Innovation? Or Just Another Industrial Policy: Analyzing the Global Innovation Cluster Initiative

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Abstract

This paper seeks to analyze the efficacy of the Canadian Global Innovation Cluster program. This policy was originally announced in 2017 and has since been progressing through additional funding and more unique projects. This study uses a regression discontinuity design to analyze both local and individual economic growth in the affected regions. Using local business counts and individual wage filings, this study discovers inconclusive results due to data conformity issues. This study also notes an insignificant impact on project funding across the nation, in that projects that are a greater distance away from their headquarters do not receive more or less funding.

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1 Introduction

Productivity in Canada is stuck in a vicious cycle, and with it, every facet of our economy struggles to push forward. There are many ways to approach this issue; one example of this is Canada's Global Innovation Cluster (GIC) program. This study aims to analyze the impact of the GIC program using a regression discontinuity design approach. This policy is a modern example of a place-based industrial policy, as presented by (Incoronato and Lattanzio 2024). These policies rely on positive market failures, such as spillover effects and agglomeration economies, to create positive economic outcomes. There is not a large amount of peer-reviewed contributions with respect to the GIC program. (Doloreux and Frigon 2022) presents the program from a more conceptual lens, analyzing how the clusters operate, and highlighting key questions of their efficacy. With this in mind, there is no empirical analysis of the program, which is what this study aims to provide. Using a regression discontinuity design, this study will present the impact of the GIC program on both the local economy and individuals living in regions where GIC projects take place.

1.1 Background

In 2017, the Government of Canada proposed a new plan within the yearly budget titled *Canada's Innovation and Skills Plan*. This document outlined a number of goals the Canadian government aimed to complete throughout 2017 to promote economic growth across Canada, and how its budget would account for these goals. Among the proposed programs was the Canadian Innovation Supercluster Initiative, now renamed the Global Innovation Cluster Initiative (GIC). The Global Innovation Cluster initiative, a place-based industrial policy aimed at bolstering local and national economic output and productivity, was set to provide $950 Million to business-led innovation superclusters (Finance 2017). As this program has progressed, funding has been increased through private industry funding and additional federal allocation. Today, the program boasts a $3.29 billion investment across the five main clusters (Innovation and Canada 2025). An economic cluster, as defined in the GIC program, represents a consortium made up of several private firms, not-for-profit organizations and some post-secondary institutions, which share a common industry.(Innovation and Canada 2025)

The cluster consortia present in the current program were chosen from over fifty applicants, leaving just five candidates chosen for the program. The industry consortia chosen to receive funding through the GIC program include Digital Technologies, Protein Industries, Advanced Manufacturing, Scale AI, and Ocean. The criteria for application to this program were relatively slim. In order for a consortium to be eligible for application, it must have a minimum of eleven organizations that share a common industry. That industry must seek to strengthen the competitiveness of key sectors, and lead to broad innovation. (European Commission, Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs 2019) If a consortium met the preceding conditions, they were invited to provide a letter of intent outlining their goals and how they aim to achieve them.

2 Theoretical Framework

2.1 Industrial Policy

Industrial policy is best described as a government policy which seeks to alter the economic structure of a given industry. Through providing incentives for specific industries, with the hopes of creating market failures with positive outcomes, these policies seek to create long-term economic growth through the modification of the local economic structure. In many early studies of industrial policy, the effect is said to be somewhat mixed. (Lane 2020) highlights how early empirical work questioned the extent to which industrial policies generated benefits to external firms or industries. This idea largely came from an inability to measure the effects of these policies empirically. However, there are many studies in recent years, including Lane (2020), that argue that with more modern econometric methods, we can better define and justify these policies.

