0.102)	(0.164)
Quota×Cluster	-0.066	-0.010	0.217	-0.276
	(0.080)	(0.088)	(0.205)	(0.293)
Post2005×Quota×Cluster	-0.137	-0.162	0.014	0.281
	(0.096)	(0.105)	(0.233)	(0.345)
Fixed effects			Province-year	
Obs.	14,707	14,707	3,166	831
R^2	0.026	0.041	0.219	0.230
F-test	480	498	86	47

Notes: Huber-White robust standard errors in parenthesis. [a] = significant at 1%, [b] = significant at 5%, [c] = significant at 10%. 'Post2005' is included but absorbed by the province-year fixed effects. Cragg-Donald Wald F-statistic. Cluster dummy is instrumented by the distance of the plant to 1871 T&C employment.

5 Conclusion

The Canadian textile and clothing sector is geographically fairly concentrated, organized around a few economic clusters, and was subject to substantial import protection until the beginning of the 2000s. Therefore, it provides an ideal laboratory for evaluating the interplay between resilience and geographic patterns in a changing environment. In this paper, we have dissected the recent changes faced by this sector between 2001 and 2013, a period where it experienced large adverse industry-specific shocks. We question the ability of geographic clusters to shelter firms from these shocks as we find no evidence supporting this view. It is rather the opposite. Eventually, our results suggest that clustered plants were about 2% more likely to die and exit than non-clustered plants. With plant-level data, we are also able to show that many textile plants changed their main line of business over the period, meaning that 'adaptation' is an important margin of adjustment for firms facing tougher competition. In that respect, we find that plants in clusters do not statistically adapt more but, when they do, are more likely to switch into services.

In the face of major disturbances — such as the 'China shock' — whether firms belong to a cluster or not does not seem to be of first-order importance, as plants roughly die evenly across space. However, local communities that host large clusters of firms will tend to suffer more. In levels, they are prone to experience more closures and exits. Therefore, knowing the exact location of industrial clusters is at least as useful as knowing whether an industry is concentrated in the aggregate, i.e., nation-wide. This substantiates the need for operational tools and methods that help us define clusters using a bottom-up approach. Such tools, as the ones developed in this paper, allow us to go beyond broad industry-level measures of geographic concentration and assess, within an industry or a region, whether plants are spatially concentrated.

Understanding where clusters are located also matters as firms' adjustments in response to adverse shocks are linked to the location of the cluster they belong to. For instance, we show that manufacturing firms are more likely to switch into services if they are clustered in major metropolitan areas. Firms in peripheral clusters do not adjust in that same way. Policies supporting transitions should thus account for the heterogeneity of clusters: clusters in smaller locations are not as likely to experience such transitions to services. Today, quite little is known on how clusters, their composition, and more generally the local environment in which plants operate, influence and shape these industrial transitions. In that matter, we view our results as first indications that 'where you cluster matters'. We plan to use the tools developed in this project to explore more deeply this assertion in future research.

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Appendix

A. Data sources and construction of variables

A.1. Construction of our economic proximity measures.

We construct five economic proximity measures s_{ij} between industries i and j: (i) the share of plants in industry i that report secondary activities in industry j; (ii) the strength of input-output links between industries i and j, based on national input-output tables; (iii) the similarity of industries i and j in terms of 553 occupational categories that they employ; (iv) the frequency with which industry i cites patents originating in industry j; and (v) the extent of labor mobility across industries i and j. Details on our plant-level data are provided in Section 3.1, whereas Appendix A.2 provides information on our industry-level data.

(i) 'Within-firm complementarities' is the share of plants in a 4-digit industry i (based on the plant's primary NAICS code) that also report at least one secondary code in another 4-digit industry j. We construct that measure year-by-year using all our manufacturing plants.

(ii) 'Input-output linkages' is the maximum element in the input-output tables between i and j (Ellison et al. 2010). Formally, it is given by $s_{ij}^{IO} = \max\{input_{ij}, input_{ji}, output_{ij}, output_{ji}\}$.

(iii) 'Occupational employment correlation' is the correlation coefficient between industries i and j's employment shares in 553 occupations, computed from the U.S. Occupational Employment Surveys (Ellison et al. 2010). We exclude all occupations that report zero employment in manufacturing industries (e.g., surgeons).

(iv) 'Knowledge flows' is the use-based share of patents that originate in industry j and are embodied (cited) in patents of industry i. See Kerr (2008) for additional details.

(v) 'Labor mobility between industries' is the share of workers leaving industry i and moving to industry j (conditional on moving), computed using 2000–2005 Current Population Survey data that is made 'panel-consistent' as decribed in Madrian & Lefgren (1999).

A.2. Industry-level and trade data.

Input-output tables. We use detailed input-output tables for the years 1998–2010, which we associate with our study period 2001–2013, respectively. These tables are constructed using the finest public release of the Canadian input-output tables at the L-level (link level), which is between NAICS 3- and 4-digit. We first disaggregate the input-output matrices to the W-level (NAICS 6-digit) using sales or employment data as sectoral weights, and then reaggregate them to the 4-digit level.[23] The shares in (ii) of Appendix A.1 are computed taking into account all industries (including primary industries and services, but excluding private consumption and the different government aggregates and imports/exports).

OES and CPS data. We construct a measure of occupational employment similarity of the workforce in the different industries. To this end, we use Occupational Employment Survey (OES) data from the Bureau of Labor Statistics (BLS) for 2002–2011 to compute the share of each of 554 occupations in each 4-digit NAICS industry.[24] We use 2002 as the starting year for the OES data to avoid the difficult concordance from SITC to NAICS. Our measure of occupational employment similarity for total employment, OES_{ij}^{0}, is computed as the correlation between the vectors of occupational shares of industries i and j. This yields (iii) of Appendix A.1.

To compute (v) of Appendix A.1, we compute an index of labor mobility across manufacturing industries. To do so, we use the 2000–2005 annual public use files of the Current Population Survey (MORG, March supplement). We extract all moves from the database (12,269 moves between manufacturing industries), and we construct a matrix that contains the share of moves from industry i to industry j, mov_{ij}. We consider that industries with a larger value of mov_{ij} are more similar in terms of their labor requirements. Note that because of sample size limitations, we cannot compute a time-varying measure

[23] Due to confidentiality reasons, we cannot directly use the W-level matrices that are internally available at *Statistics Canada*. However, tests we ran using those matrices yielded similar results to those using the matrices constructed by our methodology.

[24] There are 808 occupations in total in the OES data. We only use occupations for which there is at least some employment in manufacturing (e.g., there are no 'Surgeons' in manufacturing industries, hence we exclude them completely from our data).

of labor movements. Hence, we use the same values of mov_{ij} across all years of our geographic data.

Knowledge flows. Last, we construct proxies for 'knowledge spillovers' for (iv) of Appendix A.1 using the NBER Patent Citation database, following previous work by Kerr (2008). We construct two proxies: (i) know_{ij}^{m}, which is the maximum of the shares of patents that industry i (or j) manufacture and which originate from the other industry; and (ii) know_{ij}^{u}, which is the maximum of the shares of patents that industry i (or j) use and which originate from the other industry.

Trade protection and import/export data. Quotas on Chinese imports in the textile sector have been removed in four phases: in 1995, 1998, 2002 and 2005. Khandelwal et al. (2013) provide information on quotas faced by Chinese exporters in Canada and the year of the removal of these quotas. Products subject to quota restrictions are described in the Chinese HS8 nomenclature. We aggregate these products to the HS6 level and use the correspondence table developed by Pierce & Schott (2009) to map the quota information to the NAICS level. We consider that a NAICS industry was subject to quotas until 2005 if at least 90% of HS6 products in that industry were subject to a quota until this date. These industries are listed in Table 17, as well as the change in imports from China and the Chinese market share. For the latter, we use international trade data from *Innovation, Science and Economic Development Canada's Trade Data Online*. The data report import values by NAICS 6-digit industry, province, and trading partner from 1992 to 2011. We concord the data to our stable NAICS classification and aggregate them to the national level. We then compute industry import values from China.

ASM industry data. Finally, we complement our industry-level data with the aggregate version of the *Annual Survey of Manufacturers* (ASM), which reports industry values for employment (both production and non-production), value-added, and revenue at the 6-digit level. We also use detailed input-output tables at the 6-digit level for 2001–2013 in two-year steps. Those use-based tables are constructed from the publicly available more aggregated (*L*-level) tables, and we break them down to the 6-digit level using either sectoral employment or sales weights.

Canadian Industrial Census from 1871. To construct our historic instrument, we use the Canadian Industrial Census 1871. This census (henceforth, CANIND71) has been digitized by researchers at the University of Guelph, Ontario, and it is freely available at the following address: `http://www.canind71.uoguelph.ca`. We use all 45+ thousand plants that are available in the census. We define textile and clothing industries using the census SIC codes 5.04 ('Leather Industries'), 5.05 ('Textile Industries'), 5.06 ('Knitting Mills'), and 5.07 ('Clothing Industries'). Each establishment is associated with a historic census district, for which we can retrieve the centroid coordinates. For each historic census district, we compute a count of the textile plants in 1871, and the total employment in those industries. Figures 11 and 12 in the Supplemental Appendix W depict the geographic distribution of textile and clothing employment and plants in the Dominion of Canada in 1871. Note that there are many zeros in the data — for establishments that are run by their owner and which have no employees. To adjust for this, we consider those establishments has having one employee. This marginal change makes virtually no difference.

B. Additional tables and results

This appendix reports additional tables and results. In Table 17, we indicate whether the 6-digit T&C industry was subject to quotas under the Multifibre Arrangement (MFA). For each industry, we also report the level and the share of imports from China in 2001 and 2013. In Table 18, we replicate our main results using employment changes as the dependent variable — i.e., as the measure of resilience. In Table 19, we measure the resilience of the T&C sector after the end of the MFA and before 2008, to eliminate the impact of the Great recession. Finally, we use a continuous measure of exposure to clusters (distance to the centroid of the closest clusters) instead of the dummy variable.

Table 17: MFA quotas in Canadian textile and clothing NAICS industries.

Stable NAICS	Industry name	Subject to quotas until 2005	Imports from China 2001	Imports from China 2013	Chinese market share 2001	Chinese market share 2013
313210	Broad-woven fabric mills	**Yes**	91.8	120	0.06	0.19
313320	Fabric coating	**Yes**	1.3	17.4	0.00	0.09
315110	Hosiery and sock mills	**Yes**	5.6	137	0.05	0.50
315220	Men's and boys' cut and sew clothing manufacturing	**Yes**	347	973	0.22	0.38
315249	Women's and girls' cut and sew clothing manufacturing	**Yes**	381	1,920	0.21	0.53
315990	Clothing accessories and other clothing manufacturing	**Yes**	154	452	0.47	0.69
313110	Fibre, yarn and thread mills	No	7.8	11.5	0.02	0.08
313220	Narrow fabric mills and machine embroidery	No	3.3	17.4	0.03	0.22
313230	Nonwoven fabric mills	No	364	13.6	0.00	0.03
313240	Knit fabric mills	No	48	50,9	0.09	0.26
313310	Textile and fabric finishing	No	0.9	2.6	0.02	0.09
314110	Carpet and rug mills	No	12.3	57.4	0.02	0.08
314120	Curtain and linen mills	No	98.2	592	0.17	0.57
314910	Textile bag and canvas mills	No	71.2	139	0.46	0.49
314990	All other textile product mills and cut-and-sew clothing contracting	No	28.4	155	0.04	0.25
315190	Other clothing knitting mills	No	64.3	709	0.14	0.58
315291	Infants' cut and sew clothing manufacturing	No	15.4	121	0.23	0.57
315292	Fur and leather clothing manufacturing	No	69	58.1	0.60	0.56
315299	All other cut and sew clothing manufacturing	No	47.3	231	0.22	0.58
316110	Leather and hide tanning and finishing	No	1.8	6.5	0.01	0.06
316210	Footwear manufacturing	No	655	1,420	0.49	0.70
316990	Other leather and allied product manufacturing	No	280	733	0.56	0.70

Notes: All values are expressed in millions of current C$. Following Khandelwal et al. (2013), a NAICS industry is considered as being subject to quotas if at least 90% of the products in this industry were subject to quotas until 2005. We report quotas based on our stable NAICS industries as defined in Table 22 in online appendix S.

Table 18: Resilience as captured by employment change in T&C plants (OLS).

