# Knowledge On Tap: Measuring Sustainability Impacts of Ontario Craft Brewers

by

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# Author’s Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

## Abstract

Small businesses compose 98% of all employer businesses and employ nearly two-thirds of the entire labour force in the Canadian economy. Small businesses, however, are often exempt from environmental regulation and corporate social responsibility mandates. As a result, small business impacts on host community economic, social, and environmental factors are often not adequately documented. The craft beer sector offers a suitable environment for further exploration: these businesses are small by definition, numerous, and their production methods are resource-intensive and inefficient. This research assembles a large panel dataset and causally explores how the presence of craft breweries impact the economic, social, and environmental performance of their host localities in Ontario.

Findings indicate that the presence of a brewery in an Ontario community results in mixed sustainability outcomes: reductions in unemployment rates, nitrogen dioxide emissions, and PM2.5 emissions and increases in household income; while increasing sulfur dioxide emissions and decreasing per-capita populations of visible minorities and indigenous people. The analysis also shows that the results' magnitude and direction of effect varied depending on whether the brewery was located in an urban or rural area. This thesis presents a causal impact analysis for a growing small business segment at a provincial scale.



**Keywords:** craft beer, craft brewing, craft breweries, Ontario craft beer, impact assessment, environmental impact assessment, difference in differences, DiD, econometrics, event study, staggered cohort event study, panel data, remoteness, rurality, causal inference, TWFE, gentrification, sustainability, Sun and Abraham, CATT, interaction weighted estimator

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# List of Abbreviations

The following table describes the meaning of the acronyms and abbreviations used in this thesis.

Extended definitions are given for mathematical terms. The page on which each is first used is provided.

| Abbreviation | Meaning | Page |
|---|---|---|
| **DiD** | difference-in-differences – a statistical research design for observational studies that explores changes over time between a treated group and a control group | 1 |
| **SME** | small and medium enterprises | 1 |
| **hL** | hectoliter – the SI unit of measurement for volume equal to 100 litres | 1 |
| **LCA** | lifecycle analysis – a systematic evaluation of the sustainability impacts of a product or process for its entire life cycle, from raw material extraction to disposal | 6 |
| **Wh** | Watt-hour – a non-SI unit of measurement for energy equal to 3.6 megajoules | 1 |
| **MJ** | Megajoules – the SI unit of measurement for energy | 7 |
| **GHG** | greenhouse gas – gases that directly or indirectly trap heat in the Earth's atmosphere | 7 |
| **$SO_2$** | sulfur dioxide | 7 |
| **$NO_2$** | nitrogen dioxide | 7 |
| **PM2.5** | fine particulate matter with particles 2.5 microns or less in diameter. A micron (or micrometre) is one millionth of a meter and one thousandth of a millimetre | 7 |
| **EIA** | environmental impact assessment | 8 |
| **SA** | sustainability assessment | 8 |
| **OLS** | ordinary least squares – a statistical method used to estimate the relationship between independent and dependent variables by minimizing the sum of the squared residuals | 11 |
| **TWFE** | two-way fixed effects – a statistical method to control for spatial and temporal fixed effects in event studies. Fixed effects account for all variables – whether observed or unobserved – as long as they stay constant within the spatial or temporal boundaries | 11 |
| **StatCan** | Statistics Canada | 24 |
| **CANUE** | Canadian Urban Environmental Health Research Consortium | 24 |
| **CSV** | comma-separated variable – a file format that stores tabular data | 24 |
| **CSD** | census subdivision, a geographic identifier used by Census Canada that is roughly equivalent to a single community | 26 |
| **API** | application programming interface – a set of rules and  protocols that allows software programs to interact and communicate with each other | 28 |
| **IVT** | a multidimensional data format for Beyond 20/20 software used by Canadian Census | 28 |
| **PCCF** | Postal Code Conversion File | 35 |
| **CATT** | cohort average treatment effect of treated – the main parameter or output of the Sun and Abraham (2021) estimator used in this thesis, equivalent to the aggregated effect of all treated cohorts within the study time period. | 39 |
| **ppb** | parts-per-billion | 57 |
| **LICOat** | Low-income cut-off, after-tax – the poverty line as defined by income after taxes by the Canadian government. The cutoff value varies by year, family size, and community population. | 61 |

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# Chapter 1 – Introduction and Objectives

## 1.1 Background

The popularity of craft beer in Ontario is rising – its share of the beer market has doubled from 6% in 2014 (Weersink et al., 2018) to 18% in 2020 (LCBO, 2020; OCB, 2017). Craft breweries are defined as small, independently-owned brewers of less than 400,000 hectoliters ("hL", equal to 100 litres) per year; the majority produce less than 5000 hectoliters  (OCB, 2017). The benefit of craft breweries to communities in Ontario is significant: in 2017, craft brewers provided $323 million of economic benefit to over 100 Ontario municipalities in tourism and tax revenues – many of them rural (OCB, 2017). However, beer production is wasteful of water resources and energy. Between 4-10L of effluent and 80-120 Watt-hours (Wh) of energy are expended for every 1L of beer produced (Hoalst-Pullen et al., 2014; Ness, 2018), and as brewery size decreases, the water and energy use ratios worsen. For brewers of 1000hL per year, 34L of effluent and up to 2100Wh of energy are needed for every litre of beer manufactured (Brewers Association, 2017; Olajire, 2011).

Meanwhile, recent meta-analyses of sustainability research on small and medium enterprises (SMEs) conclude that SMEs "grossly neglect" corporate sustainability practices (Bakos et al., 2020; Das et al., 2020). Canadian law enforces measurement and reporting of business sustainability impact only to large businesses and large-scale polluters (Environment and Climate Change Canada, 2022) – meaning no systematic sustainability reporting exists for small businesses.

Researchers employing econometric methods have demonstrated the capability of difference-in-differences (DiD) statistical research designs to draw meaningful conclusions about the sustainability impacts of some industries at large geographic scales. Due to the temporally staggered founding dates of craft breweries and expected differences in craft brewery impacts depending on whether the host community is urban or rural, a DiD estimator that can accommodate those parameters is required. Therefore, this thesis uses a staggered cohort event study research design with Sun & Abraham (2021) estimators to uncover the sustainability impacts of the Ontario craft brewing industry.

## 1.2 Research Question

This study aims to determine the sustainability impacts Ontario craft brewers have on their host communities. Small businesses like craft brewers form the backbone of the economy in Ontario yet remain difficult to analyze at scale. Meanwhile, evidence exists that craft breweries may be harmful to the environment. Thus, the varying impacts of craft breweries on Ontario communities can be studied by answering the following research question:

> *What are the magnitudes and direction of sustainability impacts that Ontario craft brewers cause in their host communities?*

## 1.3 Research Objective

This thesis aims to collect and harmonize a spatiotemporal panel dataset incorporating brewery characteristics and community sustainability characteristics. A DiD causal statistical analysis of the panel dataset will determine the presence and magnitude of sustainability impacts breweries have on their host community. Specifically, this thesis seeks to estimate causal effects for an observational staggered cohort event study using the estimator described by Sun & Abraham (2021). This statistical methodology can causally explore how the presence of craft breweries impact the economic, social, and environmental performance of their host localities in Ontario.

# Chapter 2 – Literature Review

## 2.1 Review Of Literature on Craft Brewing and Sustainability

### 2.1.1 Craft Brewing and Ontario

The brewing of beer is an ancient human technology. It is also strongly linked to scientific literature; the foundational method for determining statistical significance, Student's t-test, was initially devised by William S. Gosset to analyze barley at the Guinness Brewery in Dublin, Ireland (Student, 1908; Ziliak, 2008). Several journals are dedicated to brewing research, such as the Journal of the Institute of Brewing, the Journal of the American Society of Brewing Chemists, and the Journal of Brewing and Distilling. However, the modern craft brewing revival has not been studied in as much detail. The following review of the literature on Ontario craft brewing will draw sources from peer-reviewed scientific research, unpublished student theses, industry reports, and related grey literature.

At its simplest, beer is a carbonated alcoholic beverage made from spouted barley grain called "malt" steeped in hot water to enzymatically convert starches into sugars, then filtered out, the liquid boiled with hops for flavour, and fermented with yeast. Other grains (called adjuncts) can be used in addition to barley, but malt must still be used because only malt has the starch-converting enzymes needed. Every beer style on the planet is a variation of those four or five key ingredients: water, malt, hops, yeast, and optional adjuncts (Buglass, 2010).

For this thesis, discussing the difference between the mainstream beer manufactured by large global brewing conglomerates and craft beer may be illuminating. Mainstream beer is characterized by a high ingredient proportion of adjuncts (usually corn or rice) and low usage of hops. Malt and hops are more expensive than adjuncts, so a high-adjunct and low-hop brew keeps the beer inexpensive while still broadly appealing. In contrast, craft beers tend to eschew adjuncts in favour of all-malt brews at a corresponding increase in cost. Further attempts at characterizing craft beer prove difficult because craft beer appears to be defined by its uniqueness. "Craft brews create value by being lower volume and more distinctive and rare" (Weersink et al., 2018, p. 108).

Production volume is another helpful metric by which to define craft beer. Ontario Craft Brewer's Association defines a "craft brewery" as an independently-owned brewer of fewer than 400,000 hL (OCB, 2017). Meanwhile, the government of Ontario considers a brewery with a worldwide volume of under 49,000 hL to be a "microbrewer" subject to a lower tax rate. However, the Ontario regulations do not require independent ownership to be considered a “microbrewer” (Ontario Ministry of Finance, 2022b). By these government standards, 450 craft brewers and four large brewers are licensed in Ontario as of February 2022 (Ontario Ministry of Finance, 2022a). Most Ontario craft brewers are tiny: 75% of craft brewers brew less than 2000 hL annually (Weersink et al., 2018). These 300-odd small craft brewers are the focus of this thesis because they have been neglected in the literature, and little is known about their sustainability impacts.

The current beer industry in Ontario is shaped by a reaction to oligopolies of the mid-20th century when nearly all beer production and distribution was controlled by just four brewers (Weersink et al., 2018). Even in 2023, the leading retail outlet in Ontario – The Beer Store – is wholly owned by a syndicate of Labatt, Molson, and Sleeman. These three names are recognizably Canadian brands, but each is a subsidiary of a foreign-owned brewing consortium – Anheuser-Busch InBev, Molson Coors, and Sapporo, respectively (Master Framework Agreement, 2015). By the early 1980s, stagnation in the market allowed the entry of new, much smaller brewers: Ontario's first craft brewers (Menna & Catalfamo, 2014). By the early 2000s, the embryonic craft brewing industry, together with the assistance of the Ontario Craft Brewers Association, lobbied successfully for a new tiered tax regime more favourable to small brewers. The lower taxes for small brewers enabled rapid market growth, and Ontario's craft beer market share rose from 2% in 2009 to 18% in 2021 (LCBO, 2020; OCB, 2017). There are 450 craft brewers licensed in Ontario as of February 2022 (Ontario Ministry of Finance, 2022a).

Despite the tax law changes, Ontario's legal framework for alcohol sales has the tightest restrictions in Canada. Those restrictions have implications for craft brewers, as explained in a chapter from Economic Perspectives on Craft Beer (Weersink et al., 2018). The limitations around retail sales, such as the high barrier to entry into Ontario's iconic beer retailer The Beer Store of about $24,000 per brewer, keep smaller craft brewers from accessing new customers. A legislative update in 2019 allowed craft brewers to focus on alternative retail outlets, such as selling from shops attached to their production facilities or serving beer directly from their taprooms and brewpubs (Liquor Licence and Control Act, 2019). Ontario brewers have succeeded in a challenging regulatory environment by embracing the hyper-locality that draws beer aficionados to craft beer (Ness, 2018).

Beyond legal frameworks, social sciences researchers have helped explain the growth of the craft beer industry in North America from several perspectives. Compared to large corporate brewers focused on efficiency, growth, and profit, craft brewers tend to be driven by a passion for beer (Watne & Hakala, 2013). The shared passion of craft brewers leads directly to a phenomenon of cooperative competition, where craft brewers within a region tend to cooperate on joint marketing campaigns rather than compete directly (Kraus et al., 2019). Regionality is a common theme in the social literature on craft beer. Several tourism researchers demonstrate that beer tourism in rural areas explains craft brewery success in the face of fierce competition from major brands (Murray & Kline, 2015; Reid, 2021). Indeed, craft brewers appear to reject every aspect of global brewing conglomerates. Craft brewers find pride and meaning in being intentionally small, independent, resistant to growth for growth's sake, and deliberately local (Eberts, 2014; Gaudio, 2016; Howard, 2014). This ethos of fierce iconoclasm is perhaps the defining characteristic of craft brewing in North America.

Despite the strong undercurrents of iconoclasm and uniqueness among craft brewers, the economic realities of operating small businesses lead some craft brewers to seek acquisition by large international brewing conglomerates. One such business pressure is access to exclusive distribution systems, the absence of which tends to limit the business growth of craft brewers (Kleban & Nickerson, 2012). Large brewing conglomerates seek acquisitions of profitable craft brewers with growing market share to compete in new market segments (Elzinga & McGlothlin, 2022). While being acquired by a corporate brewer can provide a path to growth for craft brewers through access to optimized supply chains and distribution, researchers have determined that when consumers are made aware that an acquired craft brewer produced a craft be, they have negative opinions about the products due to feelings of inauthenticity (Frake, 2017).

Within this complex business environment of conflicting pressures, this thesis evaluates the sustainability of craft beer in Ontario.

### 2.1.2 Craft Brewing and Sustainability

Beer is a highly processed product with a significant environmental impact. For example, every drop of the 300 million litres of beer consumed yearly in Ontario was heated to a boil and later cooled down to drinking temperature (LCBO, 2020; OCB, 2017). Several interesting patterns emerge when examining the literature on environmental factors in beer brewing.

One of the earliest systematic examinations of the sustainability impacts of brewing was Abass Olajire's survey of the global brewing industry (Olajire, 2011). The pioneering paper codified many terms sustainability researchers now use to discuss brewing and enumerates the main inputs and outputs that impact the environment. From a systems perspective, the 22-page paper is complete in coverage, if lacking in depth. Olajire does not discriminate between large industrial and craft brewers, and a close reading of the terms used indicates that small brewers are excluded from consideration entirely.

The empirical intersection of craft brewing and the environment can be found in peer-reviewed lifecycle analyses (LCA). Together they demonstrate that beer production requires significant amounts of water and energy. When surveyed, a definite trend emerges: the smaller the brewer, the more wasteful it is. Industrial-scale brewers consume about 5L of water, 100Wh of energy, and 1.5 megajoules of natural gas for every 1L of beer produced (Amienyo & Azapagic, 2016; Cimini & Moresi, 2016; Koroneos et al., 2005). LCAs of craft brewers show that these figures, known as water usage ratio, energy usage ratio, and fuel use ratio, are more wasteful than industrial brewers (Melon et al., 2012; The Climate Conservancy, 2008). Very small craft brewers, like Ontario's 300 brewers of less than 2000 hL per year, have notably worse energy and water usage ratios (Brewers Association, 2016b). The most recent versions of these values have been condensed in Table 1.

*Table 1 Median usage ratios of different-sized breweries, per litre of ready-to-drink beer*

| | Energy Usage in Wh/L | Water Usage in L/L | Natural Gas in MJ/L |
|---|---|---|---|
| **Industrial Brewer >400,000 hL/year** | 100 | 5.0 | 1.5 |
| **Large Craft >10,000 hL/yr** | 224 | 4.2 | 1.6 |
| **Medium Craft <10,000 hL/year** | 839 | 7.8 | 4.5 |
| **Small Craft <1,000 hL/year** | 2169 | 34.0 | 9.3 |

Note: one hundred Watt-hours is roughly equivalent to three D-cell alkaline batteries. A megajoule (MJ) of natural gas is roughly equivalent to the heat energy in a cubic foot of gas. Adapted from 2016 Sustainability Benchmarking Update, by Brewers Association, 2016. Copyright 2016 by Brewers Association.org

While these trends appear consistent across different regions of the world, there are problems with the data. Many of the smallest brewers are brewpubs – restaurants with small-scale brewing capacity. Because the metering of electricity and gas is rarely separated between the kitchen and the brewhouse, brewpub operators likely overestimate their usage ratios for brewhouse operations (Brewers Association, 2016b, 2016a). Another issue with these data is their regionality – none are specific to Canada or Ontario. Finally, the data here is inconsistent on packaging and refrigeration: usage ratios for packaged, kegged, and tanked-for-serving beer are combined, making comparisons difficult.