It is important to consider how exactly industrial policy seeks to benefit the industries it is levied upon. (Juhász, Lane, and Rodrik 2023) states that the main effects which provide positive economic impact can be explained through three concepts: externalities, coordination (or agglomeration) failures, and public input provision. Each of these economic theories provides a unique explanation for the rationale behind industrial policy. Positive externalities, such as human capital or knowledge spillover, play an integral role in the efficacy of industrial policy. ”Knowledge spillovers in the form of human capital are often regarded as the engine of sustained growth and development” (Chang, Wang, and Liu 2016). With respect to industrial policy, these spillover effects are the result of the enhanced economic efficiency created by the policy, whether that be through subsidy or otherwise. The support of leading industries creates an incentive for both firms and individuals in the area to partake in that industry. Having multiple firms or other actors work together or even compete creates a knowledge spillover effect, which seeks to positively benefit all of those involved. A similar phenomenon occurs when considering human capital spillovers. The creation and support of new businesses in targeted industries provides an incentive for the individuals in the targeted areas to reskill or refocus their efforts with respect to the subsidized industry. These reskilled labourers should expect to see higher wages or more job opportunities as a result of the increased concentration of labour demand in the area.

The concept of agglomeration economies, or as put by (Juhász, Lane, and Rodrik 2023), coordination failures, presents a unique characteristic of industrial policy. Agglomeration effects seek to benefit the economies they are targeted towards through the increase of economic efficiency created as a result of industrial policy. This effect is a response to an increased concentration of firms and skilled labourers, drawn by the benefits of the policy. ”The related activities may be goods and services that are complements in demand or production, or downstream and upstream activities.” (Juhász, Lane, and Rodrik 2023). Creating an incentive for new firms to enter the market, as a response to the increased demand for necessary materials or the creation of complementary goods, is a direct example of agglomeration effects. The local economy in the area benefits from this increased production in both the target industry and the local aggregate economy. However, despite the benefits of agglomeration, it is still considered a market failure (P. Kline and Moretti

2014). The effects of agglomeration economics, while beneficial as a purely economic externality, also present a social externality, which may not be beneficial in the long run. Increased industrial activity can lead to negative social externalities, such as pollution or urban congestion. Kline and Moretti also note that subsidizing agglomeration economies in a region diverts resources from other areas, resulting in a net loss in aggregate productivity. (P. Kline and Moretti 2014).

Lastly, public input provision speaks to the impact industrial policy has with respect to public amenities that may change as a result of the altered economic landscape. Amenities such as local infrastructure, education, etc, are examples of these amenities that may seek to change as a result of the policy. This is a consequence of the new needs of the targeted area. Increased production needs new roads or better highway access to bring in materials for production and output finished products. Unskilled labourers need further education or reskill programs so that they can benefit from the new opportunity. The increased need in the local area leads to benefits for both firms and individuals in the targeted areas.

2.2 Place-based Policy

Place-based policy can be best described as any government policy, whether that be through subsidy, tax incentives, etc., which seeks to benefit a targeted geographic area. These policies are not a new concept; the use of targeted policy has proven beneficial a number of times. A notable instance of this would be the Tennessee Valley Authority (TVA). The TVA's approach was to invest in, and rapidly modernize the Tennessee Valley's economy (P. M. Kline and Moretti 2013). Findings from the studies of the TVA point to a positive economic outcome as a result of the introduction of a number of place-based policies enforced upon the Tennessee Valley. Kline and Moretti (2013) find a substantial increase in both local economic efficiency and a relatively substantial impact on national productivity.

With evidence from the TVA, the efficacy of place-based policies can be assumed to be positive. However, it is important to consider how exactly place-based policies work. Through the direct targeting of a geographical area, these policies produce economic outcomes for that area. For a geography that may be deemed poor, a welfare policy may be put in place. In cases of under-developed regions, policies may aim to benefit budding industry through subsidies or tax relief. These policies often find their footing through similar externalities as industrial policy. Namely, agglomeration and spillover effects. However, unlike industrial policy, these impacts are localized by nature.

3 Data

To properly analyze the impacts of this policy, considering the externalities expected to be seen as a result of its implementation, both discrete and aggregated variables need to be considered. Namely, using wage filings, this paper aims to target the individual effect, acting as a representative outcome variable for individuals. Business counts are used to measure an aggregate impact, aiming to track the agglomeration effects of the program, specifically if the program creates positive economic spillover.

The North American Industry Classification System (NAICS) is a specification system created by the NAFTA (now USCMA) countries to provide concise definitions of industries and to classify them easily. NAICS industry specification is used as a proxy for the cluster areas. Specifically, using a relevant industry to represent the impact seen by a specific cluster.