Dependent var.	dln(Employment)			
	(1)	(2)	(3)	(4)
Cluster	-0.002	0.000	0.012	0.012
	(0.007)	(0.007)	(0.013)	(0.013)
Exporter		0.011^b		0.013^b
		(0.005)		(0.006)
Multiunit		-0.032^b		-0.033^b
		(0.015)		(0.015)
Industry breadth		0.023^a		0.019^a
		(0.006)		(0.006)
Quota			0.003	0.004
			(0.020)	(0.020)
Post2005$\times$ Quota			-0.032	-0.030
			(0.023)	(0.023)
Cluster$\times$Post2005			-0.011	-0.010
			(0.015)	(0.015)
Quota$\times$Cluster			-0.011	-0.010
			(0.015)	(0.015)
Post2005$\times$Quota$\times$Cluster			0.015	0.014
			(0.028)	(0.028)
Fixed effects	Province-year			
Obs.	13,335	13,335	13,335	13,335
R^2	0.011	0.013	0.013	0.014

Notes: The dependent variable is the change in (the logarithm of) the employment of the plant. 'Post2005' is included but absorbed by the province-year fixed effects. Huber-White robust standard errors in parenthesis. ^{a} = significant at 1%, ^{b} = significant at 5%, ^{c} = significant at 10%.

Table 19: Dimensions of resilience of T&C sector plants after the MFA and before 2008 (LPM).

	Die	Exit	Switch | Exit	Services | Switch
	(1)	(2)	(3)	(4)
Employment	-0.017^a	-0.021^a	0.001	0.021
	(0.003)	(0.003)	(0.006)	(0.018)
Exporter	-0.045^a	-0.045^a	0.049^b	0.110^b
	(0.008)	(0.008)	(0.021)	(0.048)
Multiunit	0.058^a	0.071^a	-0.038	-0.083
	(0.019)	(0.021)	(0.043)	(0.102)
Industry breadth	-0.064^a	-0.032^a	0.226^a	0.045
	(0.007)	(0.009)	(0.027)	(0.044)
Quota	0.034	-0.011	-0.178^a	0.446^a
	(0.022)	(0.024)	(0.052)	(0.143)
Post2005× Quota	0.031	0.089^a	0.194^a	-0.237
	(0.030)	(0.032)	(0.064)	(0.187)
Cluster	0.019	0.008	-0.041	0.115
	(0.015)	(0.017)	(0.042)	(0.073)
Cluster×Post2005	-0.011	0.010	0.061	-0.060
	(0.019)	(0.022)	(0.050)	(0.132)
Quota×Cluster	0.001	0.019	0.050	0.062
	(0.026)	(0.029)	(0.061)	(0.160)
Post2005×Quota×Cluster	-0.053	-0.062	0.013	-0.108
	(0.035)	(0.038)	(0.076)	(0.213)
Fixed effects			Province-year	
Obs.	10,427	10,427	2,061	425
R^2	0.037	0.036	0.119	0.345

Notes: 'Post2005' is included but absorbed by the province-year fixed effects. Huber-White robust standard errors in parenthesis. ^{a} = significant at 1%, ^{b} = significant at 5%, ^{c} = significant at 10%.

Table 20: Continuous exposure of plants to T&C clusters after the MFA (LPM).

	Die	Exit	Switch | Exit	Services | Switch
	(1)	(2)	(3)	(4)
Employment	-0.021^{a}	-0.021^{a}	0.014^{a}	-0.006
	(0.003)	(0.003)	(0.005)	(0.013)
Exporter	-0.039^{a}	-0.042^{a}	0.029^{c}	0.094^{a}
	(0.007)	(0.007)	(0.017)	(0.035)
Multiunit	0.066^{a}	0.063^{a}	-0.074^{b}	-0.047
	(0.017)	(0.018)	(0.036)	(0.084)
Industry breadth	-0.060^{a}	0.028^{a}	0.315^{a}	-0.032
	(0.006)	(0.008)	(0.018)	(0.034)
Quota	0.024	0.010	-0.087^{c}	0.562^{a}
	(0.022)	(0.025)	(0.053)	(0.091)
Post2005×Quota	-0.009	0.019	0.125^{b}	-0.339^{a}
	(0.027)	(0.030)	(0.062)	(0.121)
Distance to cluster	-0.011^{b}	-0.010^{c}	0.012	-0.036
	(0.005)	(0.006)	(0.014)	(0.022)
Distance to cluster×Post2005	0.005	0.001	-0.015	-0.002
	(0.006)	(0.007)	(0.015)	(0.029)
Quota×Distance to cluster	0.004	-0.001	-0.017	-0.031
	(0.007)	(0.008)	(0.018)	(0.035)
Post2005×Quota×Distance to cluster	0.003	0.008	0.012	0.033
	(0.008)	(0.009)	(0.021)	(0.043)
Fixed effects			Province-year	
Obs.	14,707	14,707	3,166	831
R^2	0.036	0.050	0.228	0.265

Notes: 'Post2005' is included but absorbed by the province-year fixed effects. Huber-White robust standard errors in parenthesis. ^{a} = significant at 1%, ^{b} = significant at 5%, ^{c} = significant at 10%.

Online appendix

This online appendix is structured as follows. In Appendix **S**, we present additional results and descriptive evidence. In Appendix **T**, we develop a simple model of clusters and survival and show that agglomeration economies and selection effects have ambiguous effects on plant exit (resilience). Appendix **U**, provides a short summary of the methodology used to compute the K-densities in the paper. Appendix **V** provides methodological details on how we construct our firm identifiers. Last, Appendix **W** presents a brief overview of the history of the T&C industries in Canada.

S. Additional definitions and results

S.1. Construction of the average input-output strength and occupational labor correlation measures

Table 7 reports cluster-level measures of labor correlation and input-output strength. These two measures are constructed as follows.

Let $occup_{i,j}$ denote the correlation coefficient between the vectors of shares of workers of 553 different occupations in the total employment of industries i and j. Let $input_{i,j}$ and $output_{i,j}$ denote the input and output coefficients between industries i and j. See Appendix A.2 for additional information on the data. We construct measures of the average input-output strength (IS and OS) and the average occupational labor correlation (LC) around each plant p for a given distance threshold $\overline{d}$ as follows (see Jofre-Monseny et al. 2011 for the construction of similar, albeit more spatially aggregated, measures). Let $\mathcal{D} = \{q \neq p,\ d(p,q) \leq \overline{d}\}$ denote the set of plants q other than p that are located at less than $\overline{d}$ from plant p. We then compute

$$
\begin{aligned}
IS_p &= \frac{1}{\sum_{q\in\mathcal{D}} e_q} \sum_{k\in\mathcal{D}} e_k \times input_{i(p),j(k)} \\
OS_p &= \frac{1}{\sum_{q\in\mathcal{D}} e_q} \sum_{k\in\mathcal{D}} e_k \times output_{i(p),j(k)} \\
LC_p &= \frac{1}{\sum_{q\in\mathcal{D}} e_q} \sum_{k\in\mathcal{D}} e_k \times occup_{i(p),j(k)}
\end{aligned} \tag{4}
$$

where e_q denotes the employment of plant q, and where $j(k)$ is the mapping from each plant to its industry. The former two measures capture the (employment weighted) average input or output coefficient at distance less than $\overline{d}$ around the plant. They thus provide a measure of the potential strength of input-output relationships in the region the plant is located in. The latter measure captures the (employment weighted) similarity of the other plants in terms of their occupational structure at distance less than $\overline{d}$ around the plant. This provides a measure of how similar the plant is to the others in its region regarding the labor pool from which it potentially hires.

Finally, we take the average of the measures (4) across all plants p in our clusters in 2001 to obtain the average input and output strength and occupational labor correlation for each cluster. Since the input and output measures are highly colinear, we combine them into a compound 'average input-output strength' measure for each cluster.

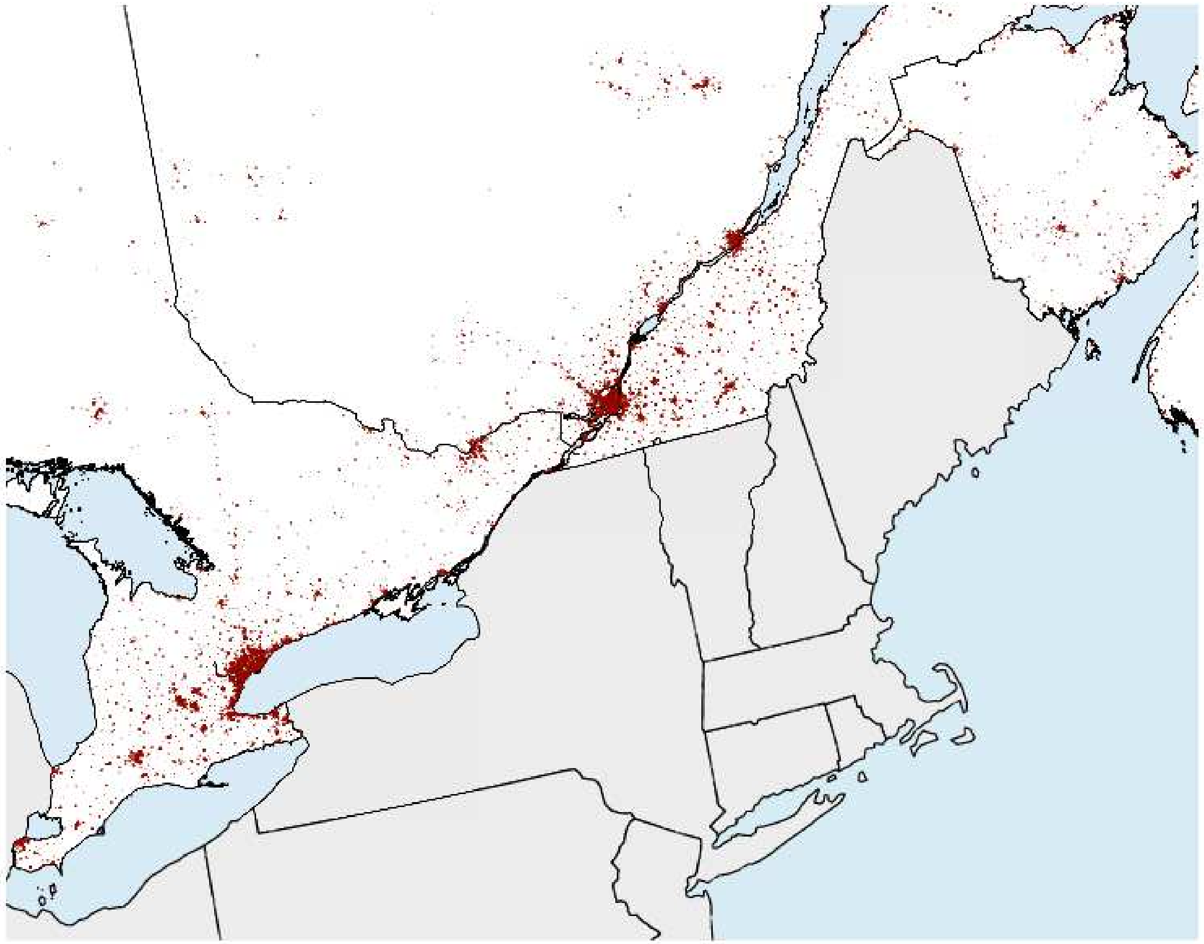
S.2. Geographic distribution

[1] Figure 5 depicts the geographic distribution of manufacturing plants in the south-eastern part of Canada in 2001. It shows that our data is very fine-grained, thus lending itself well to a continuous spatial analysis. Figure 6 zooms onto Montréal. As can be seen from the figure, the spatial resolution of our data is very fine within cities. Furthermore, one can clearly see the geographic concentration of T&C establishments along Saint-Laurent Boulevard, which started to attract clothing manufacturers, breweries, and other 'light' manufacturing industries in the second half of the 19th century.

[2] Figure 7 displays the level of clustering in the T&C sector relative to that in other manufacturing industries. More specifically, it plots the cumulative distribution of the bilateral distances in the T&C sector (the red curve; NAICS 3131–3169, see Table 22) and in other sectors (black curve). As can be seen from that figure, the T&C sector is significantly more concentrated than the other manufacturing industries, especially at short geographic distances.