Another perspective of the environmental impact of craft brewing is greenhouse gas (GHG) emissions. Of relevance are the studies that researcher Rachel Shin undertook in an unpublished master's thesis (Shin, 2018) and a later collaborative *Sustainability* article (Shin & Searcy, 2018), which focused explicitly on Ontario's craft brewing sector. These works contextualize craft brewers' GHG emissions within the background of Ontario's then-new cap and trade program. Shin’s papers are scoped from farm to table and include GHG emissions for raw ingredient agriculture, transportation, brewing, packaging, distribution, and endpoint refrigeration. Small craft brewers in Ontario do not have much control over their raw ingredients or product packaging, and distribution is beyond the scope of many Ontario brewers (OCB, 2017; The Climate Conservancy, 2008). Shin's work is relevant to this thesis because of the work done to understand the attitudes of Ontario brewers on sustainability topics and emissions control. On that topic, brewers indicated that while sustainability was important, a lack of resources, capital liquidity, and knowledge limited their ability to take on sustainable change within their organizations.

In addition to greenhouse gasses, breweries emit other pollutant trace gasses when they burn natural gas for the brewing process, such as sulfur dioxide ($SO_2$), nitrogen dioxide ($NO_2$), and fine particulate matter (PM2.5) (Buglass, 2010).

In summary, the literature on sustainable craft brewing in Ontario outlines an industry that defines itself by its uniqueness but is bound together by a high environmental toll. Locally positive social and economic outcomes balance their romantically inefficient production processes. To uncover the spectrum of sustainability impacts the Ontario craft brewing industry might have on their host communities, this thesis next examines the sustainability impact measurement literature, where researchers use systematic methods to build large-scale empirical assessments.

## 2.2 Sustainability Impact Measurement

This sub-section of two parts reviews the literature on sustainability impact measurement. The first part explores how researchers commonly measure businesses' social, economic, and environmental impacts. These methods can be "inside-out", where insights are gained from analyzing reports from the business themselves, or "outside-in", where external impact measurements are connected to businesses using various mathematical techniques. Some attention is paid to the Canadian and Ontarian context. In the second part, this thesis explores the literature on sustainability impact measurement as it applies to small businesses.

### 2.2.1 Review Of Literature on Sustainability Impact Measurement

Sustainability impact measurement is an indispensable tool for understanding human activity's environmental, social, and economic impact, including the actions of businesses. The roots of these impact measurements can be traced back to the earliest days of sustainability in the 1960s when environmental impact assessments (EIA) were an early tool of government oversight. The foundational *Limits to Growth* report argued that continued economic growth would inevitably lead to resource depletion and environmental degradation and called for sustainable practices that could be enabled by EIAs (Meadows et al., 1972). EIA matured into a different approach called sustainability assessment (SA), which seeks to deliver tradeoff-free benefits to the world rather than merely minimize impact (Bond & Pope, 2012; Hacking & Guthrie, 2008). In the years since, governments have operationalized EIA and SA methods with modern frameworks and auditing procedures for use in practice, making them mandatory for many large-scale projects (Bond et al., 2012; Esteves et al., 2012).

Governments worldwide, including Canada, have implemented legislation requiring large factories and businesses to measure and report their emissions and consumption of public resources. At the federal level in Canada, the Canadian Environmental Protection Act requires companies to report on their environmental impact and develop plans to address potential issues in advance (Environment and Climate Change Canada, 2004, 2022). The Impact Assessment Act obligates designated projects to undertake a detailed sustainability impact study. The kinds of projects that fall under the purview of the Impact Assessment Act could be summarized as "major projects" and include oil and gas exploration, transportation construction, projects involving hazardous waste, and any projects on federal or protected lands (Impact Assessment Agency of Canada, 2020).

At the provincial level, Ontario's Climate Change Mitigation and Low-carbon Economy Act of 2016 required businesses to pay for their greenhouse gas emissions in a cap-and-trade program, but it was repealed in 2018. Subsequently, environmental management of businesses fell to the Ontario Ministry of the Environment, Conservation, and Parks, which developed guidelines and tools to support businesses in measuring their environmental impact. The Ministry's Climate Change Action Plan encouraged businesses to implement emission reduction strategies, track their progress, and report on their results but did not mandate these actions (Government of Ontario, 2016). The Climate Change Action Plan was repealed in April 2022, leaving Ontario small businesses without comprehensive emissions guidelines from the government (Government of Ontario, 2022).

Next is a concise review of how the concept of social license-to-operate serves as an incentive for many large businesses to engage in self-reporting their sustainability impacts. Extensive literature examines voluntary sustainability reports, particularly within the brewing industry, focusing on large international brewing conglomerates and larger craft brewers. One highly cited article by Berrone et al. (2010) investigated the impact of 194 large firms in the USA, revealing that family-owned firms tended to exhibit lower pollution levels. It is important to note that these firms self-reported their environmental data, demonstrating the usefulness of having such reports for conducting impact research. Dasgupta et al. (2023) presented an interesting spatial analysis within a single industry context, revealing that firms in violation of US Environmental Protection Agency policy tend to influence nearby peer firms to reduce toxic emissions. This study utilized published data from the treated firms, taking an inside-out approach – which differs from the outside-in perspective of this thesis.

In contrast, the literature focusing on small businesses and craft brewers primarily aims to explain why these smaller entities often do not report sustainability data. Brammer & Pavelin (2006) examined the factors that drove firms to disclose environmental data voluntarily, finding that larger and more profitable firms are most likely to release accurate environmental impact reports. Sucena & De Oliveira

Marinho (2019) systematically analyzed sustainability reporting in Brazilian and multinational breweries, highlighting systematic flaws such as a lack of connection between sustainability achievements and company financial performance. Extensive research exists on the sustainability actions undertaken by SMEs and craft brewers and the underlying reasons for their actions. Studies explored factors such as awareness (Fuchs et al., 2023), understanding (Battisti & Perry, 2011), and values (Afolabi et al., 2022). Hillary (2004) examined why SMEs did not engage in self-reporting practices like larger companies, finding a lack of time, knowledge, and resources to be the cause. Trautwein (2021) conducted a systematic literature review on the sustainability impact assessment of start-ups, finding that the majority of examined papers take an inside-out (reporting) approach instead of an outside-in (econometric) approach.

### 2.2.2 Review of Literature on Sustainability Impact Measurement of Small Businesses and Breweries

This section aims to scrutinize the tree of research on small businesses and craft beer to ascertain whether the literature supports the methods proposed in this thesis and the imperative implied by its research questions. A recap of the research parameters will help narrow the scope of literature coverage.

The primary objective is to assess craft breweries' sustainability impacts at the community's geographic level across the entire province of Ontario. Practical limitations render performance data on the craft brewery industry – such as brewery sales, profit, and consumption rates – unavailable. Only limited information is available regarding a brewery's founding location and date. Some proxies for performance are available, such as ratings and product offerings. However, as craft breweries value distinctiveness (Weersink et al., 2018), observed impacts will necessarily be diverse. The lack of reported performance data means statistical techniques that use performance weighting cannot be used.

On the other hand, data about community-level sustainability is accessible, and statistical methods such as regressions can aggregate these data points into impact measurements. Unlike controlled experiments like human drug trials, this study's treatments - a brewery being founded – are not administered at a single predetermined time interval. As a result, any analytical technique used in this thesis must account for this staggered treatment. In a single sentence, the research seeks causal inference estimates on a panel dataset without performance weighting in the presence of heterogeneous treatment effects and staggered treatments.

##### *2.2.2.1 Non-Causative Literature*

The research aims of causal inference eliminate any qualitative research from incorporation into methods, though insights from qualitative research papers can provide valuable design considerations. Grunde et al. (2014) attempt to determine the community-level impacts of craft breweries through a sustainability lens in their master's thesis. The methods are a literature review and survey, which are insufficiently empirical. However, they indicate variables of interest for community impact analysis, such as local economy, local connection, cultural identity, and social interaction. Notably, they had hoped to explore impacts on health and well-being, but these variables were later excluded.

Given the limited research on craft breweries, insights from empirical studies focusing on correlation rather than causation can still be valuable. Apardian & Reid (2020) conducted a quantitative neighbourhood-level study investigating the relationship between craft breweries and walkability. While this paper identified a positive correlation, it made no causal claims.

##### *2.2.2.2 Quantitative SME Literature with Regression Analysis*

Robust causal estimates in observational studies are the typical domain of regression analysis. The subtype of regression analysis with the most potential for robust causal inference is DiD, though the more straightforward ordinary least squares (OLS) regressions can provide valuable insights. Nilsson et al. (2020) used OLS regressions to examine the link between breweries and neighbourhood crime but found no significant association. However, the simplistic OLS regression may not have accounted for bias in parallel trends, and the study had a limited geographic range of a single city. An earlier study by Nilsson & Reid (2019) used a similar OLS regression with two-way fixed effects (TWFE) to examine the impact of craft breweries on property values, finding a noticeable positive influence for residential property values but none for commercial properties. As in Nilsson's 2020 study, the limited geographic range of the 2019 study could not generate broadly generalizable results for the entire craft brewing industry.

Raftopoulou and Giannakopoulos (2021) provided a noteworthy illustration of a prototypical panel event TWFE DiD study linking health outcomes to unemployment. Given the study's scope and scale parameters, the fixed effects and controls are straightforward and comprehensible. However, the problem composition of Raftopoulou and Giannakopoulos does not incorporate the presence of staggered treatment.

Bonetti et al. (2021) investigated fracking drill sites and their effects on nearby watersheds using a TWFE-weighted least squares regression with numerous fixed effects and exogenous controls. The rich dataset Bonetti et al. (2021) used allowed for an uncomplicated TWFE OLS regression that could generate a robust causal result. The authors linked fracking wells to slightly increased groundwater barium, chloride, and strontium ion concentrations. As a study of sustainability impact measurement over a wide area, Bonetti et al. (2021) was a practical guide for the analysis used in this thesis.Click or tap here to enter text.

#### *2.2.2.3 SME Sector Impact Literature*

To adequately characterize the craft brewing industry in Ontario, it is necessary to employ a panel dataset and conduct research on a large scale. This approach enables statistical inferences that can provide insights into the industry as a whole. Conducting the research through case studies or with small sample sizes would not be sufficient to meet that goal. Studies focusing solely on individual communities or cities are also unsuitable as their conclusions cannot be generalized to the broader craft brewing industry. Mir and Feitelson (2007) examined two types of small business within a single city: laundry and motor vehicle repair. They found that owners took environmental actions only when profitable or regulated strictly. The Mir and Fietelson paper is an excellent example of a large sample size, sector-wide analysis at a neighbourhood scope. While valuable, the findings might not apply to the entire laundry and motor vehicle repair industries due to the limited, city-wide scale of the study. Feeney (2017) performed a state-wide impact assessment of craft breweries in Pennsylvania from the perspective of cultural heritage and their use of historic buildings, finding that craft breweries can revitalize downtown areas while preserving cultural heritage. While a systematic survey, it does not attempt to measure impact empirically.

The direction of causation is a vital aspect to consider in the literature on small businesses and breweries and their relationship with host communities. Several studies have explored the impact of community factors on the growth of these industries, establishing causal inferences opposite to the direction of effect pursued by this thesis. For example, Doroshenko & Shelomentsev (2019) conducted an econometric analysis of small businesses by region, specifically examining the influence of the youth demographic group on the development of small businesses. Through multiple statistical models, they demonstrate that an increase in the number of youths positively influences the growth of small businesses. Although this study shares similarities with the methodology proposed for this thesis, it focuses on the reverse causal relationship.

Similarly, Hong et al. (2015) examined the temporal and spatial dynamics of startup founding in Korea, utilizing a robust statistical inference estimator called the System Generalized Method of Moments. However, their analysis also establishes causal inference in the wrong direction – from the community to business. Another relevant study is the econometric exploration by Keeble and Walker (1994), which investigates the reasons behind small business failures. Multiple variables are considered to determine community factors associated with SME failure. Nevertheless, the examined effects primarily focus on the community-to-business relationship rather than the reverse direction.

#### *2.2.2.4 SME Sustainability Impact Literature*

In the context of sustainability, while there are notable large-scale studies on small businesses and breweries, they seldom address sustainability concerns directly. For instance, research in tourism and urban sciences frequently explores the sense of place and neo-localism impacts of craft breweries. Ergungor's (2010) paper on bank branch presence exemplifies a study with appropriate scope, scale, and direction of causal inference. However, its focus is limited to a single outcome of interest – the number of loans –and only tangentially related to social sustainability.

The reasonable amount of literature on community-level causal impacts of businesses nevertheless represents a gap because the businesses are large. The paper by Zhumadilov (2022) on nuclear plants is a detailed spatiotemporal study on sustainability impacts, encompassing the proper scope and techniques. However, it is essential to note that nuclear power plants are not small businesses and do not exhibit the same interactions with the community that small businesses would. Similarly, the fracking paper by Bonetti et al. (2021) aligns closely with the intended scope of this brewery research. Although individual drilled wells can be considered small, fracking wells are not businesses and have limited community interaction beyond emissions.

#### *2.2.2.5 Policy Impact DiD Literature*

While sustainability studies rarely use staggered cohort event studies with DiD statistics, policy impact studies often employ those models. Trautwein (2021) systematically reviews the cause-and-effect relationship between policies and Sustainable Development Goal attainment. Multiple studies mentioned by Trautwein employed DiD methods, indicating that policy analysis is a typical application of DiD in causal econometric analysis. An example of policy analysis that involves alcohol is the Mullachery et al. (2022) spatiotemporal staggered event DiD study on community crime and death impacts after sobriety checkpoint programs were implemented. The researchers established that treatment was associated with a 12.3% reduction in traffic fatalities compared to the pre-treatment period. The paper is a classic public health and law enforcement impact study that econometrically establishes the cause-and-effect of policy implementation.

##### *2.2.2.6 Grouping and Fixed Effects as Solutions to Heterogenous Treatment Effects*

Causal inference studies often encounter heterogeneity in treatment effects due to location. This heterogeneity manifests, for example, as differences in performance and impact between urban and rural craft brewers. In the academic literature, DiD studies offer methods to address this concern. For instance, the paper by Zhumadilov (2022) on nuclear plants deals with regionality by using crop yield as an exogenous control and incorporating spatial and temporal fixed effects to account for rising trends over time. The fracking paper by Bonetti et al. (2021) addresses spatial differences in watersheds by creating sub-groups for analysis. Groupings tend to reduce the robustness of statistical results by decreasing the sample size.

If treatment weighting data is available, it can be used to control for heterogenous treatment effects. For example, the nuclear plant paper by Zhumadilov (2022) was able to scale its impacts by the publicly available nameplate generating capacity of power plants. The fracking paper by Bonetti et al. (2021) had drill site bore size and capacity data available. Unlike those two datasets, manufacturing scale data for Ontario craft breweries is absent. Consequently, the conclusions reached in this thesis must reach a reasonable level of robustness without performance weighting.

##### *2.2.2.7 Literature on Heterogenous Treatment Effects*

An exciting observational conclusion reached by the authors of the fracking well paper was that the magnitude and direction of pollutant ion concentrations differed depending on the watershed region of the drilled wells (Bonetti et al., 2021). This uneven impact – one that depends on the location of treatments – is a feature called “heterogenous treatment effects”. It is expected that the craft breweries studied in this research will also exhibit heterogenous treatment effects, likely along levels of rurality.

In 2021, researchers Liyang Sun and Sarah Abraham published a paper that conclusively demonstrated the inability of DiD to generate reliable causal estimates in the presence of heterogenous treatment effects. They presented a solution in the form of an interaction-weighted estimator, which avoids this issue. In the context of Ontario craft breweries, Sun and Abraham's (2021) DiD interaction-weighted estimator offers a promising opportunity for meaningful causal inference, given the absence of data allowing for scaling or weighting of breweries based on their size or performance. It is not the only method of dealing with treatment effect heterogeneity. For example, Xu et al. (2023) used a nonlinear DiD analysis because they had evidence that eco-industrial parks exponentially impact their host communities over time. In other cases, expected treatment effect heterogeneity can be dismissed due to careful study design. The Nillson & Reid (2019) paper on the causal link between breweries and property values uses DiD in a standard TWFE implementation for causal inference. The authors argue that the heterogenous impacts of the breweries are not of significant concern given the localized nature of the analysis within a single city.