3.1 Wage Filings

The data collected to represent individual effects consists of monthly wage filings, given through the Statistics Canada Labour Force Survey (LFS). The LFS is a monthly survey conducted by Statistics Canada, which aims to measure the Canadian labour market (Statistics Canada 2025). This survey data, combined with other administrative data, is used to create actionable secondary data sources. Within this dataset, Canadians aged 19 and over were surveyed from 2019 to 2023, measuring the number of monthly wage filings, sorted by both CMA-level (Census Metropolitan

Area) geography and NAICS industries relevant to the cluster program.

Table 1: Wage Filing Descriptive Statistics by NAICS Sector

NAICS	Count	Mean	SD	Min	Max	Median
Agriculture, forestry, fishing and hunting [11]	1148	1575	4020	20	35500	350
Construction [23]	1148	7093	18085	50	159900	1440
Manufacturing [31-33]	1148	9809	30492	40	287030	1850
Mining, quarrying, and oil and gas extraction [21]	1148	1264	3420	20	30190	230
Utilities [22]	1148	690	1800	20	14640	140

The dataset includes many Canadian CMAs, some of which are incredibly small. This can explain the vast range seen in the data. Other measures of central tendency are provided to better describe the data. Standard deviation within industries is relatively high as well; this is likely again due to the relative sizes that are being studied.

3.2 Business Count

Analyzing the impact this policy has on business counts allows for a measurement of agglomeration in the targeted geography. Specifically, it is assumed that an increase in business counts reflects a positive agglomeration effect on that area, both by industry and by geography. This reinforces the assumption that this policy acts as a traditional industrial policy and finds positive spillovers. Like the wage filing data, this data was collected through Statistics Canada using LFS data and administrative data. It provides the number of businesses present in any given geography (CMA-level), separated by NAICS industry

Table 2: Descriptive Statistics by NAICS Industry

Industry	Count	Mean	SD	Min	Max	Median
Construction [23]	4500	4981	5668	376	17226	2031
Food manufacturing [311]	4500	274	332	12	1110	91
Forestry, fishing and hunting [11]	4000	63.9	25.5	28	109	59
Manufacturing [31-33]	4500	2258	2742	168	8791	924
Mining, quarrying, and oil and gas extraction [21]	4500	129	96.2	11	312	110
Utilities [22]	4500	44.0	28.0	11	98	38

3.3 Geographical Data

Geography is integral in the study of the GIC program, due to its reliance on both industrial and place-based policy. For this study, CSD and FSA level geographic data were procured from Statistics Canada. This data is used in the Regression Discontinuity Design, explained later in the paper. This geographic data can be used to visualize the locations of the GIC projects as well, as seen in Figure 1.

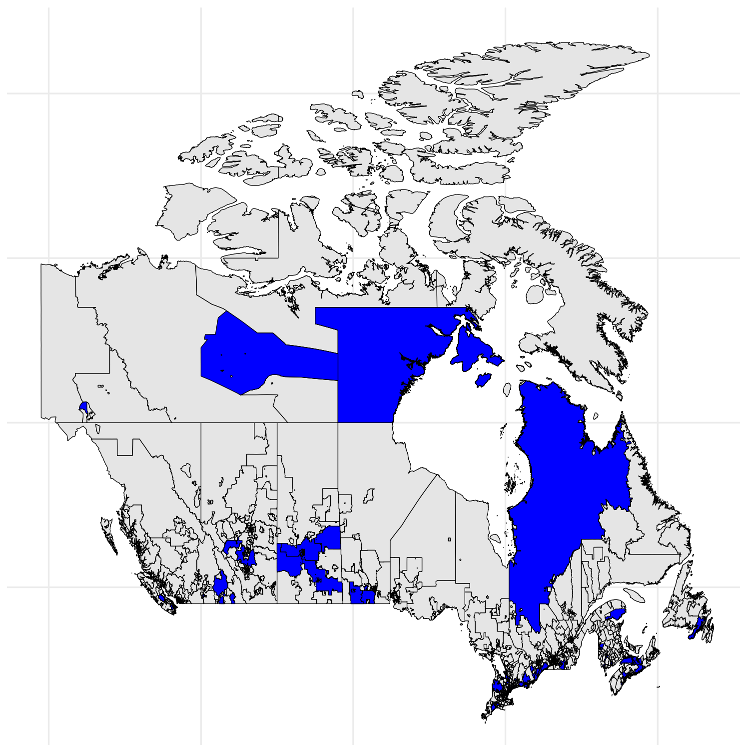

Figure 1: Location of Global Innovation Projects

3.4 Program Data

To provide contextual information, details of the GIC program were collected through the Innovation, Science and Economic Development Canada website. Over the duration of the program (2018-ongoing), there are currently 682 individual projects which have or are set to receive funding. The data collected shows individual details for each program, including date of commencement and total funding received (among other details that are less related).