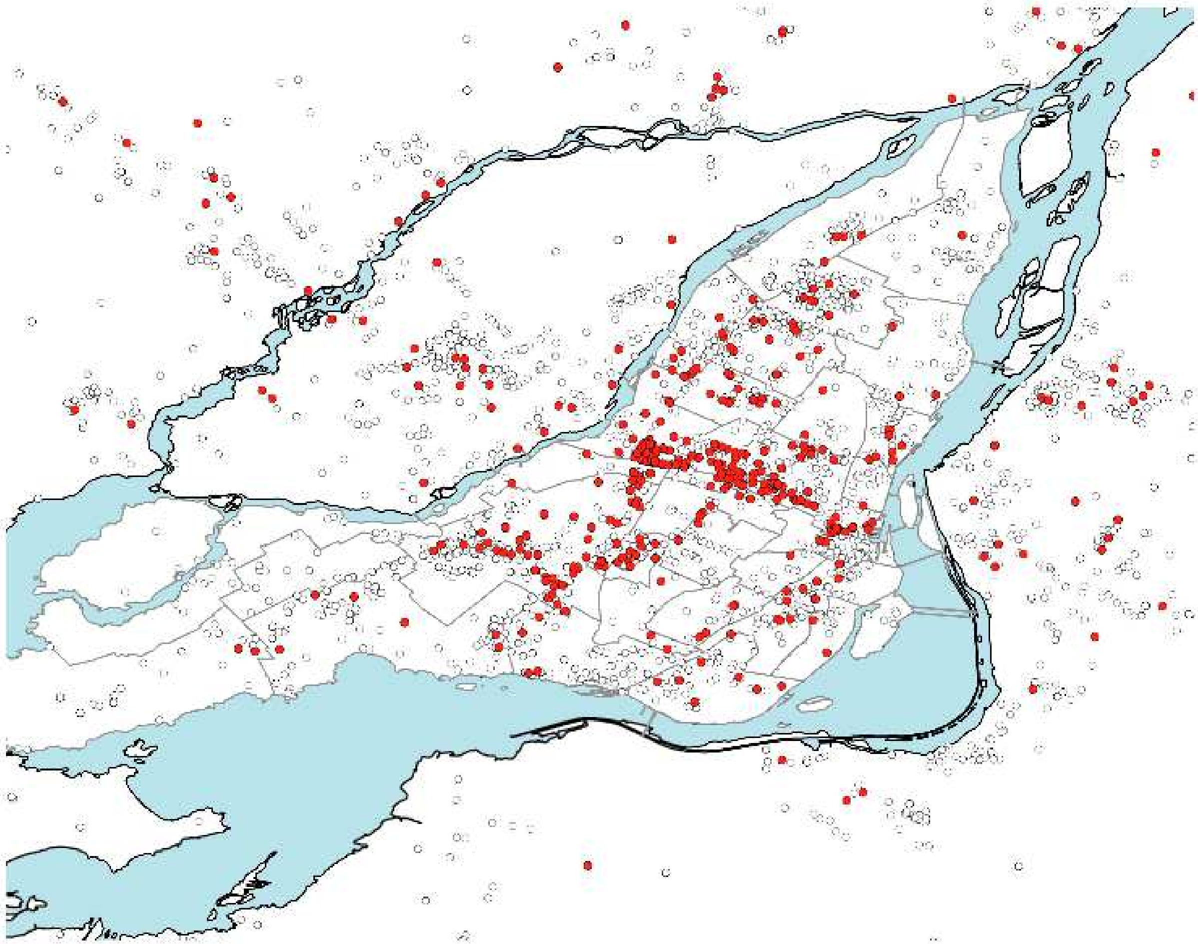
[3] Figure 8 is the employment-weighted counterpart to Figure 2 in the main body of the text. It shows the same pattern than when using plant counts as

Figure 5: Geographic distribution of manufacturing establishments in the south-eastern part of Canada, 2001.



Notes: Spatial distribution of manufacturing establishments in Canada in 2001, based on the *Scott's National All database* (manufacturing portion only).

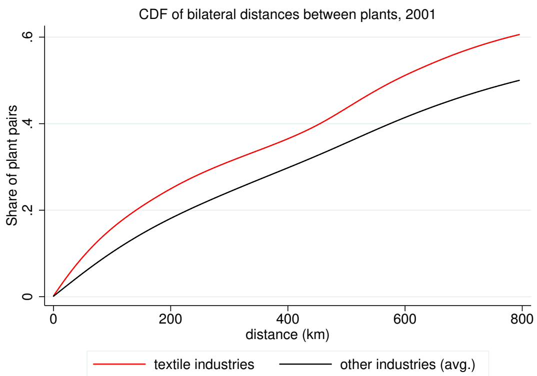
Figure 6: Saint-Laurent Boulevard ('The Main'), Montréal, 2005.



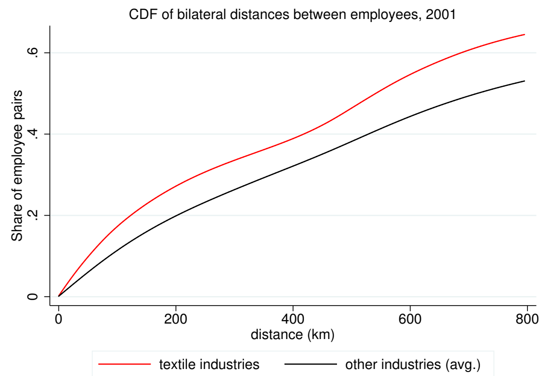
Notes: Spatial distribution of manufacturing establishments in Canada in 2001, based on the *Scott's National All database* (manufacturing portion only). Non-textile plants are depicted by black empty circles, while T&C establishments are represented with red-filled points.

Figure 7: The spatial concentration of textile industries relative to manufacturing in general.

(a) Plant counts.



(b) Employment weights.

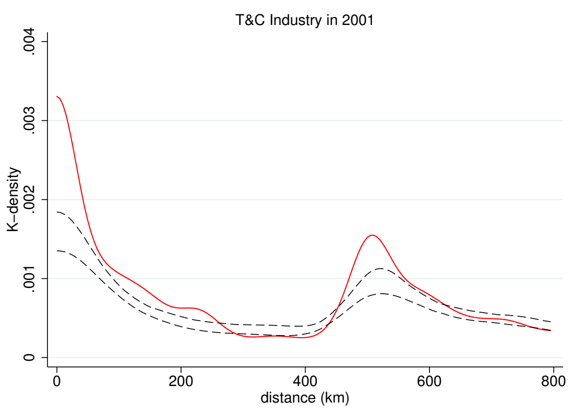


Notes: We plot the unweighted averages of the K-density CDFs at the 6-digit NAICS level for the other (non-textile) industries (black line).

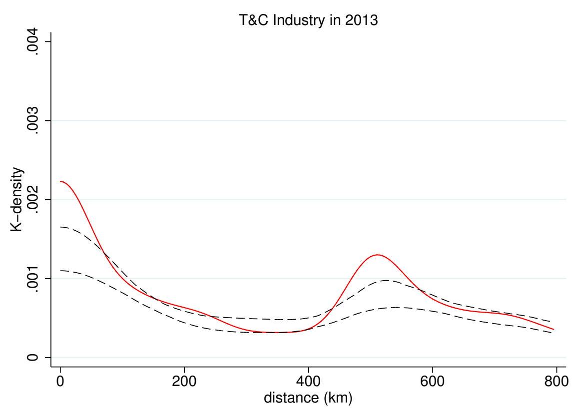
the unit of analysis. Hence, the spatial deconcentration that we document in the main body of the text does not depend on whether we use employment or plant counts.

Figure 8: Changes in the spatial concentration of the T&C sector between 2001 and 2013, weighted.

(a) 2001.



(b) 2013.

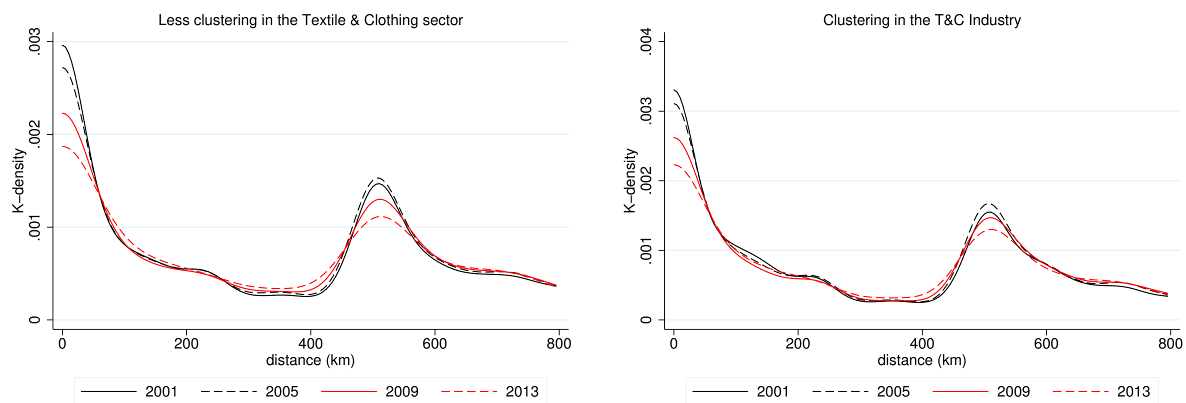


Notes: The figures report the K-densities (in solid red) and the 90% global confidence bands (in dashed black) for the T&C sector in 2001 and 2013 using employment weights. Distributions of distances that fall into this confidence band could be considered 'as good as random' and are, therefore, not considered to be either localized or dispersed.

[4] Figure 9 depicts the changes across years in the unweighted (left panel) and the employment-weighted (right panel) K-densities in the T&C sector. Clearly, we see that the geographic concentration has decreased, and the the strongest decreases occured at short geographic distances.

Figure 9: Spatial deconcentration of the T&C sector between 2001 and 2013.

(a) Plant counts. (b) Employment weights.



Notes: The figures depict the K-densities in 2001, 2005, 2009, and 2013 using plant counts (left) and employment weights (right).

[5] Figure 10 depicts the K-densities of plants that exit the T&C industry after 2001. It shows that plants exit in the T&C industry is concentrated at extremely short distances. This figure thus suggest that plants in 'geographic clusters' — which are essentially defined by the concentration of plants at short geographic distances — have been hit harder than plants that are outside of such clusters.

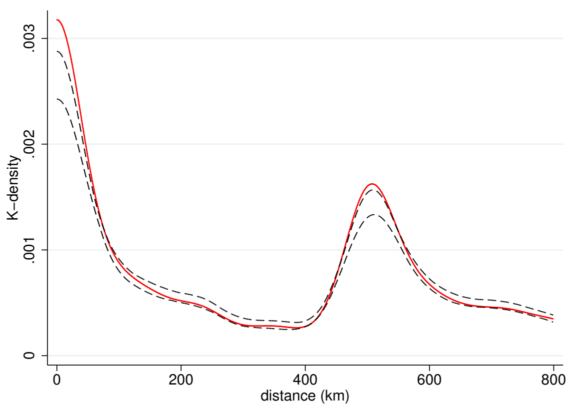
Table 21: Economic relatedness translates into geographic proximity.

Average share of plant pairs	25 km	50 km
Non-'Textile & Clothing' industry pairs	3.84%	7.37%
Mixed industry pairs	3.86%	7.42%
'Textile & Clothing' industry pairs	5.26%	10.09%

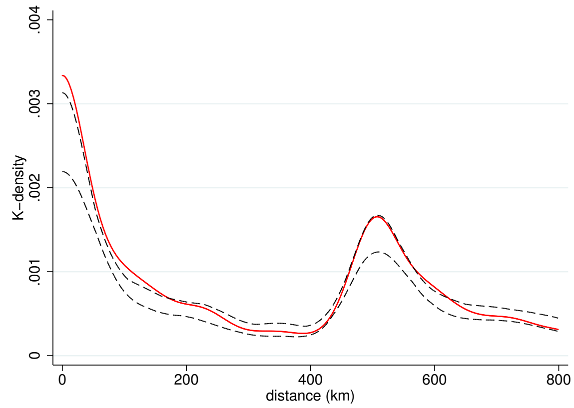
Notes: Based on our own computations, using the CDF of the coagglomeration measure in Duranton & Overman (2005). The industries belonging to our T&C sector are listed in Table 22 in online appendix S.

Figure 10: Spatial distribution of plant exits in the T&C sector between 2003 and 2013.

(a) Plant counts.



(b) Employment weights.



Notes: The figure reports the K-densities (in solid red) and the 90% global confidence bands (in dashed black) for the exit of plants in the T&C sector after 2003. Exit of plants between 2003 and 2013 is compared to the overall distribution of the T&C sector in our base year 2003.