In contrast, the analysis proposed in this thesis encompasses a broader scale, including an entire province and its urban and rural areas. It is reasonable to anticipate treatment heterogeneity, requiring techniques capable of generating reliable impact estimates in the presence of this heterogeneity. The Sun and Abraham (2021) approach can generate reliable estimates in panel datasets with expected treatment effect heterogeneity, making it an ideal method for this thesis.

## 2.3 Review of Econometric Difference-in-Differences Impact Literature

This sub-section reviews the literature on DiD, econometric event studies, and studies which use the Sun & Abraham, 2021 interaction-weighted estimator for insight into statistical methods and analysis design that will apply to the data and goals of this thesis. The insights will be gained by connecting econometric and public health research literature to this study's objectives. This sub-section avoids mathematical notation and focuses on the prerequisites and outcomes of the impact measurement methods discussed.

One relevant study by Xu et al. (2023) investigates eco-industrial parks' nonlinear and heterogeneous effects on 288 cities. The scale of the Xu et al. study is extensive, and while it focuses on industrial parks rather than small businesses, their approach bears similarities to this thesis. Instead of employing linear models or Sun & Abraham's estimator, Xu et al. employ a hybrid nonlinear regression model incorporating an interaction term involving a smoothing transformation function. Such an approach is not possible in the case of this thesis as the interaction term requires knowing aspects of the industrial parks that have no equivalent in the craft brewery dataset.

Another relevant study by Zhumadilov (2022) conducts a spatiotemporal DiD analysis to examine the impact of nuclear power plants on nearby crop yields. The study finds that crop yields increase, potentially due to increased atmospheric water. Although this study has some topical parallels to the sustainability impact sought by this thesis, it does not focus on small businesses or polluters. Zhumadilov's analysis is conducted at the county level, with control counties selected based on centroid distance, absence of nuclear power plants, and downwind status. The study employs county fixed effects to control for crop yields, which tend to be higher in Midwestern corn- and soy-belt regions. State-year fixed effects are included to account for the overall gradual increase in yields across all regions. The regression analysis follows a straightforward ordinary least squares (OLS) approach with two fixed effects. Clustered standard errors are implemented at the state level, although alternative options such as county and agricultural districts are considered. In summary, the Zhumadilov study seeks to find the same conclusions this thesis does but goes about it differently because of access to more informative datasets.

The study by Zhumadilov (2022) mentions that testing for parallel trends before performing a regression, also known as pretesting, is a common practice. However, the author highlights the potential unreliability of this test. Statisticians Roth (2022) and Sun & Abraham (2021) further suggest that standard pretesting methods – like the Wald pre-test – can result in incorrect conclusions. Callaway & Sant'Anna offer a solution in the form of a visual plot check, where evidence of parallel trends can be gathered by looking at the outputs of event study plots and ensuring pre-treatment periods cross the zero line (Callaway & Sant'Anna, 2021, 2022).

Mullachery et al. (2022) conducted a spatiotemporal staggered event DiD study to examine the impacts of sobriety checkpoint programs on nearby road-traffic mortalities. It is the only study on alcohol-related outcomes that could be found using this kind of econometric approach. This study represents a classic example of a public health and law enforcement impact analysis investigating the econometric cause-and-effect relationship of policy intervention. It does not, however, examine small businesses and their impacts.

In a long-term DiD study, Rico-Straffon et al. (2023) explored the spatiotemporal impact of logging concessions and eco-certifications on deforestation, finding only a slight reduction in forest loss when logging concessions were present. Although this study provides valuable insights within the sustainability context, it does not identify any significant impacts. The authors employ a novel DiD method called "$DiD_L$" in their analysis, allowing for finding causal estimates in the presence of non-absorbing treatments.

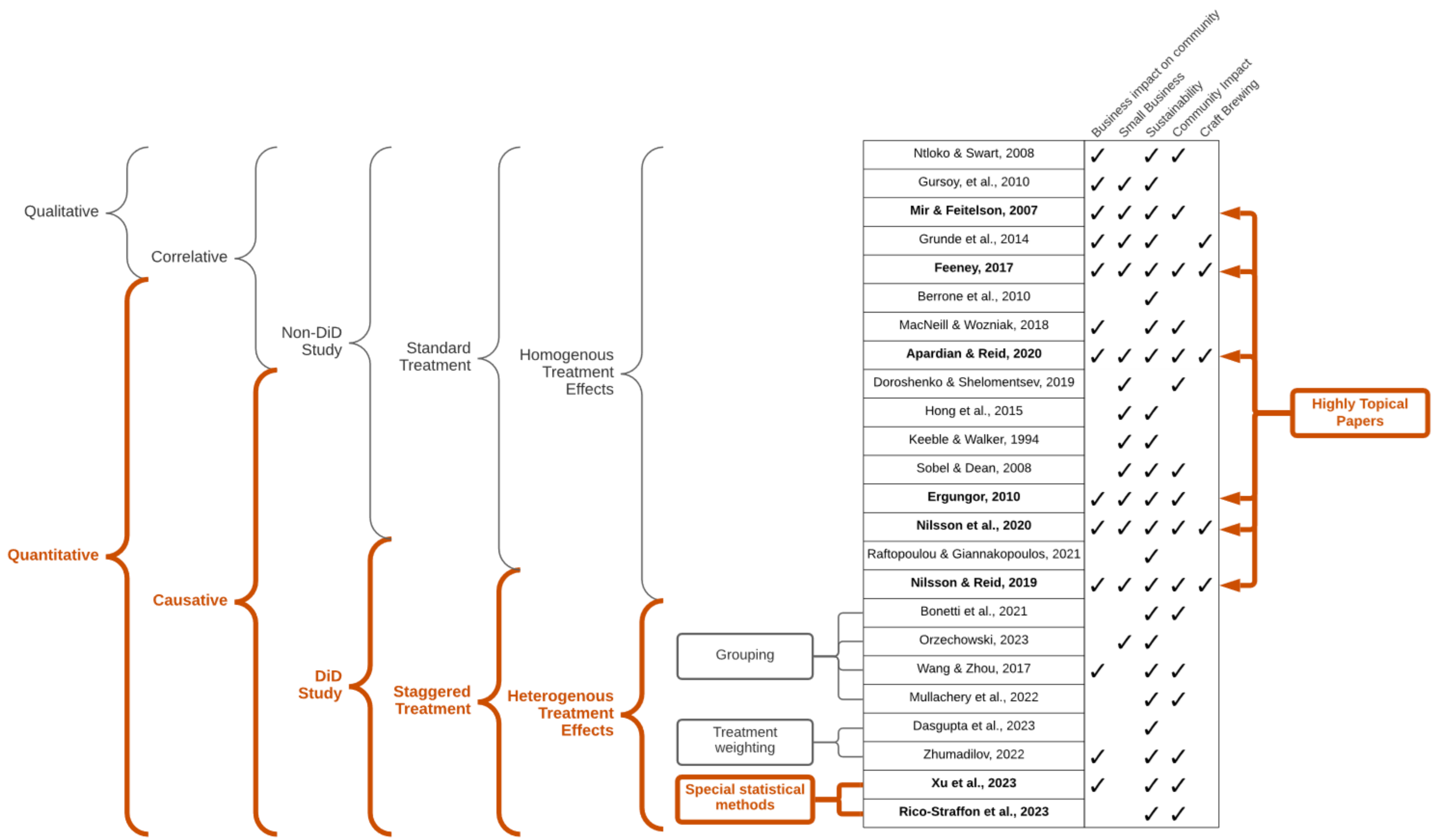
Lastly, Orzechowski (2023) adopts a fixed effects statistical approach using panel data from 1996 to 2013 to examine the impacts of Small Business Administration loans on unemployment. In this way, it is one of the few examples in the literature that examines small business impacts – but in this case, the analysis focuses on loans rather than businesses themselves. In addition, the study aggregates the results to state-level impacts rather than analyzing impacts at the community level.

## 2.4 Literature Gaps

Sections 2.1, 2.2, and 2.3 delve into the connections between craft beer and sustainability, explore the literature on how sustainability impacts can be measured causally, and list some examples of how study parameters can be handled with special statistical techniques. Literature on craft breweries to date establishes them as inefficient water and energy users when examined individually in case studies or during process analyses. However, the literature does not attempt to measure the industry systematically and quantitatively. Similarly, the broadly beneficial social aspects of craft breweries have been explored by researchers, but only at small geographic scales. While the academic literature features notable LCAs, case studies, and meta-analyses that examine the impacts of small business segments and craft breweries, there do not appear to be many attempts at "outside-in" analyses or empirical studies for any small business segment in its totality. Compounding the issue is that few small businesses or craft brewers have the knowledge, time, and need to collect or publish sustainability data. Consequently, it can be stated that there has been inadequate research on systematic impact measurement methods for small businesses, including craft brewers.

In the DiD impact measurement literature review, studies using econometric methods were evaluated for similarity to this thesis. Based on the availability of data and the research objective, the review helped to indicate which mathematical approach is most suitable. To summarize, researchers employing econometric methods have demonstrated the capability of DiD study designs to draw meaningful conclusions about the sustainability impacts of some industries at large geographic scales. Given the goals of this thesis, a DiD staggered event cohort study that can manage treatment effect heterogeneity was identified as the ideal approach.

A graphical summary is provided in Figure 1 that simultaneously examines the multiple angles of the literature review. Relevant literature covering sustainability in craft brewing and mathematical impact measurement is in the vertical table in a rectangular outline. On the left are a series of mathematical topic categories, with the targeted paths in bold orange. This sorting results in two papers which use causal inference techniques in a way closest to the desired objectives of this thesis. On the right side are a series of five subject matter identifiers. The six papers with the closest topical connection to this thesis are highlighted with bold orange arrows. No papers with good topical coverage (right) utilize the required statistical techniques, indicating a place in the literature for this thesis.




| | Business impact on community | Small Business | Sustainability | Community Impact | Craft Brewing |
|---|---|---|---|---|---|
| Ntloko & Swart, 2008 | ✓ | | ✓ | ✓ | |
| Gursoy, et al., 2010 | ✓ | ✓ | ✓ | | |
| **Mir & Feitelson, 2007** | ✓ | ✓ | ✓ | ✓ | |
| Grunde et al., 2014 | ✓ | ✓ | ✓ | | ✓ |
| **Feeney, 2017** | ✓ | ✓ | ✓ | ✓ | ✓ |
| Berrone et al., 2010 | | | ✓ | | |
| MacNeill & Wozniak, 2018 | ✓ | | ✓ | ✓ | |
| **Apardian & Reid, 2020** | ✓ | ✓ | ✓ | ✓ | ✓ |
| Doroshenko & Shelomentsev, 2019 | | ✓ | | ✓ | |
| Hong et al., 2015 | | ✓ | ✓ | | |
| Keeble & Walker, 1994 | | ✓ | ✓ | | |
| Sobel & Dean, 2008 | | ✓ | ✓ | ✓ | |
| **Ergungor, 2010** | ✓ | ✓ | ✓ | ✓ | |
| **Nilsson et al., 2020** | ✓ | ✓ | ✓ | ✓ | ✓ |
| Raftopoulou & Giannakopoulos, 2021 | | | ✓ | | |
| **Nilsson & Reid, 2019** | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bonetti et al., 2021 | | | ✓ | ✓ | |
| Orzechowski, 2023 | | ✓ | ✓ | | |
| Wang & Zhou, 2017 | ✓ | | ✓ | ✓ | |
| Mullachery et al., 2022 | | | ✓ | ✓ | |
| Dasgupta et al., 2023 | | | ✓ | | |
| Zhumadilov, 2022 | ✓ | | ✓ | ✓ | |
| **Xu et al., 2023** | ✓ | | ✓ | ✓ | |
| **Rico-Straffon et al., 2023** | | | ✓ | ✓ | |

*Figure 1 Literature Review Analysis by mathematical technique (left) and subject matter (right)*

*Table 2 Sustainability Impact Measurement Literature Assessment*

| | | | Quantitative Methods | | | | | Characterize the Industry with Panel Data | | | Subject matter and scope | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Authors** | **Year** | **Title** | **Empirical, data-driven** | **Causal inference** | **DiD** | **Staggered treatment** | **Heterogenous treatment effects** | **Large sample size** | **Event study** | **Business-to-community effect** | **Small business** | **Sustain-ability** | **Community-level impacts** | **Craft brewing** | **Notes** |
| **Apardian, R. E., & Reid, N.** | 2020 | Going out for a Pint: Exploring the Relationship between Craft Brewery Locations and Neighborhood Walkability | Yes | No | No | No | No | No | No | Yes | Yes | Yes | Yes | Yes | |
| **Berrone, P., Cruz, C., Gomez-Mejia, L. R., & Larraza-Kintana, M.** | 2010 | Socioemotional wealth and corporate responses to institutional pressures: Do family-controlled firms pollute less? | Yes | No | No | No | No | Yes | No | No | No | Yes | No | No | |
| **Bonetti, P., Leuz, C., & Michelon, G.** | 2021 | Large-sample evidence on the impact of unconventional oil and gas development on surface waters | Yes | Yes | Yes | Yes | No | Yes | Yes | No | No | Yes | Yes | No | |
| **Dasgupta, S., Huynh, T. D., & Xia, Y.** | 2023 | Joining Forces: The Spillover Effects of EPA Enforcement Actions and the Role of Socially Responsible Investors | Yes | Yes | Yes | Yes | No[1] | Yes | Yes | No | No | Yes | No | No | [1] Uses self-reported data to weight treatment effect homogeneity |
| **Doroshenko, S. V., & Shelomentsev, A. G.** | 2019 | Econometric assessment of the number of youth as a factor of the development of small business in regions | Yes | Yes | No | No | No | Yes | No | No | Yes | No | Yes | No | |
| **Ergungor, O. E.** | 2010 | Bank branch presence and access to credit in low- to moderate-income neighborhoods | Yes | Yes | No | No | No | Yes | Yes | Yes | Yes | Yes | Yes | No | |
| **Feeney, A. E.** | 2017 | Cultural heritage, sustainable development, and the impacts of craft breweries in Pennsylvania | No | No | No | No | No | Yes | No | Yes | Yes | Yes | Yes | Yes | |
| **Grunde, J., Li, S., & Merl, R.** | 2014 | Craft Breweries and Sustainability: Challenges, Solutions, and Positive Impacts [Blekinge Institute of Technology] | No | No | No | No | No | Yes | No | Yes | Yes | Yes | No | Yes | |
| **Gursoy, D., Chi, C. G., & Dyer, P.** | 2010 | Locals' attitudes toward mass and alternative tourism: The case of Sunshine Coast, Australia | No | No | No | No | No | Yes | No | Yes | Yes | Yes | No | No | |
| **Hong, E., Lee, I. H., Sun, L., & Harrison, R.** | 2015 | Entrepreneurship across time and space: empirical evidence from Korea | Yes | Yes | No | No | No | Yes | Yes | No | Yes | Yes | No | No | |
| **Keeble, D., & Walker, S.** | 1994 | New Firms, Small Firms and Dead Firms: Spatial Patterns and Determinants in the United Kingdom | Yes | Yes | No | No | No | Yes | Yes | No | Yes | Yes | No | No | |
| **MacNeill, T., & Wozniak, D.** | 2018 | The economic, social, and environmental impacts of cruise tourism | Yes | No | No | No | No | Yes | No | Yes | No | Yes | Yes | No | |