Figure 2 presents a graphical representation of the number of commencements over time, with 2020 being the height of the number of projects commenced. This initial max would correspond to the original funding amount ($90 million), and the remaining commencements coincide with additional funding provided to the program afterwards. Namely, $20 million in 2021, $750 million in 2022, and a remaining $71 million following these additional investments.

Figure 3 presents the funding allotted to projects over time. A steady decrease can be seen up until just after 2022. This is likely a result of the increased funding provided in 2022 ($750 million), which was then used to grant additional programs, or increase funding in programs that were already underway

Figure 2: Commencements over time

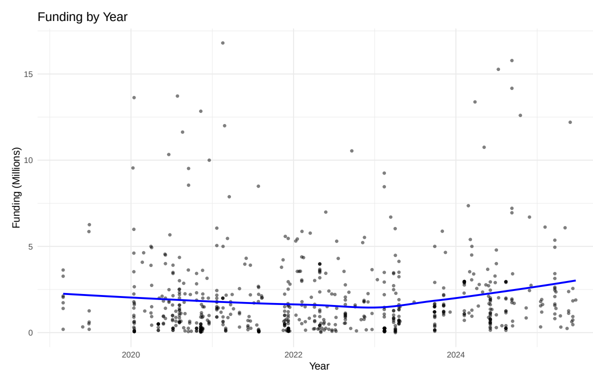

Figure 3: Funding over time

4 Empirical Framework

4.1 Regression Discontinuity Design Preface

The GIC program takes theoretical aspects of both place-based and industrial policy. This combination has previously been referred to as place-based industrial policies (Incoronato and Lattanzio 2024). I use a regression discontinuity design (RDD) to capture the impacts of this unique policy, given the border of a clusters headquarter city. Regression discontinuity design is a quasi-experimental method which seeks to measure the impact on, or around, a defined border/threshold. This analysis method finds a causal estimate by measuring the difference in potential outcomes of both treated and untreated groups, with this treatment being defined by whether a point is on or across the threshold. It is also important to highlight that there must not be a reason, other than the defined treatment, for a discontinuous function of the running variable ($dist$) (Lee and Lemieux 2010). RDD analysis can be defined in two unique ways: fuzzy and sharp RDD.

Sharp RD is a regression discontinuity design in which the threshold is defined by a discrete point; anything before that value is considered untreated, anything following is treated. In the case of the GIC program, in a sharp RD, a HQ city's border can be represented by a variable X. The treatment, defined as whether or not a project occurs within an HQ city, can be given by $D \in \{0, 1\}$, where 0 is untreated (not in the HQ city), and 1 is treated (within the HQ city. Thus, $D = 0$ when $dist > X$, and $D = 1$ when $dist < X$.

Fuzzy RD, uses a similar structure. However, rather than having a discrete cut-off, treatment is defined by the probability of treatment change around the threshold. Since there is no longer a discrete cut-off, in that treatment does not simply jump from 0 to 1, an average treatment effect (ATE) is no longer possible (Lee and Lemieux 2010). The goal of a fuzzy RD is to find the local average treatment effect (LATE), which estimates the impact of treatment around the threshold. This LATE is determined by dividing the change in outcome by the change in probability of treatment. Estimation is done through two-stage least squares regression (2SLS). This method uses two Ordinary Least Squares (OLS) regressions to determine a causal outcome. More specifically, one regression is responsible for finding the estimated probability of treatment.