[6] Table 21 shows that the individual industries that constitute the T&C sector (see Table 22) are also substantially more coagglomerated than pairs of non-T&C industries or mixed industry pairs (one T&C, and one non-T&C). For example, in 2001, on average 3.84% of bilateral distances between plant pairs not belonging to the T&C sector, and 3.86% of plant pairs in mixed (one industry belonging to T&C, and one not) were less than 25 kilometers apart. For pairs of industries belonging to T&C, the corresponding figure is 5.26%, a 37% increase. Note that out of the 3,570 4-digit industry pairs for which we computed coagglomeration measures in 2001, the 3rd and 4th most coagglomerated were T&C industry pairs: 'Apparel Knitting Mills' (NAICS 3151), and 'Cut and Sew Clothing Manufacturing' (NAICS 3152) with 9.42% of plant pairs less than 25 kilometers apart; and 'Fabric Mills' (NAICS 3132) and 'Apparel Knitting Mills' (NAICS 3151) with also 9.42% of plant pairs less than 25 kilometers apart. These findings show that the economic proximity between textile industries, as documented in Table 1, translates into geographic proximity. The combination of both proximities is what allows us to define well-identified geographic clusters as in the main body of the text.

S.3. Additional descriptives

[1] Table 22 displays the aggregation of the T&C sector in terms of the underlying NAICS 6-digit industries. Because of successive changes in the industrial classification, we aggregate all industries to a stable 6-digit classification that spans NAICS 1997, 2002, 2007, and 2012. Our T&C sector comprises 22 time-consistent 6-digit industries.

Table 22: Components and aggregation of textile industries for the T&C sector.

Industry name	**Stable NAICS**	**Aggregation**
Fibre, yarn and thread mills	313110	
Broad-woven fabric mills	313210	
Narrow fabric mills and schiffli machine embroidery	313220	
Nonwoven fabric mills	313230	
Knit fabric mills	313240	
Textile and fabric finishing	313310	
Fabric coating	313320	
Carpet and rug mills	314110	
Curtain and linen mills	314120	
Textile bag and canvas mills	314910	
All other textile product mills	314990	Aggregated
Cut and sew clothing contracting	314990	Aggregated
Hosiery and sock mills	315110	
Other clothing knitting mills	315190	
Other men's and boys' cut and sew clothing manufacturing	315220	Aggregated
Men's and boys' cut and sew suit, coat and overcoat manufacturing	315220	Aggregated
Men's and boys' cut and sew shirt manufacturing	315220	Aggregated
Men's and boys' cut and sew underwear and nightwear manufacturing	315220	Aggregated
Men's and boys' cut and sew trouser, slack and jean manufacturing	315220	Aggregated
Women's and girls' cut and sew blouse and shirt manufacturing	315249	Aggregated
Other women's and girls' cut and sew clothing manufacturing	315249	Aggregated
Women's and girls' cut and sew dress manufacturing	315249	Aggregated
Women's and girls' cut and sew suit, coat, tailored jacket and skirt manufacturing	315249	Aggregated
Women's and girls' cut and sew lingerie, loungewear and nightwear manufacturing	315249	Aggregated
Infants' cut and sew clothing manufacturing	315291	
Fur and leather clothing manufacturing	315292	
All other cut and sew clothing manufacturing	315299	
Clothing accessories and other clothing manufacturing	315990	
Leather and hide tanning and finishing	316110	
Footwear manufacturing	316210	
Other leather and allied product manufacturing	316990	

Notes: We aggregate all industries to a stable 6-digit classification that spans NAICS 1997, 2002, 2007, and 2012. Changes within the T&C industry occur mainly between the NAICS 2007 and NAICS 2012 classifications. There are several other changes for non-textile industries. The 4-digit classification remains essentially stable throughout the entire 2001–2013 period. There are 85 4-digit industries since our dataset has no plants in NAICS 3391 after our concordance has been applied.

[2] Table 23 contains descriptive information on changes in Canadian import values by industry and countries of origin. We distinguish three types of imports: imports from China, from other low-income countries, and from high-income countries. This table shows that all textile industries experienced a massive increase in imports from China over the period 1999–2011. For instance, import values from China in the 'Cut and Sew Clothing Manufacturing' (NAICS 3152) increased by more than 1.6 billion C$ between 2003 and 2007. While this trend is primarily driven by China, imports from all low-income countries have also increased in most of T&C industries. Finally, this surge in imports from low-wage countries has occurred at the expense of high-wage countries that have seen their exports to Canada to fall sharply between 1999 and 2011 in almost all industries (the only exception being 'Other Leather and Allied Product Manufacturing', NAICS 3169).

S.4. Additional results

[1] In Table 24, we analyze the aggregate changes in the number of plants, employment and productivity in T&C industries. Instead of measuring changes in trade exposures with two dummy variables — 'Post2005' and 'Quota' — as in Table 5, we use a continuous measure: the share of imports from low-income countries in total imports of the industry. The latter is interacted with (i) 'Textile', a dichotomous variable that takes value one for our 22 T&C industries, and zero otherwise, and (ii) 'excess clustering' (see Section 2.6).

The results show that industries were not significantly affected by changes in the geographic composition of trade — apart from a positive effect of the share of imports from low-income countries on industry employment, but these results are very different when we consider textile industries. An increase in the share of imports from low-wage countries is associated with: (i) a drop in the number of active plants; (ii) a fall in employment; and (iii) a rise in productivity in these industries. The estimated coefficients for the interaction terms reveal that the share of imports from low-wage countries has a stronger negative impact on the three outcomes in geographically concentrated industries. T&C industries are again very specific in their reactions to changes in the trading environment. Eventually, column (4) shows that the negative impact of the import variable on T&C employment increases with the

Table 23: Changes in import values from China and other country groups for the different textile industries.

NAICS	Industry name	Imports from China			Imports from low-income countries		
		$\Delta 1999-2003$	$\Delta 2003-2007$	$\Delta 2007-2011$	$\Delta 1999-2003$	$\Delta 2003-2007$	$\Delta 2007-2011$
3131	Fibre, yarn and thread mills	-0.701	0.535	3.797	-30.860	-41.485	-10.735
3132	Fabric mills	59.359	-10.977	9.791	-45.215	-64.515	-1.997
3133	Textile and fabric finishing and fabric coating	5.169	4.455	8.113	.547	2.531	1.912
3141	Textile furnishings mills	147.093	289.466	102.747	94.745	73.481	11.343
3149	Other textile product mills	65.887	80.471	48.053	13.069	26.800	39.075
3151	Clothing knitting mills	40.170	557.582	177.584	77.227	109.974	163.617
3152	Cut and sew clothing manufacturing	744.446	1624.757	77.262	459.394	259.150	835.000
3159	Clothing accessories and other clothing manufacturing	89.1302	89.1241	120.1234	9.7309	14.6381	33.1973
3161	Leather and hide tanning and finishing	2.626	1.244	0.864	1.976	-1.403	-1.453
3162	Footwear manufacturing	181.7469	344.4463	236.7850	19.5069	15.2499	110.0145
3169	Other leather and allied product manufacturing	79.327	204.511	170.035	1.544	0.891	27.245
		Imports from high-income countries					
		$\Delta 1999-2003$	$\Delta 2003-2007$	$\Delta 2007-2011$			
3131	Fibre, yarn and thread mills	-140.994	-98.884				
3132	Fabric mills	-447.623	-587.660	-168.280			
3133	Textile and fabric finishing and fabric coating	-38.329	-37.217	-51.611			
3141	Textile furnishings mills	-4.966	9.085	-118.278			
3149	Other textile product mills	-54.667	-65.008	-44.656			
3151	Clothing knitting mills	1.447	-181.923	-26.671			
3152	Cut and sew clothing manufacturing	-52.837	-662.498	-192.119			
3159	Clothing accessories and other clothing manufacturing	-3.422	-21.444	-3.277			
3161	Leather and hide tanning and finishing	-18.663	-106.753	-39.909			
3162	Footwear manufacturing	-92.224	-69.208	-80.607			
3169	Other leather and allied product manufacturing	27.844	22.819	12.233			

Notes: Author's computations, using *Innovation, Science and Economic Development Canada's Trade Data Online* from 1999–2011. Low-income countries are defined as in Bernard et al. (2006) by all countries with a GDP per capita below 5% of U.S. GDP per capita, and high-income countries are countries whose GDP per capita exceeds 95% of U.S. GDP per capita. All values are expressed in millions of current C$.

Table 24: Aggregate changes in the number of plants, employment, and productivity (all industries).

	Number of plants		Industry employment		Industry productivity	
	(1)	(2)	(3)	(4)	(5)	(6)
Import share LIC	0.204	0.316	1.255^{a}	1.381^{a}	1.099	1.526
	(0.289)	(0.290)	(0.468)	(0.472)	(1.365)	(1.358)
Import share LIC × textile	-11.285^{a}	-9.597^{a}	-21.457^{a}	-12.849^{a}	5.765^{b}	2.749
	(1.941)	(2.317)	(4.047)	(4.298)	(2.778)	(3.082)
Import share LIC × excess clustering		-0.834^{a}		-1.051^{a}		-3.003^{a}
		(0.322)		(0.401)		(0.926)
Import share LIC × excess clustering × textile		-1.202		-8.567^{a}		5.552^{a}
		(1.188)		(1.685)		(1.762)
Industry fixed effects	6-digit NAICS					
Additional controls	Export share of the industry to high-income countries					
Year fixed effects	Yes					
Obs.	1,588	1,588	1,566	1,566	1,564	1,564
R^2	0.985	0.985	0.953	0.955	0.903	0.904

Notes: All variables in logs, except for import shares which are in levels. 'Industry productivity' is measured by value added per worker. Low-income countries (LIC) are defined as countries whose GDP per capita is lower than 5% of U.S. GDP per capita, and high-income countries (HIC) are countries whose GDP per capita is higher than 95% of U.S. GDP per capita (Bernard et al. 2006). 'Excess clustering' is an employment-weighted measure of excess agglomeration (at 25 kilometers distance) in 2001. It is computed as the cumulative sum of the gap between the K-density and the upper bound of the confidence band (see online appendix U for more details on the procedure). 'Textile' and 'excess clustering' are absorbed by the industry dummies. Huber-White robust standard errors in parentheses. ^{a} = significant at 1%, ^{b} = significant at 5%, ^{c} = significant at 10%.

degree of geographic concentration of the industry. However, the last column shows that the positive impact of this variable on T&C productivity is only driven by these clustered industries. Even if they downsized more, geographically concentrated T&C industries experienced significant productivity gains as their exposure to imports from low-wage countries increased. Finally, there are no systematic differences between concentrated T&C industries and other manufacturing industries when it comes to plant exits.

T. A simple model of clusters and survival

We present a simple model of clusters and survival with heterogeneous firms. Assume that there are $s = 1, 2, \ldots S$ sectors and $c = 1, 2, \ldots C$ clusters. A firm with productivity m in sector s and cluster c has the production function: $y_c^s(m) = m \times A(\mathbf{L_c}) \times L^\alpha K^{1-\alpha}$, where m is firm-level productivity, L is labor input, and K is capital used. In the above production function, $A(\mathbf{L_c})$ denotes an external agglomeration effect that depends on the sectoral composition of the cluster, given by $\mathbf{L_c} = (L_c^1, L_c^2, \ldots, L_c^s, \ldots L_c^S)$.

Let w_c denote the cluster-specific wage — which is the same across sectors — and r the nation-wide rental rate of capital. Given the foregoing production function, the variable unit cost is given by

$$\gamma(m) = \frac{w_c^\alpha r^{1-\alpha}}{A(\mathbf{L_c})m}\kappa_1, \tag{5}$$

where $\kappa_1 \equiv \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}$ is a positive constant. We assume that each firm has a fixed cost F incurred in terms of output, and that it faces an iso-elastic demand that originates from consumers' CES preferences. We denote by Y_c the aggregate spending that a firm in cluster c faces. Since demand is iso-elastic, it can be written as $D(m) = [Yp(m)^{-\sigma}]/\mathbb{P}^{1-\sigma}$, where $\mathbb{P}^{1-\sigma}$ is a CES price aggregator. Profit is given by

$$\pi(m) = [p(m) - c(m)]\,\frac{Yp(m)^{-\sigma}}{\mathbb{P}^{1-\sigma}} - Fc(m), \tag{6}$$

where we suppress the cluster and sector indices c and s to alleviate notation. Given iso-elastic demands, profit maximization implies as usual a constant markup over marginal cost

$$p(m) = \frac{\sigma}{\sigma-1}c(m) \tag{7}$$

so that

$$\pi^*(m) = \frac{Y}{\mathbb{P}^{1-\sigma}} c(m)^{1-\sigma}\kappa_2 - Fc(m), \tag{8}$$

where $\kappa_2 = \sigma^{-\sigma}(\sigma-1)^{\sigma-1}$ a positive constant.