| Authors | Year | Title | Empirical, data-driven | Causal inference | DiD | Staggered treatment | Heterogenous treatment effects | Large sample size | Event study | Business-to-community effect | Small business | Sustain-ability | Community-level impacts | Craft brewing | Notes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mir, D. F., & Feitelson, E.** | 2007 | Factors affecting environmental behavior in micro-enterprises: Laundry and motor vehicle repair firms in Jerusalem | No | No | No | No | No | Yes | No | Yes | Yes | Yes | Yes | No | |
| **Mullachery, P. H., Quistberg, D. A., Lazo, M., Indvik, K., Perez-Ferrer, C., López-Olmedo, N., Colchero, M. A., & Bilal, U.** | 2022 | Evaluation of the national sobriety checkpoints program in Mexico: a difference-in-difference approach with variation in timing of program adoption | Yes | Yes | Yes | Yes | No[5] | Yes | Yes | No | No | Yes | Yes | No | [5] Uses simple grouping to control for treatment homogeneity. |
| **Nilsson, I., & Reid, N.** | 2019 | The value of a craft brewery: On the relationship between craft breweries and property values | Yes | Yes | Yes | Yes | No[6] | No | Yes | Yes | Yes | Yes | Yes | Yes | [6] Uses a small geographic boundary to control for treatment homogeneity. |
| **Nilsson, I., Wartell, J., & Reid, N.** | 2020 | Craft Breweries and Neighborhood Crime: Are They Related? | Yes | Yes | No | No | No[6] | Yes | No | Yes | Yes | Yes | Yes | Yes | [6] Uses a small geographic boundary to control for treatment homogeneity. |
| **Ntloko, N. J., & Swart, K.** | 2008 | SPORT TOURISM EVENT IMPACTS ON THE HOST COMMUNITY: A CASE STUDY OF RED BULL BIG WAVE AFRICA | No | No | No | No | No | Yes | No | Yes | No | Yes | Yes | No | |
| **Orzechowski, P. E.** | 2023 | Small business administration loans, economic development, and state-level employment | Yes | Yes | Yes | Yes | No | Yes | Yes | No | Yes | Yes | No | No | |
| **Raftopoulou, A., & Giannakopoulos, N.** | 2021 | Unemployment and health: a panel event study | Yes | Yes | Yes | No | No | Yes | Yes | No | No | Yes | No | No | |
| **Rico-Straffon, J., Wang, Z., Panlasigui, S., Loucks, C. J., Swenson, J., & Pfaff, A.** | 2023 | Forest concessions and eco-certifications in the Peruvian Amazon: Deforestation impacts of logging rights and logging restrictions | Yes | Yes | Yes | Yes | Yes[4] | Yes | Yes | No | No | Yes | Yes | No | [4] Uses novel method "DiD$_l$" from (de Chaisemartin and D'Haultfœuille, 2022) |
| **Sobel, R. S., & Dean, A. M.** | 2008 | Has Wal-Mart buried mom and pop?: The impact of Wal-Mart on self-employment and small establishments in the USA | Yes | Yes | No | No | No | Yes | Yes | No | Yes | Yes | Yes | No | An older statistical inference technique is used: spatial autoregressive regression. |
| **Volpe, R., & Boland, M. A.** | 2022 | The Economic Impacts of Walmart Supercenters | Yes | N/A | N/A | N/A | N/A | Yes | N/A | No | No | Yes | Yes | No | Paper unavailable |
| **Wang, M., & Zhou, X.** | 2017 | Bike-sharing systems and congestion: Evidence from US cities | Yes | Yes | Yes | Yes | No[3] | Yes | Yes | Yes | No | Yes | Yes | No | [3] Uses propensity score matching to control for treatment homogeneity |
| **Xu, Q., Cao, K., Dai, J., Zhu, Y., & Dai, Y.** | 2023 | Nonlinear Effects of Eco-Industrial Parks on Sulfur Dioxide and Carbon Dioxide Emissions—Estimation Based on Nonlinear DID | Yes | Yes | Yes | Yes | No[2] | Yes | Yes | Yes | No | Yes | Yes | No | [2] Uses nonlinear hybrid regression to weight treatment homogeneity |
| **Zhumadilov, D.** | 2022 | Effect of Nuclear Power Plants on Local Crop Yields | Yes | Yes | Yes | Yes | No[1] | Yes | Yes | Yes | No | Yes | Yes | No | [1] Uses self-reported data to weight treatment effect homogeneity |

## 2.5 Conclusion

This chapter aimed to explain the sustainability context of craft brewers and provide a theoretical argument that the sustainability impacts of craft breweries on their host communities may be measurable. Literature on craft breweries to date establishes them as inefficient water and energy users when examined individually in case studies or during process analyses. However, it does not attempt to measure the industry systematically and quantitatively. Similarly, the broadly beneficial social aspects of craft breweries have been explored by researchers, but at small geographic scales. Meanwhile, researchers employing econometric methods have demonstrated the capability of DiD statistical methods to draw meaningful conclusions about the sustainability impacts of some industries at large geographic scales. Therefore, this thesis asks whether the sustainability impacts of the Ontario craft brewing industry – be they economic, environmental, or social – might be uncovered using econometric analysis. The next chapter introduces the methods for collecting and analyzing a comprehensive dataset to test this hypothesis.

# Chapter 3 – Methods

This thesis aims to collect and analyze data related to the sustainability impacts of craft breweries on their host communities. The analysis involves building a dataset from publicly available sources on the Ontario craft brewing industry with a parallel dataset on community sustainability and then aligning the two datasets across spatial and temporal dimensions. The objectives are to collect and analyze these datasets to determine whether the presence of a craft brewery in an Ontario community has a causal effect on that community's sustainability. These impacts can be related to economic outcomes like unemployment rate and average household income, social outcomes like populations of visible minorities and indigenous people, or environmental outcomes like air pollution. The methods chapter serves as a guide to the steps taken to achieve these goals and as an aid to replicability.

First, the construction of the two datasets required for the statistical analysis is explored.

## 3.1 Data Collection

### 3.1.1 Summary

Two data sets are needed to complete this study: one about breweries and another about Ontario communities. Each one is collected independently and contains different kinds of information. The brewery dataset should list every craft brewery in Ontario, the date it was founded, its location, and any other characteristics that might prove helpful during an analysis – like whether it has a restaurant on-premises or is highly rated by beer aficionados. The community dataset should list every community in Ontario along with measurements of sustainability factors within that community – and do so over a 20-year timespan. A 20-year timespan was chosen as it encompasses nearly the entire existence of the craft brewing industry in Ontario. The datasets are linked together for statistical analysis along two common dimensions: one of physical location and another of time. If it is known where a brewery is located and when it was founded, then it might be possible to determine what impacts that brewery had on its host community.

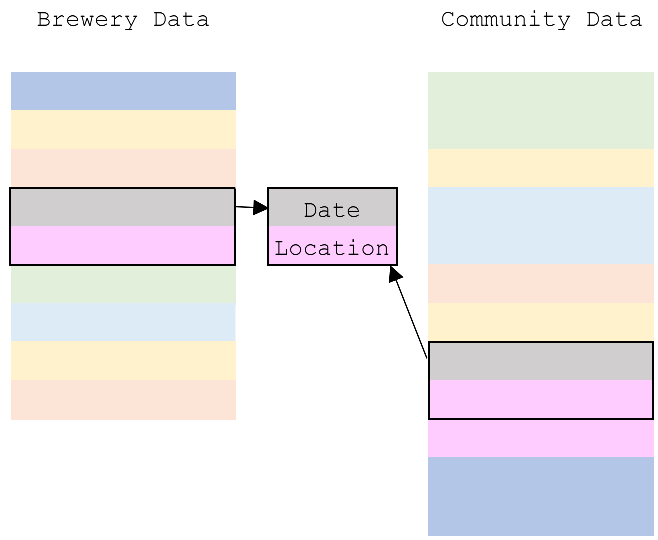



*Figure 2 Block diagram showing the collected datasets and their primary connections of date and geography*

The data for this thesis comes from three primary sources: public data from the internet, public data from Statistics Canada (StatCan), and research data from the Canadian Urban Environmental Health Research Consortium (CANUE). The first source, public data from the internet, comprised the brewery dataset. The remaining three sources comprised the community sustainability dataset.

### 3.1.2 Brewery Data Sources

Gathering a canonical list of every Ontario craft brewery containing the required spatiotemporal data is challenging. While the provincial government must license every producer of alcohol in Ontario, authorities do not maintain a publicly-available historical list. The Government of Ontario Finance Ministry maintains a list only of currently licensed breweries, and historical records are unavailable. This thesis used a downloadable comma-separated variable (CSV) version of the "Beer manufacturers, microbrewers and brands" document containing 485 licensed craft brewers with their registered names (Ontario Ministry of Finance, 2022a). Presence in the Ontario Finance Ministry list does not guarantee that the brewer is currently in business. No data other than the names were used. Data from this list was not incorporated into the primary brewery dataset but was used to check brewery names obtained in the next step.

Social media sites designed for craft beer aficionados are an alternative source of information on craft breweries. Three of the largest craft beer social media networks are Untappd, Beer Advocate, and RateBeer. The Next Glass company owns the first two, and the third is owned by a venture capital subsidiary of corporate brewer Anheuser-Busch InBev SA/NV. These websites and their accompanying smartphone applications allow users to upload data about breweries and beer offerings, creating an accurate consensus-based directory of craft breweries worldwide. Brewery owners are incentivized to upload accurate business information to these websites. Typical data about breweries on craft beer social media websites include street addresses, whether the business is a brewery, taproom, or brewpub, and user ratings. RateBeer was chosen as the primary social media source as it has a website that is publicly accessible without login, contains data on nearly 550 Ontario craft breweries, and proved amenable to automated data collection.

Information about Ontario craft breweries from RateBeer was retrieved with computer programs developed by the author that automatically browsed the webpage and saved relevant data to a spreadsheet file in a process commonly called "scraping". In all cases with data collected from RateBeer, the webpages themselves were accessible to anyone with an internet connection. They did not require an account or login credentials, indicating no expectation of privacy. The scraping process generated a data file that became the foundation of the brewery dataset and contained 448 breweries after automated and manual cleaning and de-duplication. Because RateBeer includes brewery street addresses, the dataset now contained the first required piece of data: geographic location. The other required information – date of founding and business closure – would require another data source.

Canada's Business Registries is a public search engine which provides names, locations, and dates of founding and dissolution of registered businesses in Canada. The website is a federal-provincial-territorial collaborative initiative with the Canadian Association of Corporate Law Administrators. By entering the name of a craft brewery into this search engine, one can collect the temporal characteristics required for the analysis. Similar to how the RateBeer data was collected, the author created a computer program to automate the search and collection process. The source of names used in the search was the Ontario Finance Ministry list.

In some cases, manual searches of the Canada’s Business Registries website were required because the brewery names in the Ontario Finance Ministry list did not match the name used in the business registration document. Any brewery present in the RateBeer list but not in the Ontario Finance Ministry list was also added to the search, and all entries were manually checked for accuracy. Founding and closure dates for 417 Ontario breweries were collected in this manner.

The spatiotemporal brewery dataset was created by merging entries from the RateBeer and Canada's Business Registries datasets. Due to slight mismatches in business names, fuzzy matching was used. After eliminating duplicate entries and all meaderies, wineries, and cideries from the dataset, 353 breweries remained. The merging process was performed programmatically, with no manual intervention.

*Table 3 Ontario Craft Brewery Dataset, variables list*

| NAME | LABEL | N | ANNOTATIONS | VALUE TYPE | DATA |
|---|---|---|---|---|---|
| **breweryType** | Business type | 353 | Brewery Administrative Info | Textual | RateBeer |
| **BusinessName** | Canonical brewery name, fuzzy match to baName | 353 | Brewery Administrative Info | Textual | RateBeer |
| **Rating** | Score on RateBeer by social media users | 279 | Brewery Feature | Integer | RateBeer |
| **NumRatings** | Count of ratings | 353 | Brewery Feature | Integer | RateBeer |
| **Open** | Is brewery open? Crowdsourced | 353 | Brewery Feature | Boolean | RateBeer |
| **Addr** | Full street address of brewery | 353 | Brewery Administrative Info | Textual | RateBeer |
| **Patio** | Presence of patio at brewery | 353 | Brewery Feature | Integer | RateBeer |
| **Postal_code** | Six-digit postal code of brewery | 353 | Brewery Administrative Info | Textual | RateBeer |
| **lat** | Latitude of CSD center | 353 | Brewery Administrative Info | Float | StatCan / PCCF |
| **long** | Longitude of CSD center | 353 | Brewery Administrative Info | Float | StatCan / PCCF |
| **CSDuid** | Derived CSD of brewery | 353 | Brewery Administrative Info | Textual | StatCan / PCCF |
| **GeoUID** | Copy of CSDuid, for harmonization | 353 | Brewery Administrative Info | Textual | StatCan / PCCF |
| **ofcName** | Ontario official business name | 353 | Brewery Administrative Info | Textual | Canada's Business Registries |
| **dbaName** | Ontario doing-business-as name | 353 | Brewery Administrative Info | Textual | Canada's Business Registries |
| **BusinessNumber** | Ontario Business registration ID | 273 | Brewery Administrative Info | Integer | Canada's Business Registries |
| **RegBusinessType** | Ontario business type | 279 | Brewery Feature | Textual | Canada's Business Registries |
| **Created** | Date business registered | 352 | Brewery Feature | Date | Canada's Business Registries |
| **Closed** | Date business registration ended | 352 | Brewery Feature | Date | Canada's Business Registries |

### 3.1.3 Community Sustainability Data – Level of Geography

The other dataset required for analysis is a community dataset of various sustainability indicators over time. The name for a dataset of this kind is a panel dataset. Each row in the panel dataset used in this thesis corresponds to a single community in Ontario in a single period: the census year. A researcher must make an important choice when assembling a panel dataset: the level and type of geographic granularity. The census subdivision (CSD) is a standard geographic area that StatCan defines as roughly equivalent to a community boundary. When collecting data at the level of a Canadian town, municipality, or city, StatCan commonly uses the CSD – and has done so consistently since 1999. There are 575 CSDs of widely varying size and population in Ontario, about 100 of which have at least one brewery. Figure 3 below is a map of Ontario CSDs with and without breweries. Note that CSDs vary in size, and more northern CSDs tend to be larger in area. Southern CSDs, where most of Ontario's population resides, contain most craft breweries.

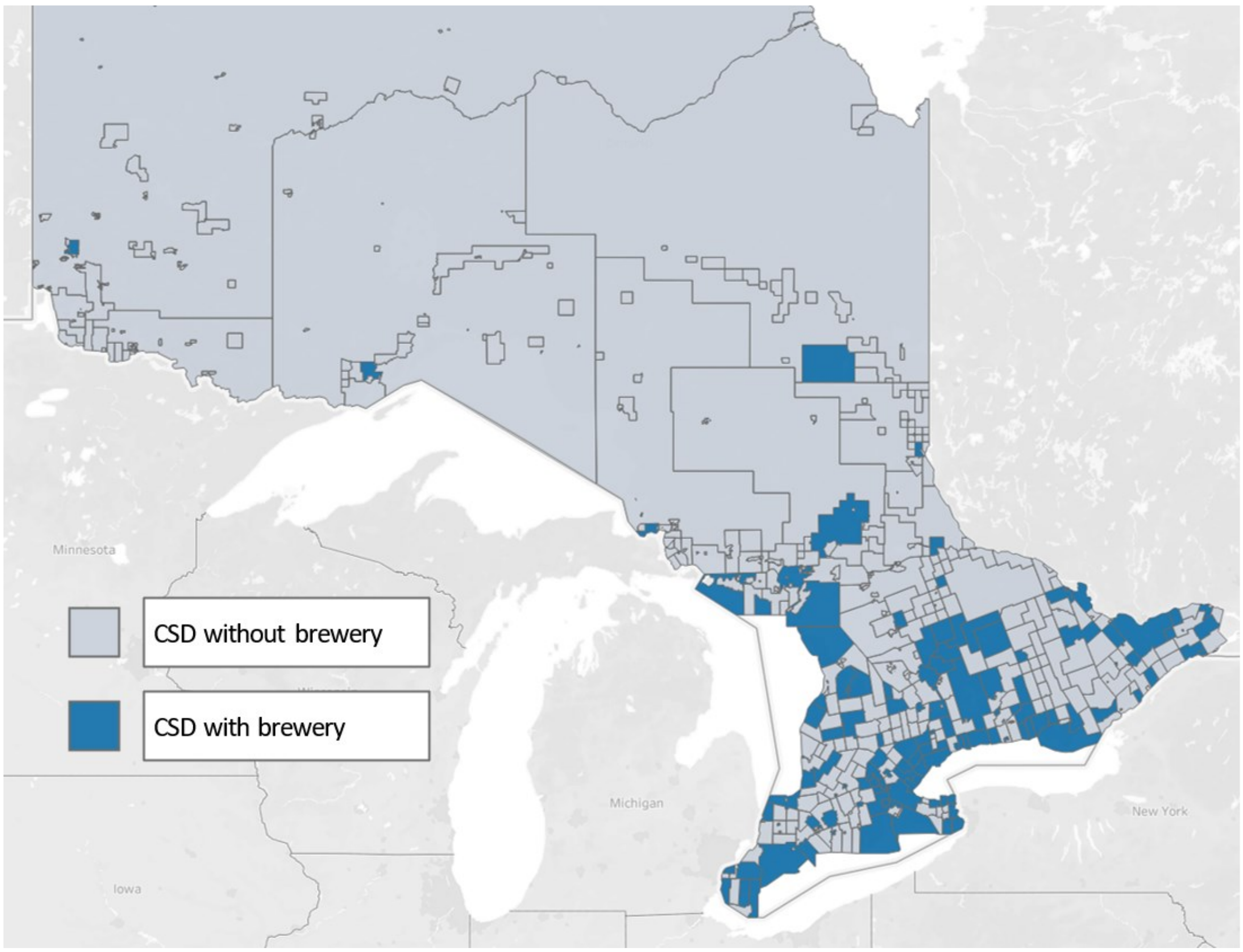



*Figure 3 Ontario Craft Breweries Map, 1984-2022 by CSD.*
*Note the roughly equal area of CSDs in urban areas, encompassing communities despite differences in population and density*

### 3.1.4 Community Sustainability Data – Statistics Canada Sources

Just like the brewery dataset, measurements of sustainability-related factors require location and time dimensions. The community sustainability dataset must list every community in Ontario together with measurements of sustainability factors within that community – and do so over the 20-year timespan that encompasses the presence of the Ontario craft beer industry. An ideal data source is the Canadian Census. The Canadian Census is administered by Statistics Canada (StatCan), an agency of the Government of Canada, and occurs every five years. Data was collected from 1996, 2001, 2006, 2011, 2016, and 2021 censuses, as these years nearly encompass the entire period of the craft brewing industry's existence in Ontario. A critical limitation is that while this gives the dataset 25 years of coverage, it only contains six data collection points, with five-year gaps between them.