4.2 Defining Geography

Considering that this analysis of the global innovation clusters are reliant on their location defining geography is imperative. As seen in Figure 1, there are several projects occurring across Canada. These projects have been outlined using Forward Sortation Area (FSA) shape data, matched with corresponding business addresses. The geography of unique cluster headquarters uses the border of the Census Subdivision (CSD) in which each HQ is located. For example, the Advanced Manufacturing cluster, headquartered in Hamilton, Ontario, uses the Hamilton CSD shapefile to define a border. This border serves as the cut-off threshold in the RDD design for this study.

Using this geographic data, I computed a distance variable that is given as the magnitude between a project's FSA centroid and its corresponding cluster headquarters. Due to the nature of the geographic data, this magnitude is originally output as a positive integer. However, for the LATE to be properly estimated, a negative value is needed to represent the projects occurring within an HQ city. To do this, I analyze each project location and convert any distance within a city border to a negative distance. This results in distances which converge upon the defined threshold. This can then be used in defining treatment groups for the RDD analysis, specifically, any project with a $dist > 0$ is untreated, and any project with $dist < 0$ is treated.

4.3 Equation and Approach

This study aims to find evidence of the program's efficacy in both an aggregate and individual manner. As aforementioned, the data for this study includes both business counts as an aggregate outcome and wage filings as an individual outcome. The identification assumption for these outcomes is that there will be a positive impact on both the number of businesses present in treated municipalities and increased wage filings for individuals. This assumption, if conclusive, would imply a positive treatment effect from this policy. With this conclusion, we can assume the GIC program to be a beneficial investment for Canada.

Initially, this study aims to find if there is a significant difference in funding, given the distance running variable. This outcome is used as a robustness check to ensure that funding is not affected by distance. As seen in Figure 3, there is a relatively linear funding across the duration of the project, with a change in slope around 2022. This was, of course, a result of additional funding introduced by the Government of Canada. However, since this is a relatively small change, we can assume funding to be consistent throughout the program. The following equation (1) is used to estimate the Wald (LATE) estimated impact of distance on project funding.

$$\tau^{Funding} = \frac{\lim_{x \to 0^-} E[Funding_i \mid Dist_i = x] - \lim_{x \to 0^+} E[Funding_i \mid Dist_i = x]}{\lim_{x \to 0^-} E[Border_i \mid Dist_i = x] - \lim_{x \to 0^+} E[Border_i \mid Dist_i = x]} \tag{1}$$

Where the numerator represents the change in potential outcome for funding, and the denominator represents the change in probability of treatment given distance. $Funding_i$ is the total funding per project, $Border_i$ is the threshold defined in the RD (in this case, the border of an HQ CSD), and $Dist_i$ is the distance running variable. This equation results in the local average treatment effect of distance on funding.

Next, to analyze the impact that this program has on individuals, we estimate the impact on total wage filings in each geography. An increase in average wage filings would suggest and postitive economic outcome as a result of the policy. This idea coincides with the theoretical expectations of both industrial and place-based policies, as a result of positive spillover effects. The following equation is used to estimate this impact.

$$\tau^{WageFilings} = \frac{\lim_{x \to 0^-} E[WageFilings_i \mid Dist_i = x] - \lim_{x \to 0^+} E[WageFilings_i \mid Dist_i = x]}{\lim_{x \to 0^-} E[Border_i \mid Dist_i = x] - \lim_{x \to 0^+} E[Border_i \mid Dist_i = x]} \tag{2}$$

Similar to that of the previous equation, Equation 2 finds the local average treatment effect given the change in potential outcome of wage filings, pre and post treatment, divided by the probability of treatment. This is a fuzzy RD setup as defined previously, where $WageFilings_i$ is the count of wage filings in a given year and geography. $Dist_i$ is the distance running variable, and $border_i$ is the threshold, in this case also the HQ CSD border.

Lastly, we analyze the impact the policy has from a local aggregate perspective. Using the number of businesses present in a geography, by year, the impact the GIC program has can be inferred on the local economy. An increase in average business counts would imply a positive economic outcome as a result of the policy. This idea also coincides with the theoretical assumptions drawn earlier in this paper. Namely, agglomeration effects as a result of the policy can lead to positive externalities. The following equation is used to estimate the impact of this policy on business counts.

$$\tau^{BusinessCount} = \frac{\lim_{x\to 0^-} E[BusiCount_i \mid Dist_i = x] - \lim_{x\to 0^+} E[BusiCount_i \mid Dist_i = x]}{\lim_{x\to 0^-} E[Border_i \mid Dist_i = x] - \lim_{x\to 0^+} E[Border_i \mid Dist_i = x]} \tag{3}$$

Where other than $BusiCount_i$, which represents the business count in a given observation, all things are equal to the previous equations.