Let M denote the mass of firms in the industry selling in the economy, and $\mathrm{d}F(\cdot)$ the productivity distribution. We denote by $\widetilde{m}$ the endogenously determined productivity selection cutoff for firms operating in the cluster. Substituting the profit-maximizing prices into the CES price aggregator, we have

$$\mathbb{P}^{1-\sigma} = \frac{M}{1-F(\widetilde{m})}\int_{\widetilde{m}}^{\infty} p(m)^{1-\sigma}\mathrm{d}F(m) = \left[\frac{\sigma}{\sigma-1}\frac{w^{\alpha}r^{1-\alpha}}{A(\mathbf{L})}\kappa\right]^{1-\sigma} M\overline{m}^{1-\sigma} \tag{9}$$

with

$$\overline{m}(\widetilde{m}) = \left[\frac{1}{1-F(\widetilde{m})}\int_{\widetilde{m}}^{\infty} m^{\sigma-1}\mathrm{d}F(m)\right]^{\frac{1}{\sigma-1}} \tag{10}$$

the average productivity of firms operating in the cluster. The profit hence becomes

$$\pi^*(m) = \frac{Y}{M\sigma}\left[\frac{m}{\overline{m}(\widetilde{m})}\right]^{\sigma-1} - Fc(m). \tag{11}$$

As usual, we have two equilibrium conditions: (i) zero cutoff profit (ZCP) for the marginal firm, $\pi^*(\widetilde{m}) = 0$; and (ii) zero expected profits (ZEP) for entrants, $E(\pi^*) = 0$.[25]

ZCP. The zero cutoff profit condition is given by

$$\frac{Y}{M\sigma}\left[\frac{\widetilde{m}}{\overline{m}(\widetilde{m})}\right]^{\sigma-1} - F\frac{w_c^{\alpha}r^{1-\alpha}}{A(\mathbf{L_c})\widetilde{m}}\kappa_1 = 0. \tag{12}$$

ZEP. The zero expected profit condition is given by

$$E(\pi) = \int_{\widetilde{m}}^{\infty} \pi^*(m)\mathrm{d}F(m) = [1-F(\widetilde{m})]\left[\frac{Y}{M\sigma} - F\frac{w_c^{\alpha}r^{1-\alpha}}{A(\mathbf{L_c})\overline{m}_H(\widetilde{m})}\kappa_1\right] = F_e, \tag{13}$$

where

$$\overline{m}_H(\widetilde{m}) = \left[\frac{1}{1-F(\widetilde{m})}\int_{\widetilde{m}}^{\infty} m^{-1}\mathrm{d}F(m)\right]^{-1}$$

[25]Note that we could replace condition (i) with $\pi^*(\widetilde{m}) = w$ if there is occupational choice between running firms (earning $\pi^*(\widetilde{m})$) or working as a worker (earning w). This makes the following analysis more involved but does not change fundamentally the results.

is the harmonic mean of productivity. We thus have

$$M = \frac{Y}{\sigma[\frac{F_e}{1-F(\widetilde{m})} + F\frac{w_c^\alpha r^{1-\alpha}}{A(\mathbf{L_c})\overline{m}_H(\widetilde{m})}\kappa_1]} \tag{14}$$

which we can substitute into (11) to get

$$\left[\frac{\frac{F_e}{1-F(\widetilde{m})}A(\mathbf{L_c})\widetilde{m}}{F w_c^\alpha r^{1-\alpha}\kappa} + \frac{\widetilde{m}}{\overline{m}_H(\widetilde{m})}\right]\left[\frac{\widetilde{m}}{\overline{m}(\widetilde{m})}\right]^{\sigma-1} - 1 = 0. \tag{15}$$

Parametrization. To derive sharper results, we now impose a specific parametrization for productivity. Assume that the latter is distributed as $F(m) = 1 - (m^{\min}/m)^k$, so that $1 - F(\widetilde{m}) = (m^{\min}/\widetilde{m})^k$ and $\mathrm{d}F(m) = k(m^{\min})^k m^{-k-1}$. As usual, we assume that $1 + k - \sigma > 0$ for all integrals to converge. In that case, $\overline{m} = \left[k\widetilde{m}^k \int_{\widetilde{m}}^\infty m^{\sigma-k-2}\mathrm{d}m\right]^{\frac{1}{\sigma-1}} = \left[\frac{k}{1+k-\sigma}\right]^{\frac{1}{\sigma-1}}\widetilde{m}$ and $\overline{m}_H = \widetilde{m}[(k+1)/k]$.

Equilibrium. Using the above parametrization, equation (11) becomes

$$\left[\frac{\frac{F_e}{(m^{\min})^k}A(\mathbf{L_c})\widetilde{m}^{k+1}}{F w_c^\alpha r^{1-\alpha}\kappa_1} + \frac{k}{k+1}\right]\frac{1+k-\sigma}{k} - 1 = 0 \tag{16}$$

We thus finally obtain the expression for the equilibrium cutoff productivity as follows:

$$\widetilde{m}^{k+1} \propto \overline{m}^{k+1} = C\frac{w_c^\alpha}{A(\mathbf{L_c})} \tag{17}$$

with $C = \frac{\kappa_1 k\sigma}{(k+1)(1+k-\sigma)}\frac{F}{F_e}(m^{\min})^k r^{1-\alpha} > 0$ a bundle of parameters.

What are the implications of (17)? As can be seen from that expression, $\widetilde{m}$ is increasing in w_c and decreasing in $A(\mathbf{L_c})$: higher wages in the cluster push the selection cutoff up as in Melitz (2003), whereas external agglomeration effects ('agglomeration economies') make it easier for less productive firms to survive.

Without specifying a full equilibrium model — which is beyond the scope of our exercise here — we take into account that there is a labor supply function to the cluster, i.e., $w_c = w_c(L)$, where $L \equiv \sum_s L_c^s$ is the total labor employed in the cluster. Hence, (17) can be expressed as

$$\widetilde{m}^{k+1} \propto \overline{m}^{k+1} = C\frac{w_c(L)^\alpha}{A(\mathbf{L_c})}, \tag{18}$$

so that the effect of local industry size on the selection cutoff is given by:

$$\frac{\partial \ln \widetilde{m}^s}{\partial \ln L_c^r} = \frac{1}{k+1}\left[\alpha \frac{\partial \ln w_c(L_c)}{\partial \ln L_c^r} - \frac{\partial \ln(A^s(\mathbf{L_c}))}{\partial \ln L_c^r}\right]. \tag{19}$$

A simple way to close the model is to impose the 'canonical assumptions' on utility, geographic labor mobility, and housing supply. Assume hence that workers consume housing H and some (non-housing) consumption bundle C, and that utility is given by $U = C^{1-\gamma}H^{\gamma}$. Assume further that the housing stock in the cluster is given by $\overline{H}_c$. In that case, the indirect utility of a worker in cluster c is given by $V_c = \frac{w_c(L_c)}{\mathbb{P}^{1-\gamma}R^{\gamma}}(1-\gamma)^{1-\gamma}\gamma^{\gamma}$, where R is the rental price of housing, and $V_c = \overline{V}$ for all $c = 1, 2, \ldots, C$ if workers are freely mobile ($\overline{V}$ is determined nation-wide in equilibrium, but we take it as given here, making thus the implicity assumption that every cluster is small in the aggregate economy). Since $HL_c = \overline{H}_c$ because of housing-market clearing, we have $R = \frac{\gamma w_c L_c}{\overline{H}}$. Substituting into the indirect utility, we have

$$\overline{V} = \frac{w_c(L_c)^{1-\gamma}}{L_c^{\gamma}} \times \frac{(1-\gamma)^{1-\gamma}\overline{H}_c^{\gamma}}{\mathbb{P}^{1-\gamma}} \quad \Rightarrow \quad \frac{\partial \ln w_c(L_c)}{\partial \ln L_c} = \frac{\gamma}{1-\gamma}\left[1 - \frac{\partial \ln \overline{H}_c(L_c)}{\partial \ln L_c}\right], \tag{20}$$

assuming that the cluster is small in the national economy so that both the price index and $\overline{V}$ are fixed. Plugging (20) into (19), we finally obtain:

$$\frac{\partial \ln \widetilde{m}^s}{\partial \ln L_c^r} = \frac{1}{k+1}\left\{\alpha \frac{\gamma}{1-\gamma}\left[1 - \epsilon_H(L_c)\right] - \epsilon_{sr}(\mathbf{L_c})\right\}, \tag{21}$$

where $\epsilon_H(L_c)$ denots the housing supply elasticity in the cluster and $\epsilon_{sr}(\mathbf{L_c})$ the measure of agglomeration economies in sector s due to a shock to employment in sector r.

Implications for plant death and industry switching. As can be seen from (21), how productivity changes with changes in labor employed in the cluster depends on: (i) the labor share in production, as measured by α; (ii) the elasticity of the housing supply function, which captures partly the elasticity of labor supply to the cluster; and (iii) the strength of the (own- and cross-industry) agglomeration effects. If the labor share α is small, or if labor supply is elastic enough (w_c is flat enough), a positive shock to employment in the cluster makes the selection cutoff fall, i.e., survival gets easier for firms. Conversely, a negative shock that hits some firms and thus decreases L_c makes the selection cutoff rise, i.e., it gets harder for the remaining firms to survive. Hence, there is *amplification of negative shocks because of agglomeration effects*. The reverse holds if the labor share is large or if the labor supply schedule is steep enough. In that case, negative shocks to the cluster may well reduces the survival threshold, which stabilizes the cluster.

In the face of negative shocks, some firms may no longer be able to operate. How this affects the cluster — and how the remaining firms react — crucially depends on the specification of the external agglomeration effects, $A(\mathbf{L_c})$, as in Helsley & Strange (2014). Firms can obviously just go out of business ('die'). However, we could also think about a model in which firms can switch from industry s to industry t. Which industry are firms likely to switch into? Assume that for a firm operating in sector s and switching to a new sector t we have $A^t(\mathbf{L_c}^{-t}, L_c^t) \to \epsilon \approx 0$ if $L_c^t \to 0$, i.e., own productivity becomes fairly small if the firm switches into a new industry in which there are no other firms around and in which it has not conducted previously business. In that case, if there is switching, a firm will clearly only switch into industries where there is a large enough local presence to begin with. Alternatively, the firm may switch into an industry in which it has some prior experience.

U. Computing K-densities and their cumulatives

The following description largely draws on Behrens & Bougna (2015). To compute the kernel density distribution of bilateral distances, as well as the cumulative distribution, and to compare it with randomly drawn distributions, we proceed as follows.

First step (kernel densities). Consider sector s with n plants. We compute the great circle distance, using postal code centroids, between each pair of plants in that sector. This yields $n(n-1)/2$ bilateral distances for sector s. Let us denote the distance between plants i and j by d_{ij}. Given n etablishments, the kernel-smoothed estimator of the density of these pairwise distances, which we henceforth call K-density as in Duranton and Overman (2005), at any distance

d is:

$$\widehat{K}(d) = \frac{1}{hn(n-1)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} f\left(\frac{d - d_{ij}}{h}\right), \tag{22}$$

where h is the optimal bandwidth (set according to Silverman's rule), and f a Gaussian kernel function. The distance d_{ij} (in kilometers) between plants i and j is computed as:

$$d_{ij} = 6378.39 \cdot \text{acos}\left[\cos(|\text{lon}_i - \text{lon}_j|)\cos(\text{lat}_i)\cos(\text{lat}_j) + \sin(\text{lat}_i)\sin(\text{lat}_j)\right].$$

We also compute the employment-weighted version of the K-density, which is given by

$$\widehat{K}_W(d) = \frac{1}{h\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}(e_i + e_j)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} (e_i + e_j) f\left(\frac{d - d_{ij}}{h}\right), \tag{23}$$

where e_i and e_j are the employment levels of plant i and j, respectively. The weighted K-density thus describes in some sense the distribution of bilateral distances between employees in a given industry, whereas the unweighted K-density describes the distribution of bilateral distances between plants in that industry.

Since the K-density is a distribution function, we can also compute its cumulative (CDF) up to some distance d:

$$\text{CDF}(d) = \int_0^d \widehat{K}(i)\text{d}i \quad \text{and} \quad \text{CDF}_W(d) = \int_0^d \widehat{K}_W(i)\text{d}i. \tag{24}$$

The CDF at distance d thus tells us what share of plant pairs (or of employees) is located less than distance d from each other. Alternatively, we can view this as the (kernel smoothed) probability that two randomly drawn plants (workers) in an industry will be at most d kilometers away.

Second step (counterfactual samples). Using the full distribution of all manufacturing plants in our sample, we randomly draw as many locations as there are plants in sector s. To each of these locations, we assign randomly a plant from sector s, using its observed employment. This procedure ensures that we control for the overall pattern of concentration in manufacturing as a whole, as well as for the within-sector concentration. We then compute the bilateral distances of this hypothetical sector and estimate the K-density of the bilateral distances. Finally, for each sector s, we repeat this procedure 1,000 times. This yields a set of 1,000 estimated values of the K-density at each distance d.