StatCan collects and reports data on hundreds of factors, those of interest being social and economic variables such as population, income, demographics, education, and employment. An essential step in collecting data from the Canadian Census was determining which variables StatCan collected in all six census periods. For example, if StatCan collected an interesting variable only in the 2016 Census, it cannot be used in the analysis. After eliminating these incomplete variables, a total of twenty-eight remained. Nine variables contained administrative or geographic information valuable for the analysis, and nineteen variables contained socio-demographic data relevant to the sustainability characteristics of Ontario communities. Details on the variables can be found in Table 4.

Data from the Canadian Census was gathered programmatically, using the *cancensus* library for R (von Bergmann et al., 2021. StatCan does not have a public application programming interface (API) for census data gathering, so the *cancensus* library uses the CensusMapper API. CensusMapper is a free, third-party web service that stores and delivers all public data from the Canadian Census from 1996 through 2021. This API is consistent, reliable, and repeatable and has been used many times by other researchers (Armstrong et al., 2021; Cucuzzella et al., 2022; Forté et al., 2021; Swett, 2018; VandenBrink, 2019). API usage limits prevent users from collecting large amounts of data simultaneously, so downloaded census data was cached within the development environment. Over several months, data were collected by R programs developed by the author through the API. Some datasets were too large to download through the CensusMapper API. They were downloaded manually as a CSV or IVT file (a multidimensional data format for the Beyond 20/20 software) from the StatCan website and imported into the dataset using R.

Another geographic data variable added to the dataset from StatCan was the 2016 and 2021 index of remoteness, a composite score of a CSD's remoteness that can be used to determine relative measures of urbanity or rurality. StatCan states, "The Index of Remoteness is determined by the distance that separates a community from all the population centres in a given travel radius, as well as the population size of these centres" (Statistics Canada, 2023a. This variable was downloaded and added to the dataset using the *cansim* R library (von Bergmann & Shkolnik, 2022a. No indirect API access is needed because *cansim* connects directly to StatCan's central socioeconomic time series database (von Bergmann & Shkolnik, 2022b. A critical value in the Index of Remoteness is an index value of 0.4 or above, indicating rural areas; while values under 0.4 could be considered urban or semi-urban (Alasia et al., 2017). The critical value of 0.4 is about 70% of the total Index of Remoteness scale value.

### 3.1.5 Community Sustainability Data – CANUE Data

While StatCan has comprehensive coverage of socio-demographic information, the organization collects very little environmental data at the level of granularity equivalent to the CSD. This lack of collection applies to the census and any other statistical collection program undertaken by StatCan. A comprehensive environmental dataset with an appropriate level of geographic granularity was thus sought and identified.

The Canadian Urban Environmental Health Research Consortium (CANUE) is an interdisciplinary collaboration to advance understanding of how the urban environment affects human health. The non-governmental consortium is funded by the Canadian Institutes of Health Research and is affiliated with the University of Toronto, the University of Victoria, and Compute Canada. Approved researchers can request from CANUE comprehensive sets of environmental and health data, such as air pollution, water demand, and composite human health indices. While CANUE focuses on understanding the complex relationships between the environment, human health, and sustainability in urban environments, many of their datasets are available outside urban areas or cover all of Ontario. The author completed a data access request and was permitted access to CANUE data as needed for this thesis.

Unlike the Canadian Census data, variables provided by CANUE have varying collection dates. Many variables have data collected at only two points in time, while others follow the census data years, and some collect data yearly. CANUE data years begin in 2000 and end in 2019, though most end in 2016. These varying dates limit the ability to make causal inferences about environmental impact.

Spatially, the CANUE data has been harmonized to six-digit postal codes – a level of geographic granularity more detailed than the project standard of CSD. These postal codes were geocoded into CSDs for integration into the community sustainability dataset - a discussion of how postal codes were mapped to CSDs is in Section 3.2, Data Harmonization. In total, seventy-two variables were downloaded, thirty-two of which ended up in the final dataset after removing duplicates and invalid entries. Details on the variables can be found in Table 4.

*Table 4 Community Sustainability Dataset, variables list.*
*All variables were collected, but not all were used in the statistical analysis*

| Name | Label | Annotations | Type of value | Geography | Data | Years with Data |
|---|---|---|---|---|---|---|
| **ALE_01** | Unique identifier of the dissemination area (eight digits) | Geographic | Decimal | Postal code | CANUE | 2006, 2016 |
| **ALE_06** | ALE Index | Chemical Exposure | Decimal | Postal code | CANUE | 2006, 2016 |
| **CMG_04** | Dissemination/Enumeration area unique identifier | Geographic | Decimal | Postal code | CANUE | 2001, 2006, 2016 |
| **CMG_05** | Maximum Distance from Postal Code to Nearest Dissemination Area | Geographic | Decimal | Postal code | CANUE | 2001, 2006, 2016 |
| **CMG_10** | Principal Component Factor Score - Instability | Chemical Exposure | Decimal | Postal code | CANUE | 2001, 2006, 2016 |
| **CMG_11** | Principal Component Factor Score - Deprivation | Chemical Exposure | Decimal | Postal code | CANUE | 2001, 2006, 2016 |
| **CMG_12** | Principal Component Factor Score - Dependency | Chemical Exposure | Decimal | Postal code | CANUE | 2001, 2006, 2016 |
| **CMG_13** | Principal Component Factor Score - Ethnic Concentration | Chemical Exposure | Decimal | Postal code | CANUE | 2001, 2006, 2016 |
| **GRLAN_01** | Annual Mean Value at Postal Code | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2019 |
| **GRLAN_05** | Annual Mean of Means 1000m | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2019 |
| **GRLAN_09** | Annual Max of Means 1000m | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2019 |
| **LCZ_01** | Local Climate Zone at Postal Code | Chemical Exposure | Textual | Postal code | CANUE | 2001, 2006, 2011, 2016 |
| **LCZ_02** | Dense Urban (% of pixels in 1 km2) | Chemical Exposure | Decimal | Postal code | CANUE | 2001, 2006, 2011, 2016 |
| **LCZ_03** | Open Urban (% of pixels in 1km2) | Chemical Exposure | Decimal | Postal code | CANUE | 2001, 2006, 2011, 2016 |
| **LCZ_04** | Residential (% of pixels in 1km2) | Chemical Exposure | Decimal | Postal code | CANUE | 2001, 2006, 2011, 2016 |
| **LCZ_05** | Industrial-Commercial-Paved (% of pixels in 1km2) | Chemical Exposure | Decimal | Postal code | CANUE | 2001, 2006, 2011, 2016 |
| **LCZ_06** | Natural (% of pixels in 1km2) | Chemical Exposure | Decimal | Postal code | CANUE | 2001, 2006, 2011, 2016 |
| **LCZ_07** | Water (% of pixels in 1km2) | Chemical Exposure | Decimal | Postal code | CANUE | 2001, 2006, 2011, 2016 |
| **LCZ_08** | Unknown (% of pixels in 1km2) | Chemical Exposure | Decimal | Postal code | CANUE | 2001, 2006, 2011, 2016 |
| **LGTNLT_01** | Nighttime Light Brightness at Postal Code | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2013 |
| **NO2LUR_01** | Original LUR Annual Average Concentration at Postal Code (ppb), Circa 2006 | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2016 |
| **NO2LUR_02** | Annual Average NO2 Concentration at Postal Code (ppb) | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2016 |
| **O3CHG_01** | O3 Annual average (ppb) | Chemical Exposure | Decimal | Postal code | CANUE | 2002 to 2015 |
| **O3CHG_02** | O3 Warm Season (May-Sept) Average (ppb) | Chemical Exposure | Decimal | Postal code | CANUE | 2002 to 2015 |
| **O3CHG_03** | O3 Annual Average of the Highest Rolling 8-Hour Average Per Day (ppb) | Chemical Exposure | Decimal | Postal code | CANUE | 2002 to 2015 |
| **PM25DAL_01** | Annual average PM2.5 Concentration (ug/m3) | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2012 |
| **PM25DAL_02** | Annual Average PM2.5 Concentration (ug/m3) within 10km | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2012 |
| **PM25DALB_01** | Annual average PM2.5 concentration (ug/m3) version2 | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2016 |
| **SO2OMI_01** | 3 Year Annual Average SO2 Concentration (ppb) | Chemical Exposure | Decimal | Postal code | CANUE | 2007 to 2015 |
| **WBNRC_04** | Annual Total Rainfall (mm) | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2015 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **WBNRC_05** | Annual Total Snowfall (mm) | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2015 |
| **WBNRC_13** | Annual Total Potential Evapotranspiration (mm) or Water Demand | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2015 |
| **WBNRC_14** | Annual Total Acutal Evapotranspiration (mm) | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2015 |
| **WBNRC_15** | Annual Total Surplus (mm) | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2015 |
| **WBNRC_16** | Annual Total Deficit (mm) | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2015 |
| **WBNRC_20** | Average of Monthly Minimum Soil Moisture (%) | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2015 |
| **WBNRC_22** | Relative Index of Wetness/Dryness | Chemical Exposure | Decimal | Postal code | CANUE | 2000 to 2015 |
| **GeoUID** | 6-digit CSD or Census Subdivision. Named GeoUID for convenience | Geographic | Textual | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **RegionName** | StatCan name of CSD | Geographic | Textual | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **Area** | Size of CSD in km2 | Geographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **Population** | Total population of CSD | Geographic | Integer | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **Dwellings** | Total dwellings of CSD | Geographic | Integer | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **Households** | Total households of CSD | Geographic | Integer | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **CD_UID** | 4-digit Census division | Geographic | Textual | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **PR_UID** | 2-digit provincial identifier | Geographic | Textual | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **CMA_UID** | 3- or 5-digit Census Metropolitan Area, if CSD is located in one | Geographic | Textual | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **medHHinc** | Median household income | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **avgHomeValue** | Average value of dwellings, non-farm and non-reserve | Sociodemographic | Average | Decimal | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **Year** | Year of data collection | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **FSA** | Derived: 3-digit post code. From: CSD. Via: PCCF | Geographic | Textual | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **LICOat** | % per capita below low-income cutoff, after taxes | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **oLang_firstEnglish** | % per capita who speak English as first language | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **oLang_firstFrench** | % per capita who speak French as first language | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **age_young** | % per capita aged 0-14 | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **age_working** | % per capita aged 15-64 | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |

| | | | | | | |
|---|---|---|---|---|---|---|
| **age_youngAdult** | % per capita aged 20-34 | Sociodemographic | per capita | Decimal | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **age_elder** | % per capita aged 64+ | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **citImm_Citizens** | % per capita who are Canadian citizens | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **citImm_Immigrants** | % per capita who are/were immigrants | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **aboriginalID** | % per capita with aboriginal status | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **visMinority** | % per capita with visible minority | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **edu_none** | % per capita without HS diploma | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **edu_HSdip** | % per capita with HS diploma | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **edu_higherEd** | % per capita with any kind of post-HS diploma or certification | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **unemploymentRate** | % per capita unemployed | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **workersNoFixedAddr** | % per capita who work at no fixed address | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **workersUsualPlace** | % per capita who work at a usual location | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **mobility5** | % per capita who have moved to current CSD within the past 5 years | Socio-demographic | Decimal | CSD | Census Canada | 1996, 2001, 2006, 2011, 2016, and 2021 census |
| **Remoteness** | Remoteness index, higher is more remote | Geographic; Sociodemographic | Decimal | CSD | StatCan | 2016, 2021 |

## 3.2 Data Harmonization and Geo-Temporal Alignment

The two completed datasets – breweries and community sustainability – incorporate information from multiple sources. Each source has a different style of formatting and organization. This section details the steps taken to clean and harmonize the dataset and how these steps impact the data quality.

Assembling a dataset that includes all three pillars of sustainability – social, economic, and environmental – presents significant difficulties due to using multiple data sources. Chief among those challenges is geographic alignment or geocoding. Remember that the chosen geographic identifier is the census subdivision or CSD. Therefore, every row in each dataset must include a single CSD number which accurately places the row's data within the community in which it occurs. However, not all data sources encode their geography at the CSD level, necessitating alignment.

Data collected from Statistics Canada has no issue with geographic alignment, as each data point was collected at the CSD level. As the primary dataset to which other data is aligned and appended, the StatCan dataset contains administrative and socio-demographic data. Administrative data includes the CSD number, year, name of the region, area in square kilometres, and the population at the time of data collection. The rest of the StatCan data includes social and economic data but no data on environmental factors or public health data.

Data collected from social media sites on breweries and CANUE on environmental exposure are all geographically specified by a six-digit postal code. Using postal codes as a geographic identifier poses problems because they are not based on geographic boundaries or community identifiers but rather on the volume of postal deliveries in a specific area. Using boundaries of postal routing would not align with the thesis goals of measuring community impact.

Further complicating the issue is that postal code geography does not always correspond to census geography. In other words, postal codes do not respect CSD boundaries, and a single postal code may be linked to multiple CSDs. Luckily, research has shown that over 88% of all Ontario postal codes link to a single CSD (Pinault et al., 2020). A 2004 estimate of the minimum geocoding rate for spatial analysis showed that 85% was acceptable (Ratcliffe, 2004). That remains a gold standard in the field. However, a 2020 study suggests that the minimum acceptable hit rate should be higher when geocoding errors are non-uniform – such as the common tendency for rural areas to have worse geocoding accuracy (Briz-Redón et al., 2020). Strong theoretical support exists that converting postal codes into CSD can enable reliable mathematical analysis.

In Canada, StatCan publishes the Postal Code Conversion File (PCCF). This database file allows for the linkage of six-character postal codes to CSDs, among other standard geographic identifiers like latitude and longitude pairs (Statistics Canada, 2023b). Because postal codes shift over time, StatCan publishes yearly updates to the PCCF file to reflect these changes (Canadian Institute for Health Information, 2018). To accurately link postal codes to CSDs in the datasets assembled for this thesis, the author obtained PCCF files from the University of Waterloo Geospatial Centre for the following years: 2006, 2010, 2015, and 2022. These correspond well to the 2006, 2011, 2016, and 2021 census years. The brewery postal codes were converted easily to CSDs using the PCCF file because most breweries are located in urban or semi-urban areas where postal codes map to a single CSD. Converting CANUE data from postal codes to CSDs has a potentially greater risk of missing links because that data covers all of Ontario. Nevertheless, missing links between postal codes and CSDs in the CANUE dataset were rare, with 0.0013% missing data in the worst case, as shown in Table 5 below.