5 Results

Analyzing the GIC program through an RDD has presented many challenges. Initially, defining a geographic threshold for both outcome variables cannot be meaningfully completed. Since the programs are spread across the country and not clustered geographically, a geographic border cannot be defined at the census subdivision level. To rectify this, the use of the FSA level of data can be used. However, data access for the outcome variables is not readily available at this level of granularity. Due to this constraint, gaining a ”negative” distance to define the treated group in the RD is impossible with the current data available at the time of this study. As a result, the only meaningful results that have been collected are the estimates of how distance impacts the funding a project receives. Initial results of distance on funding can be seen in Table 3

This outcome suggests the hypothesized results were correct. An insignificant impact can be estimated given a project's distance from the respective cluster HQ. This result was expected and could be recognized in the raw data taken from the project dataset. The second stage regression

Table 3: Distance on Funding Estimates

	Local Polynomial Regression	
	Left of Cutoff	Right of Cutoff
Sample Information		
Number of observations	70	550
Effective observations	66	540
Unique observations	26	324
RD Estimates		
First-stage RD effect	-1.000 (robust $p = 0.000$)	
Treatment RD effect	0.020 (robust $p = 0.961$)	

finds a local average treatment effect of 0.02, which, with context, would correspond to $20000. With a p-value of 0.961, it can be noted that this estimate has no statistical significance.

With these results in mind, reflecting on the study's outcome is extremely important. There are many reasons for the failure to meaningfully complete the RDD, the most pressing being the lack of quality data, which fits the requirements to define the regression. As previously mentioned, the granularity of the data from a geographic perspective prevents the assignment of a meaningful threshold. When estimating the results seen in Table 3 a distance variable could be created with both positive and negative distances, due to the specification of geography at an FSA level. Currently, there is no readily available data for business counts or wage filings at this granular level.

Furthermore, the granularity of NAICS data for both outcome variables does not properly define the projects involved in the GIC program. Specifically, the Scale AI cluster and the Digital Technologies clusters do not have an accurately corresponding NAICS code. Due to this constraint, it would be inaccurate to measure any estimate for these two clusters. The remaining three clusters can be defined by more specific NAICS codes; however, there was no readily available data for this level of specificity either. Using more general NAICS codes (as were presented in the data section) allows for a broad view of the industry, but may not properly provide context for the area of intent specified by the GIC program clusters.

6 Conclusion

The Global Innovation Cluster program provides an extremely unique approach to a traditional industrial/place-based policy. Defining clusters by both geography and industry is not unheard of, as seen through the work of (Incoronato and Lattanzio 2024), which analyzes the impact of place-based industrial policy, but has presented a challenge when attempting to analyze their economic impact. The Government of Canada has put this program in place and has provided continued funding to enhance Canada's focus on key industries. Suggestive evidence based on the government's continued support of this program implies that it has proved to be beneficial. However, that conclusion cannot be drawn by this study. The approach taken in this study was to find an estimated impact for the program as a whole. Specifically, highlighting potential positive externalities, such as knowledge spillovers or other agglomeration effects. However, due to the issues presented in the results section of this paper, it may be more lucrative for any further analysis of this program to be done by measuring the output of the individual projects. Measuring the individual projects could be used to find an average effect of efficiency for firms, rather than for economic development. Future work on this topic must include more definitive data. Better-defined geographic data will allow for the regression discontinuity design analysis to produce meaningful results, and more granular NAICS codes can provide data that better represent the industries this program includes. Researchers interested in this program may look to estimate the impact of not just the program itself, but its individual clusters.

Despite inconclusive results found in this study, it is important not forget about the GIC program. Given the economic hardships faced in Canada currently, seeking better policy has never been more important. Innovation and increased productivity are paramount for the future of Canada's economy. Creating growth through positive externalities is one way Canadian policymakers can work towards a stronger economy, and a stronger Canada.

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