Third step (confidence bands). To assess whether a sector is significantly localized or dispersed, we compare the actual K-density with that of the counterfactual distribution. We consider a range of distances between zero and 800 kilometers to construct our K-densities and confidence bands.[26] We then use our bootstrap distribution of K-densities, generated by the counterfactuals, to construct a two-sided confidence interval that contains 90 percent of these estimated values. The upper bound, $\overline{K}(d)$, of this interval is given by the 95th percentile of the generated values, and the lower bounds, $\underline{K}(d)$, by the 5th percentile of these values. Distributions of observed distances that fall into this confidence band could be 'as good as random' and are, therefore, not considered to be either localized or dispersed.

Fourth step (identification of location patterns). The bootstrap procedure generates a confidence band, and any deviation from that band indicates localization or dispersion of the sector. If $\widehat{K}(d) > \overline{K}(d)$ for at least one $d \in [0, 800]$, whereas it never lies below $\underline{K}(d)$ for all $d \in [0, 800]$, sector s is defined as globally localized at the 5 percent confidence level. On the other hand, if $\widehat{K}(d) < \underline{K}(d)$ for at least one $d \in [0, 800]$, sector s is defined as globally dispersed. We can also define an index of global localization, $\gamma_i(d) \equiv \max\{\widehat{K}(d) - \overline{K}(d), 0\}$, as well as an index of global dispersion

$$\psi_i(d) \equiv \begin{cases} \max\{\underline{K}(d) - \widehat{K}(d)\} & \text{if} \quad \sum_{d=0}^{800} \gamma_i(d) = 0 \\ 0 & \text{otherwise.} \end{cases} \tag{25}$$

Intuitively, if we observe a higher K-density than that of randomly drawn distributions, we consider the sector as localized. Similarly, if we observe a lower K-density than that of randomly drawn distributions, we consider the sector as dispersed. Last, the strength of localization and dispersion can be

[26] The interactions across 'neighboring cities' mostly fall into that range in Canada. In particular, a cutoff distance of 800 kilometers includes interactions within the 'western cluster' (Calgary, AB; Edmonton, AB; Saskatoon, SK; and Regina, SK); the 'plains cluster' (Winnipeg, MN; Regina, SK; Thunder Bay, ON); the 'central cluster' (Toronto, ON; Montréal, QC; Ottawa, ON; and Québec, QC); and the 'Atlantic cluster' (Halifax, NS; Fredericton, NB; and Charlottetown, PE). Setting the cutoff distance to 800 kilometers allows us to account for industrial localization at both very small spatial scales, but also at larger interregional scales for which market-mediated input-output and demand linkages, as well as market size, might matter much more.

measured by $\Gamma_i \equiv \sum_d \gamma_i(d)$ and $\Psi_i \equiv \sum_d \psi_i(d)$, which corresponds roughly to a measure of the 'area' between the observed distribution and the upper- and lower-bounds of the confidence band. It can be viewed as the excess probability of drawing a plant of sector s at a given distance from another plant of that sector, conditional on the overall distribution of manufacturing.

V. Construction of firm identifiers for the multiunit dummy

The Scott's database — which has a very exhaustive coverage of the manufacturing sector since it is based on the Canadian Business Register — provides plant-level data but does not allow to easily group establishments into firms. We therefore exploit relevant information in the database to associate the establishments with the firms (or the firms' divisions) they belong to. The affiliation with a firm can be backed out in two ways: (i) by cross-comparison of the establishments' legal names; and (ii) by cross-comparison of the unique plant identifiers which are stable across time. Although the procedure of creating the firm identifiers is fairly straightforward, it is subject to the problems that typically arise when working with string variables and which lead to measurement error.

Table 25 shows that most establishments systematically feature the company name. Unfortunately, others do not. Using the data in Table 25, the idea underlying the assignment procedure is simple: if two establishments have identical legal names they must belong to the same firm (legal entity). We thus loop over the sorted legal names of the establishments, where the running variable is the firm identifier. Since the usual 'string problems' arise, we pre-clean the data to allow for more accurate results. In particular, we trim the plant names to get rid of extra spaces and unify general naming patters (e.g., replacing the rare cases of "&" instead of "and", "mngmt" instead of "mgmt", etc.). We also eliminate differences in legal names stemming from the fact that Canada is a bilingual country, i.e., although 'Enterprise Rent-A-Car' and 'Entreprise Location d'Autos' belong to the same firm, the loop will split them into two different firms depending on the primary language of the province of operation.

Table 25: Raw Scott's data for creating firm identifiers.

Year	scottsid	companyname	prov	empl
2001	317028	Lafarge Canada Inc.	13	2
2001	317029	Lafarge Construction Materials	13	2
2001	321875	Lafarge Canada Inc.	13	5
2001	382430	Lafarge Canada Inc.	48	37
2001	403219	Lafarge Construction Materials	35	8
2001	403221	Lafarge Construction Materials	35	22
2001	458100	Lafarge Canada Inc.	48	6
2001	458102	Lafarge Canada Inc.	48	3
2001	18317132	Lafarge Canada Inc.	12	84
2001	18323452	Lafarge Canada Inc.	12	19
2001	18855322	Air Liquide Canada Inc.	35	75
2001	18858178	Air Liquide Canada Inc.	35	12
2001	18858871	Air Liquide Canada Inc.	35	5
2001	18862939	Air Liquide Canada Inc.	59	26
2001	18862971	Air Liquide - Okanagan	59	26
2001	18881913	Air Liquide Canada Inc.	35	3
2001	18887333	Air Liquide Canada Inc.	35	100
2001	18901654	Air Liquide Canada Inc.	24	6
2001	18924713	Air Liquide Canada Inc.	24	7
2001	18933235	Air Liquide Canada Inc.	24	8
2001	18940933	Air Liquide Canada Inc.	35	10

Notes: Excerpt from the 2001 Scott's All National manufacturing directories. We only report a selected number of variables that are of interest to us. 'scottsid' is a unique plant-specific identifier (starting 2003); 'prov' denotes the census province code; 'empl' is the number of employees.

The comparison of time-invariant plant identifiers allows us to associate a plant in year t with itself in year $t+1$. This provides a refinement of the assignment of the firm identifier in case the establishment's name has changed in a way that the preliminary data treatment could not accommodate. However, use of this 'tool' is limited to the 2003-2013 sample due to a structural change in the plant identifier design implemented by Scott's. Although we can match the plant identifiers for many plants between 2001 and 2003 using a correspondence file provided by Scott's, we loose a number of plants when doing so. This explains why we exclude the year 2001 from our exit analysis.

As a check of our assignment procedure, Table 26 reports the correlations between the shares of multiunit plants by industry in our data and in both the (manufacturing portion of the) Business Register (BR) and the Annual Survey of Manufacturers (ASM) Longitudinal Microdata file. These correlations use special-tabulation data that have been vetted for release by Statistics Canda, i.e., data that excludes very small industries (both in terms of plants and in

Table 26: Correlations between the multiunit shares in our data, the BR, and the ASM.

	Unweighted						Plant-count weighted					
	NAICS 4-digit			NAICS 6-digit			NAICS 4-digit			NAICS 6-digit		
	Our	BR	ASM	Our	BR	ASM	Our	BR	ASM	Our	BR	ASM
BR data	0.78	–		0.77	–		0.82	–		0.83	–	
ASM data	0.84	0.94	–	0.80	0.95	–	0.87	0.96	–	0.86	0.96	–

Notes: Our data come from the *Scott's National All Business Directories* database. Other data come from the manufacturing portion of the Business Register (BR) and the Annual Survey of Manufacturers (ASM) Longitudinal Microdata file. They have been computed as special tabulations by Statistics Canada. The vetted data have been approved by Statistics Canada and are available from the authors upon request.

term of multiunit plants). As one can see from the table, the correlations are generally high, hovering around 0.8 for the BR and 0.85 for the ASM. They are slightly higher when weighting industries by plant counts, i.e., the small industries have a slightly worse match in terms of the shares of plants identified as belonging to multiunit firms than the large industries. This is expected, because share errors are more substantial in small samples.

Using a slightly different sample, we also checked the correlations between our shares and the confidential data multiunit shares from Statistics Canada. The correlations are slightly lower, between 0.7 and 0.84, when using the confidential data. This is expected because misclassifications of plants in small industries — the confidential data includes all industries, even those for which the multiunit shares cannot be released either because the industries are too small or because there are not enough multiunit plants in those industries — have a very strong effect on shares, whereas that effect is much smaller in industries with many plants. Overall, the results in Table 26 suggest that our procedure to detect multiunit plants works sufficiently well to have confidence in the quality of our control. We do not expect systematic errors in the construction of this variable, and the measurement error introduced should (if anything) bias the coefficient of our control towards zero.

W. Detailed historical context

W.1. Early period (1850–1910): The emergence of industrial and geographic concentration.

This paper is about industry dynamics, trade protection, and geographic patterns. Without providing a detailed historical account — which is beyond the scope of our study — putting those factors into a historical context is important to understand how they jointly shaped the textile landscape between the 1850s and the end of the 20th century.[27]

The origins of the Canadian textile industry can be traced back to the 1820–1840 period, depending on the type of fabric considered. The transition from subsistence production to industrial enterprise occurred mostly between 1840 and the end of the 19th century, using domestic capital, on the one hand, and technology imported from Great Britain and the U.S., on the other hand. Policy changes and economic shocks first triggered industry expansion and then a wave of mergers and consolidation between 1870 and 1900. It is during that period that the macro-structure of the textile industry took shape, where all the large players that would dominate the landscape until after World War II were put in place. The fundamental geographic structure of the textile industry also emerged during that period. Initially centered in the province of Ontario, it progressively shifted to Québec as wool lost its dominant position to cotton and, later, to man-made fibers.

Numerous factors may serve to explain the expansion of the textile industry in the second half of the 19th century:[28] (i) the growth of the internal market

[27]The subsequent developments largely draw on Rouillard (1974) and McCullough (1992). While there are numerous detailed historical accounts of the primary textile industry (i.e., industries that transform primary fibers into fabrics), there are much less such accounts of the secondary textile industry (i.e., industries that transform fabrics into clothes and other derivatives). The historical elements related to the political economy, trade, and industrial restructuring of textiles after World War II are mostly drawn from Mahon (1984).

[28]See Gaudreau (1995) for the history of the Magog Textile and Printing Company, which provides a nice case study that illustrates well the various key elements of success: (i) the vision of local (and national) capitalists, which were able to raise funds and to lobby government for protection; (ii) the presence of hydraulic power, namely the Magog river which flows year-round; (iii) generous tax breaks (25 years) negotiated with the local authorities; and (iv) the

(between 1870 and 1910 the Canadian population almost doubled); (ii) improvements in market access (the expansion and extension of the railroad system across the country; and the political integration as formalized by the 1867 'Constitution Act' that officially proclaimed Canadian Confederation); and (iii) strong import protection under the Macdonald national policy.

We will not discuss the former two points, which are about market size, and focus instead on the latter, which is linked to trade protection. Historically, the Canadian market was a difficult one, for manufacturing in general and for textiles in particular: "*In textile, as in many other sectors, capitalists were confronted to stringent operating conditions. By its large geographic extent and its low population size* [...], *Canada was a very difficult market, especially for firms located outside big cities. Besides, it requires dealing with a major obstacle: the American and British competition.*" (Gaudreau 1995, p.19, our translation). Despite support for free trade from many segments of the economy — especially the export-oriented staples industries like grains, ore, and lumber — as well as the public, Canada resorted to trade protection in manufactured goods early on: in the face of a geographically spread-out market and fierce competition, trade protection was seen as an option to make viable nascent manufacturing industries. The tension between the export promotion of staples and concessions in import protection for some manufacturing industries (including textiles) was one of the fundamental dynamics of the Canadian political economy during the second half of the 19th and most of the 20th century (Mahon 1984).[29] In textiles, cotton imports from the U.S. and wool imports from Great Britain, both raw materials and fabrics, were important for Canada but put substantial pressure on the textile industries. Indeed, the young Canadian industries had neither the scale nor the experience of their British or American counterparts and had to rely on their technologies. Hence, from its inception, the textile industry was evolving in a fairly competitive international context.[30]

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advent of the railroad, with the opening of the Waterloo-Magog line and, later, the connection to the Canadian Pacific.

[29] The tension between free trade and protectionism can be seen early on from the fate of the Canadian-American Reciprocity Treaty (the Elgin-Marcy Treaty of 1854): "*The treaty was abrogated by the Americans in 1866 for several reasons. Many felt that Canada was the only nation benefiting from it and objected to the protective Cayley-Galt Tariff imposed by the Province of Canada on manufactured goods.*" (quote from Wikipedia).