*Table 5 CANUE data dropped due to missing links during postal code-to-CSD conversion.*

| Dataset Name | Dataset Content | Total Dropped Due to Missing PCCF Links | % Missing |
|---|---|---|---|
| **ALE** | ALE Indices | 0 | 0.0000% |
| **CMG** | Canadian marginalization indices | 0 | 0.0000% |
| **GRLAN** | Greenness indices | 12 | 0.0011% |
| **LCZ** | Local Climate Zone | 7 | 0.0006% |
| **LGTNLT** | Nighttime Light Brightness | 0 | 0.0000% |
| **NO2LUR** | NO2 Concentration | 12 | 0.0011% |
| **O3CHG** | O3 Concentration | 11 | 0.0010% |
| **PM25DAL** | PM2.5 concentration | 9 | 0.0008% |
| **SO2OMI** | SO2 Concentration | 11 | 0.0013% |
| **WBNRC** | Water balance metrics | 9 | 0.0008% |

## 3.3 Statistical Methods

As discussed in Section 2.3, Review of Spatiotemporal Assessment Literature, this thesis aims to mathematically investigate craft brewers' sustainability impacts on their host communities by establishing causal inference. The dataset collects variables for time and place – the founding dates of breweries and their host communities. Causal inference requires a study design that can argue that nothing else happened at the same time and place that could have affected the community sustainability measurements other than the presence of a brewery. These identifying assumptions arise from the study parameters and the collected data's boundaries. This section uses study parameters to create identifying assumptions arguing in favour of a causal interpretation of the results. The assumptions also delineate the statistical methods that will comprise an equation generating results.

In summary, given the parameters of the data collected and the industry itself, a difference-in-differences (DiD) statistical analysis method with Sun & Abraham estimators will be used. This section explores how this technique is implemented in practice and the rationale for decisions made when constructing the analysis.

### 3.3.1 Research/Mathematical Design

#### *3.3.1.1 Difference-in-Differences Study Designs and Panel Data*

At its most basic, estimating causal effects in DiD studies involves comparing the changes in an outcome variable between a treatment group and a control group over time. In classical experimental designs, the treated and control groups are assigned by the investigators. In this observational study, treated and control groups are not actively assigned but instead identified within a dataset. As a result, it would be more accurate to refer to the different groups in this thesis as “affected” and “non-affected”. The terms “treated” and “control” will be used for simplicity and conceptual clarity, even though they are not strictly accurate. Due to study design limitations, once a community is assigned to the treatment group, it cannot leave that group – a condition known as “absorbing treatments”. A discussion of the implications of absorbing treatments can be found in Section 5.3.

The treatment group contains communities with craft brewers, and the treatment itself (also known as an intervention) is the founding of a craft brewery within a community. Control groups are communities without craft brewers, a condition sometimes called “never treated”. A statistical comparison between these two groups can be used to isolate the impact of treatment from other factors that may influence the outcome. By comparing the differences between these two groups before and after an intervention, an estimate of the causal effect of the intervention on the outcome may be calculated. Outcome variables can be any measured value connected to a craft brewery's impact within a community.

*Table 6 Difference-in-differences Study Parameters and Panel Data, data year 2021*

| DiD Study Parameter | Panel Data Equivalent | Source Dataset | Count | Data Format |
|---|---|---|---|---|
| Outcome variable | Any column of sustainability data measurement | Community sustainability | 56 possible variables | Decimal percentage, integer |
| Treatment group | Any CSD with a brewery | Match between community sustainability and brewery | 126 | Categorical 7-digit value |
| Control group | Any CSD without a brewery | Match between community sustainability and brewery | 412 | Categorical 7-digit value |
| Intervention date | The founding year of a brewery | Brewery | 353 [1984-2022] | 4-digit year plus two time dummy variables |

#### *3.3.1.2 Controls in DiD Studies*

The sustainability impacts experienced by a host community with a craft brewery may stem from factors other than the brewery itself, including anthropogenic and natural causes. DiD study designs using the Sun & Abraham estimator use several forms of controls as part of an ordinary least squares (OLS) regression to create mathematical baselines that are theoretically free of these confounding effects. In other words, an equation can be constructed that predicts the outcome variable in the absence of a brewery by observing the outcomes in control groups. Then, estimates of the causal effect are generated by comparing the actual outcome to that prediction baseline. The careful selection of controls ensures that the estimates are meaningful and robust rather than coincidental. For example, suppose a researcher wishes to measure the impact of breweries on water quality. In that case, the researcher should control for the amount of rainfall which could affect the concentration of pollutants when measured. However, the researcher should not control for rates of tobacco consumption because that does not have a causal link to water quality. These kinds of controls are called exogenous controls. Due to the wide selection of variables analyzed in this thesis, the selection of exogenous controls is difficult or impossible due to the large number of variables that might have causal links to sustainability outcomes.

Another kind of control in DiD studies are fixed effects. For each outcome variable of interest, there must also be controls for the temporal and geographic aspects of breweries so that each combination of time and location can serve as its own baseline. These baseline controls are fixed effects, which control for observed or unobserved factors within those groups. Geographic or spatial fixed effects control for the differences between communities. For example, if there are two similar towns located near each other and one has a factory while the other does not, the former might be expected to have more air pollution than the latter. A spatial fixed effect can subtract or demean these differences, thereby controlling for them. Similarly, time-based or temporal fixed effects control for the trends that occur over time, like broad macroeconomic trends or the effect of new laws that apply across all of Ontario at a particular time. The following section explains how these fixed effects are used in OLS regressions.

#### *3.3.1.3 Two-Way Fixed Effects Regressions*

Practically, causal effect estimates are generated from ordinary least squares (OLS) regressions. In this thesis, the OLS regressions are mathematical formulas that test whether the presence of a brewery within a community or over time within a community is associated with a specific sustainability measurement after controlling for local and time-varying baselines. This thesis uses OLS regressions with a set of fixed effects to construct local and time-varying baselines for sustainability variables of interest in communities without craft breweries against which anomalous measures of sustainability variables of interest associated with communities with craft breweries are estimated. Two forms of OLS regressions are used in the study. Equation 1 is a two-way fixed effects (TWFE) regression with leads and lags of treatment, a statistical method commonly used when treatments do not occur at a single point in time (i.e. they are staggered). This equation is convenient for introducing DiD designs, but note that it was not used to create the results in this thesis.

*Equation 1 TWFE regression with leads and lags of treatment, as implemented with the* did *library.*

$$Unemployment_{it} = \alpha_i + \alpha_t + \sum_{l=-K}^{-2} \beta_l D_{it}^{l} + \sum_{l=0}^{L} \beta_l D_i t^{l} + \epsilon_{it}$$

Where:

- $Unemployment_{it}$ is the measurement of interest in some treated CSD $i$ in year $t$
- $\alpha_i$ are the spatial fixed effects
- $\alpha_t$ are the temporal fixed effects
- $\sum_{l=-K}^{-2} \beta_l D_{it}^{l}$ is the leads term:
    - $K$ is the number of leading periods
    - $D_{it}^{l}$ is the “relative time” term for being $l$ time periods leading $i$’s initial treatment time. $l$ is a relative time indicator equivalent to $t-1$ or $t+4$, and treatment time is when $l = 0$

    - $\beta_l$ is a regression estimand
- $\sum_{l=0}^{L} \beta_l D_i t^l$ is the lags term:
    - $L$ is the number of lags
    - $D_i t^l$ is a time indicator for the presence of a brewery
    - $\beta_l$ is a regression estimand
- $\varepsilon_{it}$ is the error term

#### *3.3.1.4 Cohort Event Study Regressions using Sun & Abraham (2021) Estimates*

Sun & Abraham (2021) argue that the technique used in Equation 1 gives results that may be biased because treatment effects from other time periods can contaminate the lead and lag coefficients ($\beta_l$). Their technique, represented in Equation 2, avoids lead and lag contamination and softens some of the required assumptions in the experimental setup.

*Equation 2 Sun & Abraham-type cohort regression, as implemented with the* fixest *library*

$$Unemployment_{it} = \alpha_i + \alpha_t + \sum_{e} \sum_{l \neq -1} \delta_{el}(1\{E_i = e\} \cdot D_{it}^{l}) + \epsilon_{it}$$

Where:

- $Unemployment_{it}$ is the measurement of interest in some treated CSD $i$ in year $t$
- $\alpha_i$ are the spatial fixed effects
- $\alpha_t$ are the temporal fixed effects
- $\sum_e \sum_{l \neq 1} \delta_{el}(1\{E_i = e\} \cdot D_{it}^{l})$ is the interaction weighting term which sums the cohort effects $e$ at all periods except the one immediately preceding treatment
- $1\{E_i = e\}$ is the cohort term, which is interacted with $D_{it}^{l}$, the “relative time” indicator. $E_i$ is a treatment date, and $e$ is a cohort indicator that shares the same treatment date as $E_i$.
- $\delta_{el}$ is a cohort regression estimand
- $\varepsilon_{it}$ is the error term

The purpose of this equation is to generate $CATT_{el}$, an interaction-weighted estimator for all cohort-time combinations in Equation 2. CATT stands for “cohort-specific average treatment effect on the treated”. This value represents the direction and magnitude of a brewery’s impact. In this example, it is the average effect on unemployment in a community when its first brewery is founded. Equation 1 and Equation 2 look very different when implemented in R code, due to syntax requirements and the conceptual abstractions of R library functions. Below is an example of the R code equivalent of Equation 1, using the *fixest* library:

```r
twfeReg <- fixest::feols(unemploymentRate)
~ 1
+ i(time_to_treatment, ref = c(-5, -1000))
| GeoUID + Year,
csdCDdata)
```

where *twfeReg* is a data structure that holds the regression results; *fixest::feols* is the *fixest* library function for a fixed effects OLS regression; *unemploymentRate* is the sustainability variable of interest – in this case, the unemployment rate in a CSD; *1* is a dummy exogenous control (when exogenous controls are used, the *1* is replaced with one or more variables representing the controls); the *i()* term is the TWFE interaction that excludes the period just before treatment (-*5*) and the never-treated (-*1000*); *time_to_treatment* is the relative time measure that allows for staggered treatments; *GeoUID* is the location fixed effect; *Year* is the time fixed effect; and *csdCDdata* is the panel dataset name.

Below is an example of the R code equivalent of Equation 2, using the *fixest* library:

```r
sa20RegRT <- fixest::feols(unemploymentRate)
~ 1
+ sunab(year_treated, Year)
| GeoUID + Year,
csdCDdata)
```

where *sa20RegRT* is a data structure that holds the regression results; *fixest::feols* is the *fixest* library function for a fixed effects OLS regression; *unemploymentRate* is the sustainability variable of interest – in this case, the unemployment rate in a CSD; *1* is a dummy exogenous control; *sunab* is the *fixest* library function to generate Sun & Abraham estimates; *year_treated* is a *sunab* time dummy variable equivalent to the census year in which the CSD first got a brewery and defines the cohort; *Year* is a *sunab* time period variable; *GeoUID* and *Year* are the location and time fixed effects; and *csdCDdata* is the panel dataset name.

#### 3.3.1.5 Managing Treatment Effect Heterogeneity in Sun & Abraham (2021) Estimates with Interaction Terms

A common issue affects Equation 1 and Equation 2: neither has a method to deal with treatment effect heterogeneity, the inescapable differences in effect between breweries in urban areas and those in rural areas. The fixed effects terms in Equation 1 and Equation 2 do control for the known group means within a single community and over time (examples: a slight decrease in unemployment in one town but an increase in a town nearby; or the implementation of new Ontario craft brewery tax legislation in 2019), but otherwise assume that all communities in Ontario are similar to each other.

Adding a term that interacts rurality with time helps to define and account for the effect of rurality and urbanity levels of communities on the breweries' impact while also controlling for trends that occur over time within those pseudo-groups of communities. The specific variable used for remoteness and rurality is the level of *Remoteness* converted into deciles. A notable advantage of using the interaction term is that the output of the updated OLS regression applies to the entire study area, which makes understanding the result easier. Using a single analysis group means the equation incorporates the largest sample size possible for maximum statistical robustness.

*Equation 3 Sun & Abraham-type cohort regression with the rurality-time interaction term, as implemented with the* fixest *library*

$$Impact_{itr} = \alpha_i + \alpha_t + \alpha(t \times r) + \sum_{e} \sum_{l \neq -1} \delta_{el}(1\{E_i = e\} \cdot D_{it}^{l}) + \epsilon_{itr}$$

Where:

- $Impact_{itr}$ is the measurement of interest in some treated CSD $i$ in year $t$, incorporating the CSD rurality decile value $r$
- $\alpha_i$ are the spatial fixed effects
- $\alpha_t$ are the temporal fixed effects
- $\alpha(t \times r)$ is the rurality-time interaction term
- $\sum_e \sum_{l \neq 1} \delta_{el}(1\{E_i = e\} \cdot D_{it}^{l})$ is the interaction weighting term which sums the cohort effects $e$ at all periods except the one immediately preceding treatment
- $1\{E_i = e\}$ is the cohort term, which is interacted with $D_{it}^{l}$, the “relative time” indicator. $E_i$ is a treatment date, and $e$ is a cohort indicator that shares the same treatment date as $E_i$.
- $\delta_{el}$ is a cohort regression estimand
- $\varepsilon_{itr}$ is the error term

As with Equation 2, the purpose of Equation 3 is to generate $CATT_{el}$, an interaction-weighted estimator for all cohort-time combinations that represents the average effect on unemployment in Ontario communities when their first brewery is founded. Below is the implementation of the R code equivalent of Equation 3, using the *fixest* library:

```
sa20RegRT <- fixest::feols(unemploymentRate)
~ 1
+ i(RemotenessDecile, Year)
+ sunab(year_treated, Year)
| GeoUID + Year,
csdCDdata)
```

where *sa20RegRT* is a data structure that holds the regression results; *fixest::feols* is the *fixest* library function for a fixed effects OLS regression; *unemploymentRate* is the sustainability variable of interest – in this case, the unemployment rate in a CSD; *1* is a dummy exogenous control (when exogenous controls are used, the *1* is replaced with one or more variables representing the controls); *i(RemotenessDecile, Year)* is the rurality-time interaction term; *sunab* is the *fixest* library function for the Sun & Abraham method; *year_treated* is a *sunab* time dummy variable equivalent to the census year in which the CSD first got a brewery and defines the cohort; *Year* is a *sunab* time period variable; *GeoUID* and *Year* are the location and time fixed effects; and *csdCDdata* is the panel dataset name.

### 3.3.2 Satisfying Cohort Event Study Assumptions with Sun & Abraham (2021) Estimates

#### *3.3.2.1 Parallel Trends*

Per the findings presented in the Sun & Abraham (2021) paper, it is suggested that if parallel trends do not hold for a specific group, that group should be excluded from the analysis. Specifically, parallel trends in baseline outcomes should hold for all CSDs that get a brewery for the first time within the cohort while also holding for control CSDs. In the case of staggered event studies, it may be challenging to argue meaningfully for the presence of parallel trends with standard tests like Ward's Test (Roth, 2022; Sun & Abraham, 2021). However, careful experimental design and statistical controls can help address parallel trends assumptions. The Ontario-wide scope of this thesis ensures that macroeconomic trends and regulatory regimes apply to the entire panel dataset. Spatial fixed effects help to remove unobserved differences between communities, while temporal fixed effects help to remove unobserved differences due to changes over time. When these differences are subtracted or demeaned in the OLS regression, it can be argued that parallel trends will be present in the pre-treatment periods of all cohorts. Robustness checks can also be performed to further visually argue for the presence of parallel trends, as detailed in Section 4.4.

Using exogenous controls or cohort grouping can help build datasets with a greater likelihood of parallel trends but tend to reduce statistical significance by reducing the sample size. Instead, this thesis introduces a rurality-time interaction term to the OLS equation. The interaction term controls for the changes within remoteness deciles over time and decomposes the effects of rurality, thereby helping to increase the likelihood of parallel trends within the statistical analysis.

#### *3.3.2.2 Treatment Effect Homogeneity*

Another assumption for the use of Sun & Abraham (2021) is that the panel dataset contains a degree of treatment effect homogeneity – suggesting that the treatment profile within each time cohort should be similar. This profile may exhibit static, dynamic, or even nonlinear characteristics but should remain consistent within the time cohort. For the panel dataset used in this thesis, no issues are anticipated regarding temporal effect homogeneity, as all breweries in the same time cohort will experience the effects of externalities such as Ontario law changes or economic change at the same time.