[30] Import competition in textiles from the U.S. and from Great Britain remained important

Within that context, the Macdonald conservative government imposed in 1879 strong import protections — tariffs almost doubled, reaching close to 30% — which came to be known as the 'Macdonald national policy'. The story of the Canadian textile industry after that date is a classic one of import substituting industrialization. Many new large textile plants opened and industry output rose substantially until the 1890s in both the cotton and wool industries, both protected by import tariffs. Yet, as we will see below, the wool industry took a different path than the cotton industry and this led to a profound shift in the geographic patterns of textiles in Canada. Improved market integration within the Confederation and the higher import tariffs shifted market shares substantially towards domestic firms: the imports of cotton textiles fell by about 40% from 1870 to 1890, while spending on these textiles remained fairly constant. In a nutshell, the growth of the textile industry was driven by the interactions between a growing internal market and 'infant industry' protection vis-à-vis the U.S. and Great Britain.

The geography of the textile industry in place at the end of the 20th century largely took shape around the end of the 19th century, driven by the different paths that the wool and cotton industries took between 1870 and 1900. Figures 11 and 12 depict the geographic distribution of textile and clothing employment and plants in the Dominion of Canada in 1871, based on the Industrial Census from that date. Starting with the geographic patterns of wool, the location of the early industry was dictated by local market size and access to skilled labor, the availability of raw materials, as well as proximity to hydraulic power: "*[m]ost of the early woolen mills were set up in Ontario, west of Ottawa* [...] *where there was good sheep-raising country, skilled Scottish weavers, and good access to customers.*" (Balakrishnan & Eliasson 2007). The industry was, though predominantly concentrated in Ontario, geographically fairly dispersed within that province.[31] The geographic dispersion of the wool industry was mirrored

until the early 1970s. Indeed, even in 1968, 30.3% of cotton fabrics and 47.6% of wool fabrics were imported from the U.S. and the UK, respectively (Mahon 1984).

[31] In 1871, Lanark, Waterloo, and Sherbrooke concentrated most of that industry, but by 1886 the Eastern Townships of Québec and the large cities — Toronto and Montréal — had grown in importance in that industry. The knitting industry, historically strongly linked to the wool industry, was also concentrated in Ontario, which had 70–80% of employment in the 19th century. In 1871, 73% of woolen draperies in Canada were produced in Ontario, with 83% of employment concentrated in that province (McCullough 1992, p.123). Until the 1930s, Toronto

by the dispersion of ownership and capital across many small establishments. Actually, the wool industry was not very capital intensive, had a large number of establishments and, therefore, displayed fairly little industrial concentration throughout most of its existence.[32] It remained a relatively fragmented industry which, as we will see below, made it harder to adjust to negative shocks through the use of collusive agreements on prices or production volumes. The cotton industry was, by contrast, from the beginning more geographically concentrated than wool. Although it was initially located in both Ontario and Québec, it was more capital intensive and had larger plants, thus implying that its activity was automatically more concentrated geographically. Because of its important capital and labor requirements, it was also more likely to be established in larger cities, i.e., it was a more urban industry than wool.

Why did wool initially locate in Ontario and cotton predominantly in Québec? While there is inevitably some randomness to these early historic patterns, they can be linked to trade ties, immigration patterns, natural advantage, and the availability (and geographic concentration) of capital and skilled labor. First, there was a sizable British immigrant labor force in Ontario, and Great Britain had developed a lot of expertise in wool trade. As stated above, there was also a lot of raw material in Ontario, which produced a majority of wool in Canada. Québec lacked iron ore and coal deposits — which are key for the development of early heavy industries — but had an abundant, relatively cheap, and skilled labor force, concentrated in the relatively densely populated Saint Lawrence lowlands between Québec City and Brockville. Many French Canadians had acquired the 'skills of the trade' in the New England cotton industries.[33] Furthermore, some of the important capitalists involved in the development of

remained Canada's 'knitting capital'.

[32]By the end of the 19th century, the wool industry was still not dominated by a few large firms, although some firms like the Paton Manufacturing Company in Sherbrooke — the largest woolen factory in Canada — or the Canada Woolen Company in Ontario were substantial players.

[33]The French Canadian workers also had a reputation for being skilled at textile manufacturing. As pointed out by historians, "*the inherent ability of the New England operatives as a distinct asset of the northern industry, the French Canadians in particular receiving a large share of the approbation*" (J. H. Burgy, 1932, p.167 "The New England Cotton Textile Industry", Baltimore, MD: Waverly Press). Around the turn of the 19th century, 46% of the textile labor force in New England was originally French Canadian.

the cotton industry in Québec had ties with Lancashire, which was the cotton capital of Great Britain. For example, William Hobbs from Magog brought in specialized workers from Lancashire to operate the new printing equipment that he purchased in Britain for his textile and printing plant that opened as the first of its kind in Canada in 1884 (Gaudreau 1995).

Second, Québec offered a geographically advantageous location. Good access to railroads, with Montréal being a national hub, allowed to import raw cotton from the U.S. and to dispatch finished products to geographically dispersed markets. Furthermore, Québec's river system allowed to use cheap hydraulic power (instead of more expensive steam-engine power) and, starting in the early 20th century, even cheaper hydro-electricity. The Montreal Cotton Company manufacture in Salaberry-de-Valleyfield began operating in 1896–1897 with an electric drive system. It is almost sure that this was the first Canadian textile manufacture using such a technology. As noted by Rouillard (1974, pp.45–46, our translation): "*It is the power of the flow of the [Saint Lawrence] river next to Valleyfield that gave William Hobbs the idea to construct his cotton mill there* [...] *It is precisely the insufficient availability of hydraulic energy and the high cost of running steam engines that compelled in 1898 the Dominion Cotton to close its factory in Brantford, Ontario* [...] *Québec's rivers favor the implantation of industries for which energy consumption is an important element of production costs.*"

Third, and contrary to wool, cotton was very capital intensive as already stated. It also had a financing scheme of a more capitalistic nature, essentially publicly traded companies versus more 'family business' in the wool industry. Raising funds to provide both starting capital and working capital was thus important. Local capitalists in smaller places had difficulties providing the huge amounts of funds required to operate large cotton textile mills. This shifted power to larger urban centers, which provided both capital and a large and relatively cheap labor force. Montréal, being Canada's financial capital during that period, had a distinct advantage when it came to providing funds. Combined with the access to water power and railway it offered, it thus naturally became Canada's cotton capital: "*This control — based on the financial resources of Montréal, the availability of labor force and electric power, and the access to markets and railroads — causes the vast majority of the industry to be located within a hundred mile radius around this city*" (McCullough 1992, p.162, our translation).

While the initial differences in geographic patterns favored Ontario for wool, and while cotton was more concentrated because of larger plants — but fairly evenly spread between Ontario, Québec, and the Maritimes in the beginning — a substantial geographic shift occurred between 1870 and 1900. While cotton saw an extraordinary increase in employment and output, wool stagnated and declined (production fell by 8%, while imports soared by 215%, despite the Macdonald national policy). The decline in wool progressively reduced the importance of Ontario for textiles and increased the importance of Québec that started to specialize in cotton. By 1900, 56% of cotton employment was located in Québec, against only 20% in Ontario.[34]

What triggered this important geographic shift? Since the Macdonald national policy protected wool and cotton on roughly similar terms, the reason has to be sought somewhere else. It probably started with the 1882–1883 recession and how that recession impacted the cotton and wool industries differently. During 1882–1883, it became clear that there was substantial excess capacity in all textile industries, due essentially to the large expansion in the wake of the 1879 trade protection. Cotton and wool adjusted to that excess capacity in different ways. The cotton industry saw the formation of large enterprises that controlled many textile mills and manufactures — with mergers initiated by D. Morrice and A.F. Gault ('the cotton king') who laid the foundations for the Dominion Textile which dominated the textile landscape for the century to come. The new 'cartelized' industry tried to limit price and quantity competition by leaving production capacities idle and by colluding tacitly (or openly) on prices and quantities. Those strategies worked relatively well, given the small number of players in the new industry. The wool and knitting industries had a much harder time to adjust than the cotton industry. As explained above, the industry was less capital intensive and more fragmented. It did not see a large wave of mergers and acquisitions, to that the number of firms remained large. Consequently, cartel agreements of the type seen in the cotton industry never worked well in the more fragmented wool industry. Many manufactures thus disappeared and the industry shrank in importance. Given its geographic concentration in Ontario, that province was especially

[34]Even within Québec, the cotton textile production was fairly clustered: 32% in Montréal; 14% in the Eastern Townships; 9.5% in Montmorency; and 12.5% in Shawinigan-Trois Rivières (McCullough 1992). Until recently, up to two-thirds of Canadian cotton employment was located in Québec. Montréal was for many years the center of the cotton industry in Canada.

hit. The effects of the excess capacity crisis were amplified later by changes in trade protection that affected essentially the wool industry. In 1897, trade protection was relaxed as the 'principle of the British preference' was introduced. The latter slashed tariffs and restrictions on imports from the Commonwealth countries, including Great Britain but also India and Pakistan. In 1899, additional concessions were granted to British textile imports, in return the export concessions for Canadian staple industries: "*the Canadian state was prepared to cede a portion of the domestic textile market to suppliers located in countries that were important customers of Canadian staples exports.*" (Mahon 1984, p.50).

The combined effect of industry consolidation and trade liberalization led to the strong geographic shift. Starting in the 1880s, Québec became the province of choice for the cotton textile industry. For example, the Dominion Textile Corporation concentrated its operations in Québec, and by 1930 it operated almost exclusively there. Between 1880 and 1890, cotton textile output in Canada, except Québec, rose by 26% from 4.6 to 5.8 million dollars. However, it rose by 73% from 3.5 to 6.1 million dollars in Québec (Rouillard 1974, p.11). Québec's national share of the cotton industry rose from 43% in 1890 to 69% in the 1920s, while the share of Ontario and the Maritimes fell. The concentration of the cotton industry necessarily also drew other related segments of textile, clothing, and shoe industries in its wake, which already happened to be fairly concentrated in Montréal.[35] Eventually, cotton overtook wool in the 1890s as the most important textile industry, thereby cementing Québec's dominance.

W.2. Later period (1910–1980): Shifting protection, lobbying, and industrial restructuring.

From 1910 to after World War II, the Canadian textile industry grew further and diversified. The importance of wool declined, synthetics emerged and developed rapidly, and knitting became more important. This period was one of

[35]While less is known about the history of the clothing industry, the evidence we have suggests that it started with a high level of concentration in larger cities, especially Montréal: "*By the mid-1850s, large-scale clothing manufacturing companies were typically located in Montréal with one factory employing eight hundred people* [...] *sole-sewing machines made it efficient to concentrate shoe manufacturing in steam-driven factories. By the 1860s, there were five major shoe manufacturers located in Montréal that produced the majority of the footwear sold in Canada.*" (Balakrishnan & Eliasson 2007, p.271)

maturity, characterized by slow industry growth and less volatility, though the inter-war years were subject to substantial fluctuations in the degree of trade protection. Furthermore, the industry continued to shift towards Québec during that period. Although the wool industry remained concentrated in Ontario until after World War II — when Québec finally overtook Ontario in that industry — it lost a lot of significance to the cotton industry first and, after World War I, to the rapidly growing man-made fibers industries.[36] By 1950, Québec also overtook Ontario in knitting, although the latter maintained about one-third of the Canadian knitting employment even after that date.[37] In the wake of World War II, the textile industry was geographically strongly concentrated in Québec which had the largest national share in those industries.

One key development of the inter-war years was the emergence and strong growth of artificial silk and synthetics (mostly rayon, nylon, and later polyester). For example, the output of artificial silk was multiplied by 13 between 1925 and 1936.[38] The man-made fiber industry was initially dominated by American and British capital and it was extremely concentrated: two firms — Courtaulds and Canadian Celanese — dominated it. The synthetics industry started operating in eastern Ontario and Québec, and it became eventually again fairly concentrated, both in geographical and industrial terms. Just like cotton, that industry was capital intensive.

A second key development of the inter-war years was the substantial shifts

[36]Silk and synthetics grew mostly starting around 1910–1920. In 1940, synthetics overtook wool as the second-largest primary textile segment in Canada. At the same time, the import shares of synthetics in Canadian sales fell from 36% in 1910 to about 20% in 1940, thereby showing that the Canadian synthetics industry competed efficiently against its international rivals.