However, it is expected that treatment effects will vary spatially. Thankfully, the rurality-time interactor term allows for addressing this kind of treatment effect heterogeneity. By avoiding grouping, the rurality-time interactor also allows for a single CATT result, representing the sum of the effects in every remoteness decile. The most important benefit of a single CATT result is that a single meaningful impact value can be reported for all of Ontario.

#### *3.3.2.3 Anticipatory Effects*

The final assumption in the Sun & Abraham (2021) method is that the data lacks anticipatory effects. Theoretically, none should exist in the panel dataset, given the small business subject matter. In addition, this concern is addressed in the mathematical design by the inherent temporal imprecision resulting from using 5-year data groups. Certain exceptional cases may arise where the establishment date of a brewery falls near the end of a 5-year period. Given that breweries are typically founded before they commence brewing and selling beer, anticipatory effects spanning one to two years may occur.

To ensure the robustness of the findings, two potential checks can be conducted to determine whether this effect is significant. One robustness check would be adding an additional year to all brewery start dates, recalculating the OLS regression, and then comparing the CATT values. An alternative approach would involve assigning breweries with start dates close to the end of a 5-year period to the subsequent period, followed by another recalculation of CATT values.

## 3.4 Conclusion

The literature review concluded by arriving at a method by which the sustainability impacts of Ontario craft breweries on their host communities might be measured. This chapter on methods concludes by comprehensively detailing how that method was implemented in practice. Assembling the panel dataset required for a DiD cohort event study involved a lengthy search for proper sustainability measurements over multiple decades and multiple sources in order to have enough data to generate reliable statistical estimates. Issues of geographic alignment were resolved by choosing the CSD as the best compromise between maintaining a conceptual community boundary and preserving the accuracy of the measured data. The review of the statistical methodology serves as a framework through which the results may be interpreted and subjected to checks of robustness, which is the purpose of the following chapter.

# Chapter 4 – Results and Context

This chapter presents the mathematical results of the staggered event study explained in Chapter 3 to discover the community-level sustainability impacts of Ontario craft breweries. The results show that a DiD study design with the Sun & Abraham interaction-weighted estimator can uncover robust and statistically significant impacts on factors like populations of visible minorities and aboriginal identifying people, the value of homes, rates of unemployment, and sulfur dioxide air pollution levels. In other cases, results show that breweries have different impacts depending on the level of rurality, as in the case of mobility and poverty indicators. Finally, other sustainability indicators show inconsistent or insignificant results when there is no evidence to suggest a causal impact or when insufficient data is available to create conditions of statistical robustness. The results suggest that craft breweries have notable, measurable sustainability impacts on their host communities that are sometimes mixed in their outcomes. Identifying assumptions such as parallel trends, cohort treatment effect homogeneity, and lack of anticipatory effects described in section 3.3.2 argue in favour of a causal interpretation of the results.

As explained in section 3.1, the data used in the study was composed of data from several sources in a panel dataset. The panel dataset comprises two main parts: a community sustainability dataset and a brewery dataset. In the following subsection, the community dataset is examined.

## 4.1 Descriptive Results: Community Dataset

Five time periods were selected, and there is a row for every CSD in the province of Ontario for each of those periods. The five time periods correspond to Canadian census years from 2001 to 2021 and thus span twenty years. Data from 1996 was collected but excluded from the analysis due to misalignment problems with CSDs. In 1996, Ontario was comprised of 947 CSDs. By the next census in 2001, many of these CSDs were consolidated or redrawn, leaving 587 in Ontario. Subsequent census years only minimally redrew CSD boundaries, so the set from 2001 to 2021 was used in the analysis.

Below is Table 7, a table of the continuous variables in the community dataset. An essential value in the table is the sample sizes or N values. Over five sampling periods, the average number of CSDs included in the study is about 531 – less than the total number of CSDs in Ontario. This discrepancy is the cumulative result of removing CSDs with fewer than 40 residents or missing latitude-longitude data. About 30% of the total CSDs are treated, and 70% are control units. Despite a baseline sample size of

2659 rows, all the sustainability variables (from the *unemploymentRate* row onwards) have missing data and thus a smaller sample size. Variables from the Canadian Census have data from each sampling year, and missing data tends to come from control CSDs. Pollution variables from the CANUE sources tend more towards a 40% treated and 60% control split of sample sizes, while the composite indices of *instability* and *deprivation* achieve only a 50/50 split. Small sample sizes will have implications for statistical significance on each of these variables, as seen in Section 4.5.

There are notable trends of urbanity and rurality in the summary statistics. Treated CSDs tend to be smaller in area and greater in population. Similarly, economic variables around income, labour, and housing show very different summary statistics between treated and control groupings. These differences would present significant issues of bias for traditional regression analyses, requiring weights to be applied. The staggered event study approach used in this thesis estimates counterfactual untreated outcomes for treated units, which helps eliminate this potential bias (Cunningham, 2021; de Chaisemartin & D'haultfoeuille, 2022; Sun & Abraham, 2021).

*Table 7 Summary Statistics, Community Panel Dataset*
*Each variable from* UnemploymentRate *onwards was analyzed with an OLS regression following Equation 3. Complete results can be seen in Appendix B.*

| Variable | Description | Source | Group | N | Mean | Std. Dev. | Min | Pctl. 25 | Pctl. 75 | Max |
|---|---|---|---|---|---|---|---|---|---|---|
| **GeoUID** | 6-digit CSD identifier | Census | *All* | *2659* | - | - | - | - | - | - |
| | | | *Treated* | *629* | - | - | - | - | - | - |
| | | | *Control* | *2030* | - | - | - | - | - | - |
| **Area** | Size of CSD in $km^2$ | Census | *All* | 2659 | 1797 | 19934 | 0.11 | 52 | 459 | 436789 |
| | | | *Treated* | 629 | 461 | 620 | 5.1 | 136 | 559 | 3622 |
| | | | *Control* | 2030 | 2211 | 22798 | 0.11 | 41 | 426 | 436789 |
| **Population** | Total population of CSD | Census | *All* | 2659 | 24099 | 131762 | 41 | 640 | 10914 | 2794356 |
| | | | *Treated* | 629 | 85703 | 260876 | 179 | 8777 | 71594 | 2794356 |
| | | | *Control* | 2030 | 5010 | 11749 | 41 | 450 | 6196 | 202022 |
| **popDensity** | Population density of CSD, in $km^2$ | Census | *All* | 2659 | 158 | 387 | 0.0071 | 5.5 | 70 | 4428 |
| | | | *Treated* | 629 | 436 | 643 | 0.96 | 24 | 767 | 4428 |
| | | | *Control* | 2030 | 71 | 191 | 0.0071 | 4.2 | 30 | 2004 |
| **Households** | Total households in CSD | Census | *All* | 2659 | 9145 | 51657 | 12 | 248 | 4256 | 1160892 |
| | | | *Treated* | 629 | 32592 | 102571 | 70 | 3482 | 27409 | 1160892 |
| | | | *Control* | 2030 | 1880 | 4016 | 12 | 170 | 2372 | 69314 |
| **UnemploymentRate** | % per capita unemployed in CSD | Census | *All* | 2624 | 0.099 | 0.078 | 0 | 0.054 | 0.12 | 1 |
| | | | *Treated* | 629 | 0.073 | 0.028 | 0 | 0.054 | 0.086 | 0.23 |
| | | | *Control* | 1995 | 0.11 | 0.086 | 0 | 0.053 | 0.14 | 1 |
| **CD_ unemploymentRate** | % per capita unemployed in census district | Census | *All* | 2659 | 0.085 | 0.023 | 0.037 | 0.067 | 0.1 | 0.16 |
| | | | *Treated* | 629 | 0.076 | 0.024 | 0.037 | 0.059 | 0.087 | 0.16 |
| | | | *Control* | 2030 | 0.087 | 0.022 | 0.037 | 0.071 | 0.1 | 0.16 |
| **LICOat** | % per capita below low-income cutoff, after taxes | Census | *All* | 2303 | 0.057 | 0.052 | 0 | 0.023 | 0.079 | 0.4 |
| | | | *Treated* | 626 | 0.069 | 0.044 | 0 | 0.035 | 0.095 | 0.25 |
| | | | *Control* | 1677 | 0.053 | 0.055 | 0 | 0.018 | 0.071 | 0.4 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **medHHinc** | Median household income, log transformed | Census | *All* | 2388 | 11 | 0.31 | 9.1 | 11 | 11 | 12 |
| | | | *Treated* | 625 | 11 | 0.24 | 10 | 11 | 11 | 12 |
| | | | *Control* | 1763 | 11 | 0.33 | 9.1 | 11 | 11 | 12 |
| **avgHomeValue** | Average value of dwellings, non-farm/reserve | Census | *All* | 2108 | 12 | 0.62.2 | 10 | 12 | 13 | 14 |
| | | | *Treated* | 628 | 12 | 1.3 | 5.2 | 12 | 13 | 14 |
| | | | *Control* | 1480 | 12 | 0.6 | 10 | 12 | 13 | 14 |
| **age_working** | % per capita aged 15-64 | Census | *All* | 2626 | 0.64 | 0.048 | 0.33 | 0.62 | 0.68 | 0.88 |
| | | | *Treated* | 629 | 0.64 | 0.037 | 0.5 | 0.62 | 0.67 | 0.74 |
| | | | *Control* | 1997 | 0.64 | 0.051 | 0.33 | 0.61 | 0.68 | 0.88 |
| **age_youngAdult** | % per capita aged 20-34 | Census | *All* | 2626 | 0.16 | 0.046 | 0 | 0.13 | 0.18 | 0.49 |
| | | | *Treated* | 629 | 0.16 | 0.031 | 0.069 | 0.14 | 0.18 | 0.28 |
| | | | *Control* | 1997 | 0.16 | 0.049 | 0 | 0.13 | 0.18 | 0.49 |
| **oLang_firstEnglish** | % per capita who speak English as first language | Census | *All* | 2610 | 0.92 | 0.16 | 0.031 | 0.94 | 0.98 | 1 |
| | | | *Treated* | 629 | 0.93 | 0.12 | 0.12 | 0.95 | 0.97 | 1 |
| | | | *Control* | 1981 | 0.91 | 0.16 | 0.031 | 0.93 | 0.99 | 1 |
| **edu_higherEd** | % per capita with any post-HS diploma or certification | Census | *All* | 2624 | 0.36 | 0.1 | 0 | 0.32 | 0.43 | 0.71 |
| | | | *Treated* | 629 | 0.41 | 0.054 | 0.22 | 0.38 | 0.45 | 0.62 |
| | | | *Control* | 1995 | 0.35 | 0.11 | 0 | 0.3 | 0.42 | 0.71 |
| **aboriginalID** | % per capita with aboriginal status | Census | *All* | 2624 | 0.22 | 0.36 | 0 | 0.016 | 0.16 | 1 |
| | | | *Treated* | 629 | 0.028 | 0.029 | 0 | 0.012 | 0.034 | 0.24 |
| | | | *Control* | 1995 | 0.28 | 0.39 | 0 | 0.019 | 0.63 | 1 |
| **visMinority** | % per capita with visible minority | Census | *All* | 2624 | 0.03 | 0.076 | 0 | 0 | 0.025 | 0.82 |
| | | | *Treated* | 629 | 0.075 | 0.13 | 0 | 0.014 | 0.067 | 0.82 |
| | | | *Control* | 1995 | 0.016 | 0.043 | 0 | 0 | 0.018 | 0.66 |
| **mobility5** | % per capita moved to current CSD in past 5 years | Census | *All* | 2624 | 0.3 | 0.082 | 0 | 0.25 | 0.35 | 0.69 |
| | | | *Treated* | 629 | 0.34 | 0.058 | 0.11 | 0.3 | 0.38 | 0.54 |
| | | | *Control* | 1995 | 0.28 | 0.085 | 0 | 0.23 | 0.33 | 0.69 |
| **instability†** | Composite index,residential instability | CANUE | *All* | 1090 | 0.93 | 0.2 | 0.23 | 0.8 | 1 | 1.8 |
| | | | *Treated* | 361 | 0.94 | 0.22 | 0.37 | 0.82 | 1.1 | 1.8 |
| | | | *Control* | 729 | 0.93 | 0.2 | 0.23 | 0.8 | 1 | 1.6 |
| **deprivation†** | Composite index, economic deprivation | CANUE | *All* | 1090 | 1.1 | 0.26 | -0.35 | 0.89 | 1.2 | 1.9 |
| | | | *Treated* | 361 | 0.98 | 0.25 | 0.12 | 0.81 | 1.1 | 1.8 |
| | | | *Control* | 729 | 1.1 | 0.26 | -0.35 | 0.93 | 1.3 | 1.9 |
| **no2Conc†** | Annual Avg NO2 Conc. (ppb) | CANUE | *All* | 1414 | 1.5 | 0.54 | 0.13 | 1.1 | 1.9 | 3.5 |
| | | | *Treated* | 432 | 1.8 | 0.56 | 0.4 | 1.4 | 2.1 | 3.5 |
| | | | *Control* | 982 | 1.4 | 0.49 | 0.13 | 1.1 | 1.8 | 3.3 |
| **o3Max†** | O3 Annual Avg., Highest Rolling 8-hr Avg (ppb) | CANUE | *All* | 1716 | 3.5 | 0.17 | 2.5 | 3.5 | 3.6 | 3.9 |
| | | | *Treated* | 500 | 3.6 | 0.11 | 2.7 | 3.6 | 3.7 | 3.8 |
| | | | *Control* | 1216 | 3.5 | 0.18 | 2.5 | 3.5 | 3.6 | 3.9 |
| **pm25dalC†** | Annual avg. fine particulate (PM2.5) exposure (ppb) | CANUE | *All* | 1717 | 1.7 | 0.33 | 0.18 | 1.5 | 2 | 2.7 |
| | | | *Treated* | 500 | 1.9 | 0.25 | 1.1 | 1.8 | 2.1 | 2.7 |
| | | | *Control* | 1217 | 1.7 | 0.34 | 0.18 | 1.5 | 1.9 | 2.5 |
| **so2†** | 3 Year Annual Average SO2 Conc. (ppb) | CANUE | *All* | 945 | 0.31 | 0.21 | 0 | 0.15 | 0.43 | 1.3 |
| | | | *Treated* | 262 | 0.35 | 0.23 | 0.01 | 0.2 | 0.47 | 1.3 |
| | | | *Control* | 683 | 0.29 | 0.2 | 0 | 0.14 | 0.39 | 1.2 |
| **natural†** | Local Climate Zone: Natural (% pixels in 1km$^2$) | CANUE | *All* | 1717 | 78 | 24 | 2.5 | 66 | 98 | 100 |
| | | | *Treated* | 500 | 66 | 29 | 2.5 | 42 | 93 | 100 |
| | | | *Control* | 1217 | 83 | 20 | 3.3 | 74 | 99 | 100 |

*† Data collected at postal code and converted by the author to CSD.*

In addition to the continuous variables representing Ontario community sustainability data, the community dataset contains administrative data used to characterize communities. The most important of these to this thesis is the data representing the relative values of rurality or urbanity: the *Remoteness* variable. As discussed in Section 3.1.4, this variable applies to each CSD and characterizes its level of rurality. Given the tendency of craft breweries to cluster in more urban areas, it is essential to identify the precise amount of urbanity or rurality in every CSD. For the analysis, the continuous rating of *Remoteness* was converted into deciles to obtain ten groupings. Alasia et al. suggest that a *Remoteness* value of 0.4 and greater represents a genuinely rural area (2017), and when converted into deciles, this corresponds to deciles from seven to ten. In Figure 4 below, the CSDs of the province of Ontario are coloured by their decile level. It is clear from a visual examination that rural CSDs make up the majority of land area in Ontario, while the urban CSDs are clustered around the southern border with the United States. Ontario's two largest cities –Toronto and Ottawa – can be observed among the blue and orange CSDs.