[37]Knitting and hosiery, which are related to wool expanded notably because of increased demand for knit underwear and stockings. The heydays of the knitting industry were between 1900–1930, when it exceeded the wool industry and was approximately on par with the cotton industry in terms of employment. This industry, like wool, remained more dispersed, was less capital intensive, more local, and operated at a smaller industrial scale. A large part of its success can be explained by the import surcharge of 33% that targeted German imports of knit products starting in 1903. However, much of the imports came from Britain under the preferential rules.

[38]While tariffs and protection on most textile industries fell after World War I and until the 1930s, only synthetics managed to lobby for increasing protection, which explains part of its growth.

in trade protection. Tariffs spiked in 1930–1932 in the wake of the Great Depression of 1929, except for imports from Great Britain and the Commonwealth. Part of the tariff increases were due to the textile industries' ability to efficiently lobby for protection (see, e.g., the Turgeon report of 1938, which explicitly points out that there was abusive lobbying by the textile industries).

The textile industry prospered until about 1951 (the date at which it recorded the highest employment level ever in Canada). Much of this was due to the war-time economy and restrictive trade policies, which stimulated domestic textile production. Following the 1951 peak, the structural problems of the textile industry became more obvious: it started to experience increasing problems due to a decrease in protection and a rise in imports; a stagnation of its exports; a rise in labor costs; and the increasing market share of synthetics which, in a stagnating market, came at the expense of traditional fabrics such as wool and cotton. Especially the growth of synthetics during and after World War II (a 211% increase between 1940 and 1950), which competed with the natural fibers, caused increasing difficulties for the traditional textile industries. They suffered from a 'triple squeeze' in their profit margins due to import competition, higher wages starting in the 1960s, and a decrease in market shares. It followed many bankruptcies and several mergers which further consolidated the industry, which mechanized even more and renewed a large part of its older equipment. The result was that Canadian primary textiles emerged as one of the most concentrated textile industries in the world (Mahon 1984, p.52). A few very large players dominated the market: DuPont, Canadian Celanses, Courtaulds, and Dominion Textile, all of which either operated in or expanded into synthetics and opened several new plants in Québec between 1957–1967.

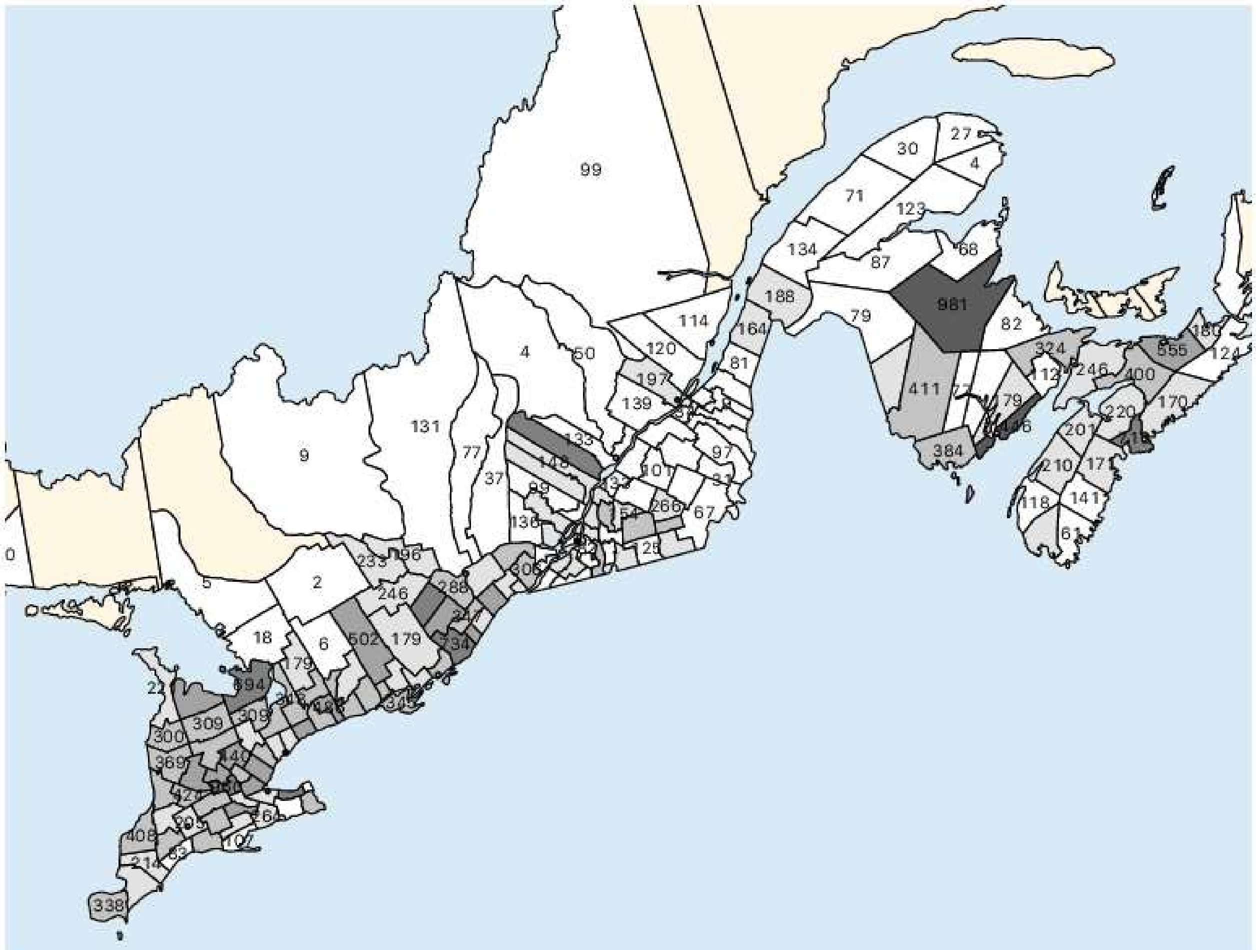
In the end, the industry — which developed in a fairly protected environment in the 19th century — had difficulties adjusting to international competition in the face of lower protection. Even synthetics, which did well on average, saw its employment fall from 13,000 employees after World War II to about 8,500 employees in 1968, although sales doubled over that period.[39] Trade protection broadly decreased after World War II, as the public was in favor of lower tariffs, although the textile industry lobbied hard to maintain them. Yet, following Canada's entry into the GATT in 1947, the tendency for the

[39]Despite the general difficulties of the textile industries, synthetics resisted well, with about 85% of domestic market share. The other textile industries lost much ground to imports.

future was clear. Despite temporary measures — following the U.S., Canada implemented its first voluntary export restraints (VER) with Japan in 1958 — free trade was progressing. The debate about trade protection and the textile industry resurfaced in the 1960s, when the textile industry drew an increasing awareness to the 'low-cost import problem'. As is often the case, the 'low-cost import problem' was more of a strawman than a real problem. Indeed, increasing imports from the U.S. due to a weak dollar were a more serious problem, and according to some historians even the major problem (Mahon 1984). In 1974, 74% of textile imports were from high-income countries, and 54% of those were from the U.S. Hence, as noted by Mahon (1984, p.72): "*textile capital began to agitate for a "national policy for textiles" by the end of the 1960s.*"

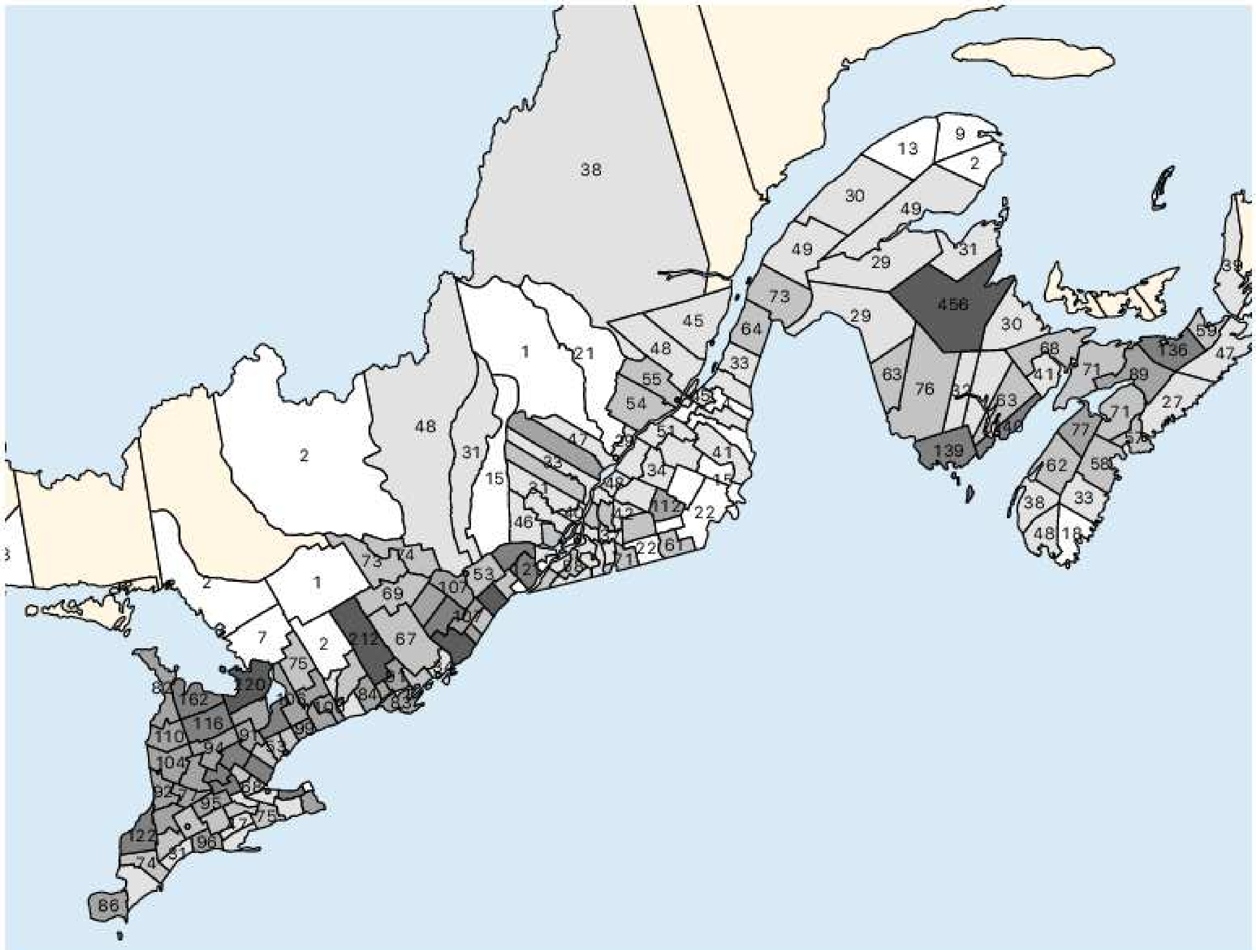
In 1969, a demand for a new agreement on textiles was in the air. Several factors explain why this happened. On top of the increased import competition and rising wages, mounting separatism in Québec — the province with the highest stakes in textiles due to the geographic patterns of that industry — was exploited by the textile industry to weight into the balance and to push the Québec government to force the textile question onto the national stage. Geography and policy interacted to shape future industry dynamics. The outcome was the 1971 textile policy that aimed to wrestle some power and trade concessions from the staples industries (the old conflict resurfaced). This was completed by the 'Multifibre Arrangement' (MFA) in 1973, which was signed by Canada and which posed the framework for an 'orderly' (i.e., 'protected' from the perspective of the textile industries in developed countries) growth in world textile trade. Most of the MFA remained in place until 2005, which is the starting point of our analysis.

Figure 11: Geographic distribution of T&C employment in the Dominion of Canada, Industrial Census of 1871.



Notes: Based on the Canadian Industrial Census 1871 (Source: Canadian Industry in 1871 — CANIND71 — University of Guelph, Ontario, 1982–2008; `http://www.canind71.uoguelph.ca`). Textile and clothing is defined by SIC 5.04, 5.05, 5.06, and 5.07. Numbers on the map represent the total T&C employment in the historical census district. Yellow indicates missing data. The cities of Montréal, Toronto, and Québec have employment figures of 10,265, 4,053, and 3,503, respectively.

Figure 12: Geographic distribution of T&C establishments in the Dominion of Canada, Industrial Census of 1871.



Notes: Based on the Canadian Industrial Census 1871 (Source: Canadian Industry in 1871 — CANIND71 — University of Guelph, Ontario, 1982–2008; `http://www.canind71.uoguelph.ca`). Textile and clothing is defined by SIC 5.04, 5.05, 5.06, and 5.07. Numbers on the map represent the total number of T&C establishments in the historical census district. Yellow indicates missing data. The cities of Montréal, Toronto, and Québec have establishment figures of 421, 167, and 232, respectively.