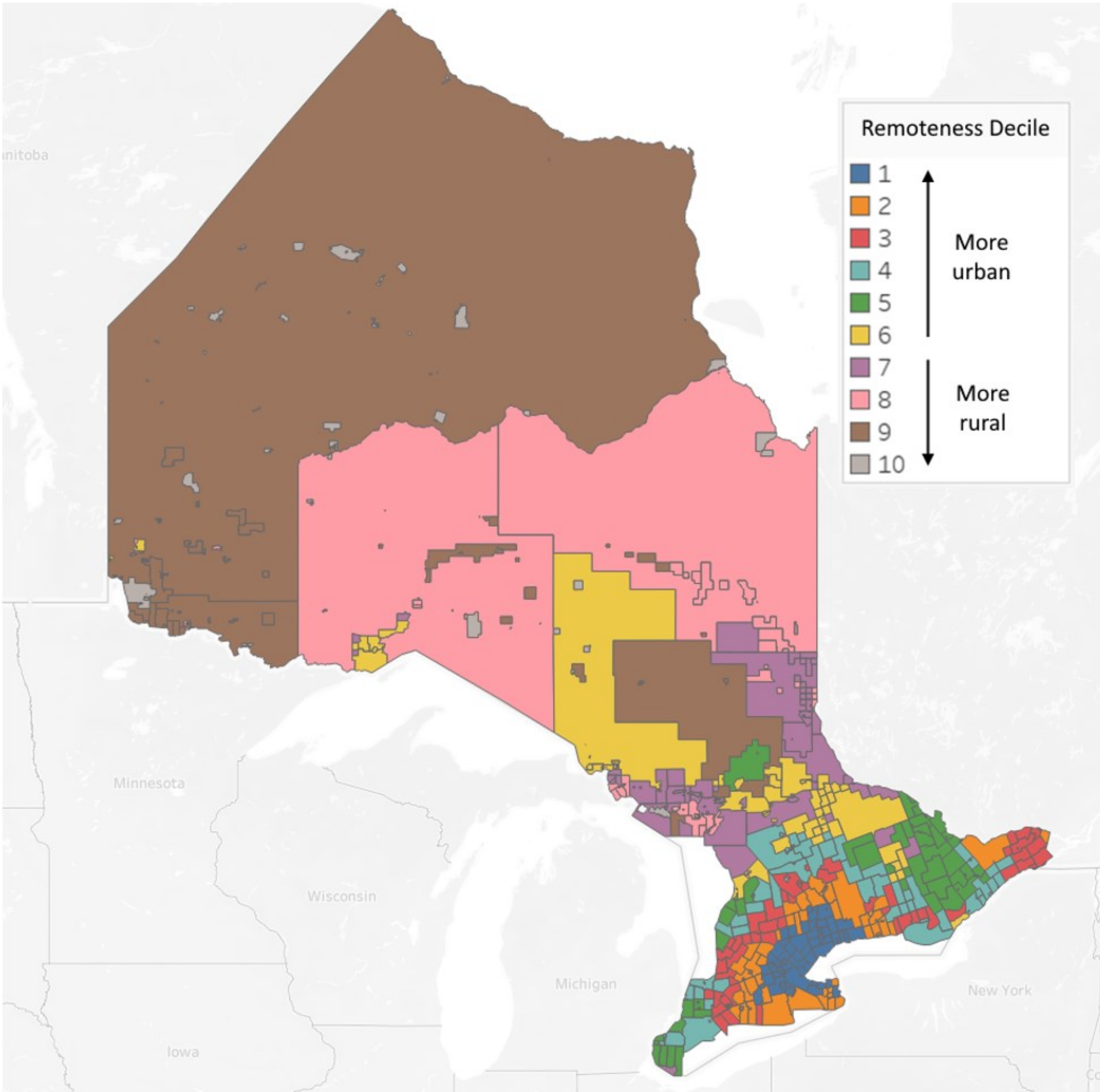



*Figure 4 Ontario CSDs by Remoteness Decile.*
*Decile values of 7 and greater (purple, pink, brown, and grey) are considered rural.*

## 4.2 Descriptive Results: Brewery Dataset

The brewery dataset is aligned differently from the community dataset. Rather than a panel dataset, the brewery dataset is a simple list of craft breweries in Ontario. The pertinent values are administrative: the location and dates of founding and closure are the only values used during the analysis. Other data, including characteristics of each brewery in continuous numerical form, were collected but not used.

In Table 8 are listed the continuous variables collected. In the context of this dataset, a *Brewpub* is a craft brewery with an attached restaurant, while a *Brewery* does not have a restaurant. Locations designated as *Brewery* may serve packaged food or collaborate with food trucks or other external food providers. Given the crowdsourced nature of the data, the author does not entirely trust the *Brewpub* and *Brewery* groupings. While none of these data were used in the analysis, some exciting values exist. In data sourced from RateBeer, *Brewpubs* have a much greater average number of ratings than *Breweries* (8 to 2.9), yet the rating value itself remains similar on average. The situation is different with rating counts from BeerAdvocate, where the ratio of Brewpub and Brewery counts of ratings are reversed (35 to 48), though the ratings themselves are nearly identical.

*Table 8 Summary Statistics, Brewery Dataset*

| Variable | Description | Group | N | Mean | Std. Dev. | Min | Pctl. 25 | Pctl. 75 | Max |
|---|---|---|---|---|---|---|---|---|---|
| **Count** | Number of breweries | *All* | 353 | - | - | - | - | - | - |
| | | *Brewpub* | 89 | - | - | - | - | - | - |
| | | *Brewery* | 264 | - | - | - | - | - | - |
| **Rating** | User rating out of 100 on RateBeer | *All* | 279 | 71 | 5 | 57 | 69 | 73 | 98 |
| | | *Brewpub* | 76 | 71 | 6.3 | 59 | 69 | 73 | 98 |
| | | *Brewery* | 203 | 70 | 4.4 | 57 | 69 | 72 | 88 |
| **NumRatings** | Count of RateBeer user ratings | *All* | 353 | 4.2 | 9.6 | 0 | 1 | 4 | 138 |
| | | *Brewpub* | 89 | 8 | 17 | 0 | 1 | 6 | 138 |
| | | *Brewery* | 264 | 2.9 | 4.1 | 0 | 1 | 3 | 46 |
| **beersActive** | Count of beer offerings in production | *All* | 279 | 28 | 33 | 1 | 9 | 31 | 297 |
| | | *Brewpub* | 67 | 22 | 24 | 1 | 6.5 | 24 | 123 |
| | | *Brewery* | 212 | 29 | 35 | 1 | 9.8 | 33 | 297 |
| **beersRetired** | Count of beer offerings no longer in production | *All* | 200 | 24 | 41 | 1 | 2 | 28 | 325 |
| | | *Brewpub* | 43 | 21 | 32 | 1 | 2 | 24 | 129 |
| | | *Brewery* | 157 | 25 | 43 | 1 | 3 | 32 | 325 |
| **baReviewCount** | Count of BeerAdvocate user reviews | *All* | 279 | 45 | 65 | 1 | 10 | 52 | 622 |
| | | *Brewpub* | 67 | 35 | 48 | 2 | 9.5 | 35 | 213 |
| | | *Brewery* | 212 | 48 | 70 | 1 | 10 | 56 | 622 |
| **baReviewAvg** | User rating out of 5 on BeerAdvocate | *All* | 279 | 3.1 | 0.88 | 0 | 3 | 3.6 | 4.2 |
| | | *Brewpub* | 67 | 3 | 1.1 | 0 | 2.8 | 3.7 | 3.8 |
| | | *Brewery* | 212 | 3.1 | 0.79 | 0 | 3 | 3.6 | 4.2 |
| **baReviewConfidence** | Bayesian-weighted user rating score on BeerAdvocate† | *All* | 181 | 3.3 | 0.14 | 2.9 | 3.2 | 3.4 | 3.8 |
| | | *Brewpub* | 33 | 3.3 | 0.12 | 3 | 3.2 | 3.4 | 3.5 |
| | | *Brewery* | 148 | 3.3 | 0.14 | 2.9 | 3.2 | 3.4 | 3.8 |

† *Calculated by the author.*

With the founding dates of craft breweries present in the brewery dataset, it is now possible to plot the growth of the Ontario craft brewery industry over time. In Figure 5 below, Ontario's first craft brewery was founded in 1984. This brewery, initially called Brick Brewing Company and now called Waterloo Brewing Company, was purchased by the Carlsberg Group in December of 2022 and is no longer considered a craft brewery. The graph also shows the relatively slow growth period from 1984 until about 2009, when the number of craft breweries in Ontario rapidly grew. The founding rate dropped significantly after peaking in 2016 with 59 new breweries. It is unknown the degree to which the closures during the COVID-19 pandemic of 2020-2023 impacted the number of new craft breweries.

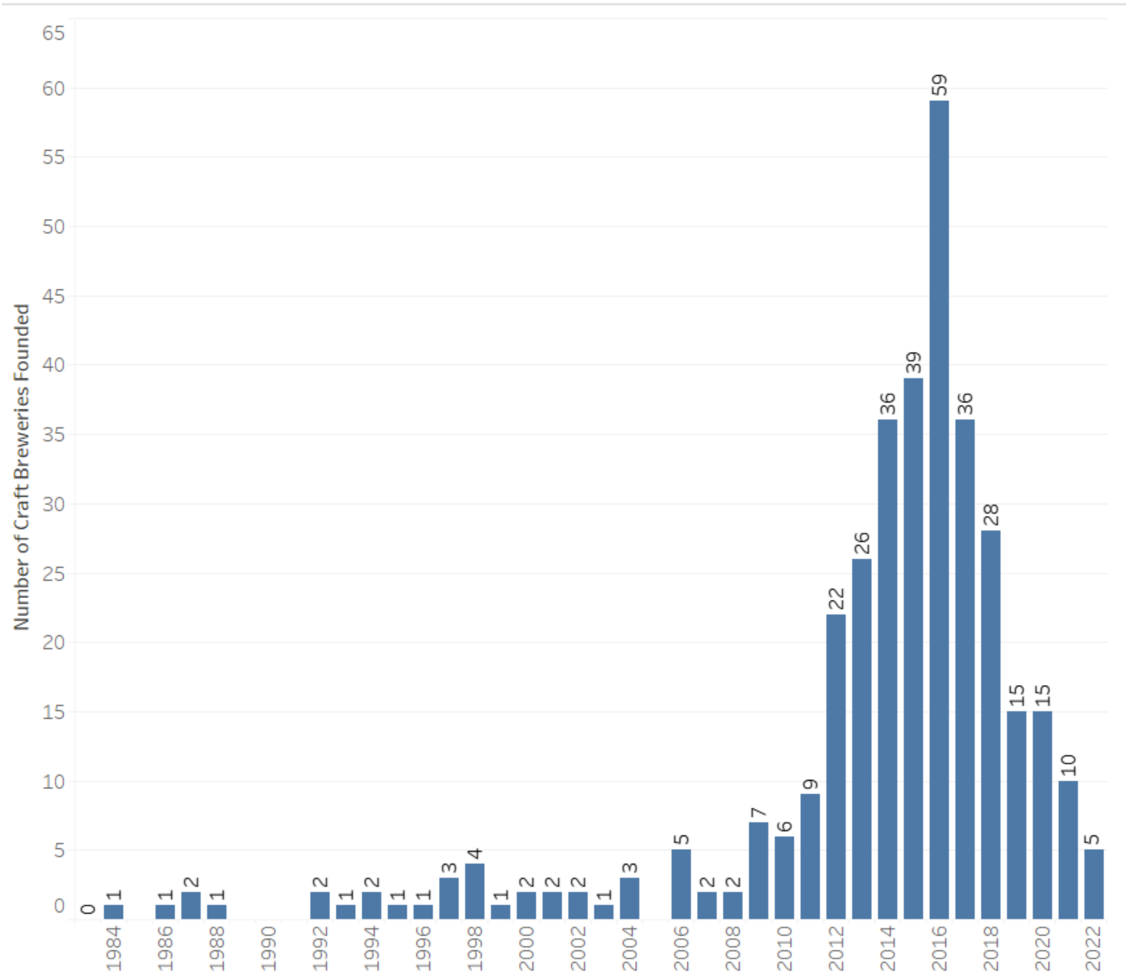



*Figure 5 Ontario Craft Brewery Openings, 1984-2022*

Data on craft brewery postal addresses were collected, which after geolocation to latitude and longitude coordinates, allows for plotting the locations of Ontario craft breweries on a map of the province. In Figure 6 below, each blue dot represents a single craft brewery. Clusters of breweries can be seen in the urban concentrations around Toronto and Ottawa. Further away from the border regions, the numbers of breweries decrease. The northernmost brewery in Ontario, the blue dot at the top left of the map, is Lake of the Woods Brewery in Kenora. The remainder of Ontario is cropped off the map to show detail.

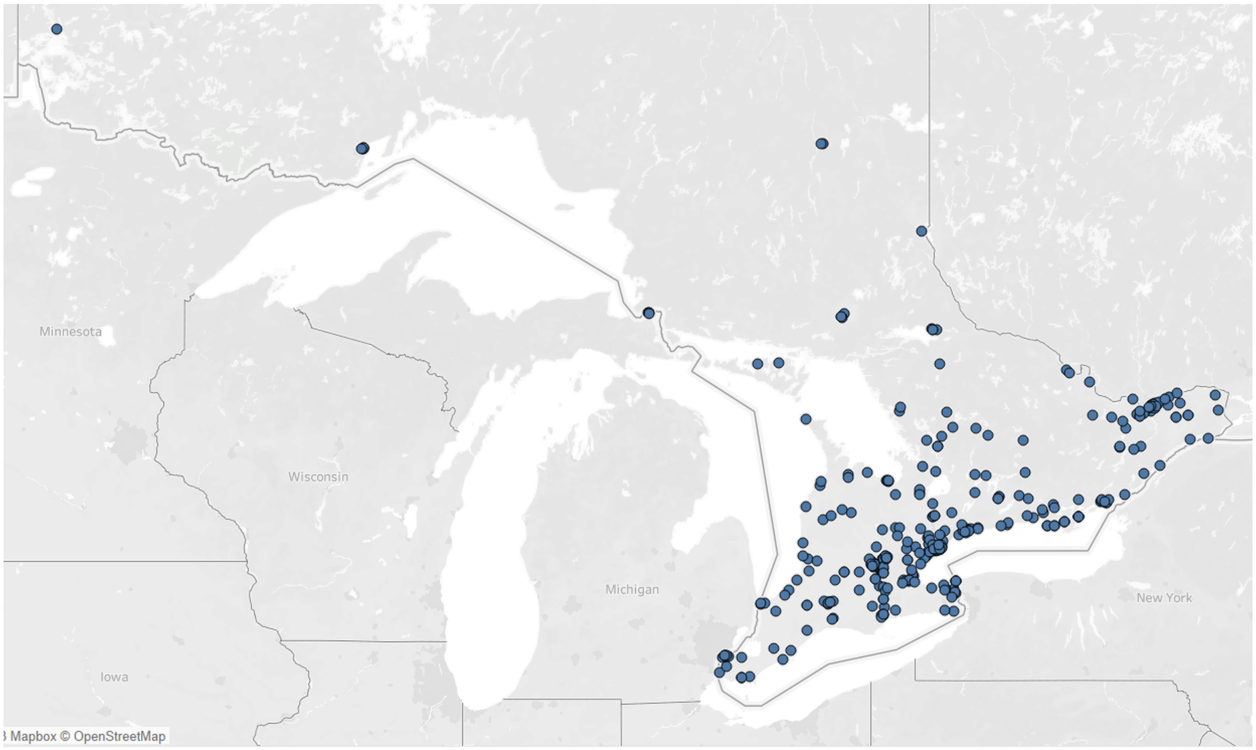



*Figure 6 Map of Ontario Craft Brewery Locations by Latitude and Longitude Coordinates, 1984-2022*

While latitude and longitude are helpful for purely mapping purposes, the mathematical analysis requires breweries to be located within CSDs to split these regions into treated (a craft brewery is present during the study period) and control (no craft brewery is present). Using the procedure outlined in 3.2, the postal codes of breweries were translated into CSDs. The geolocation process allows CSDs to be assigned as either treated or as controls and then mapped. Due to the use of the Sun & Abraham (2021) estimator, the assignment of treated CSDs is binary and cannot be revoked – a situation known as "absorbing treatments". From the date a brewery is founded in a CSD, that CSD becomes part of a treatment cohort and does not become a control. A side effect of absorbing treatments is that multiple breweries do not have an additional impact on the results.

Figure 7 below shows these treated and control CSDs on an Ontario map. Again, note the clustering of treated CSDs near the southern border region of Ontario and the relative sparseness of treated CSDs in northern regions.

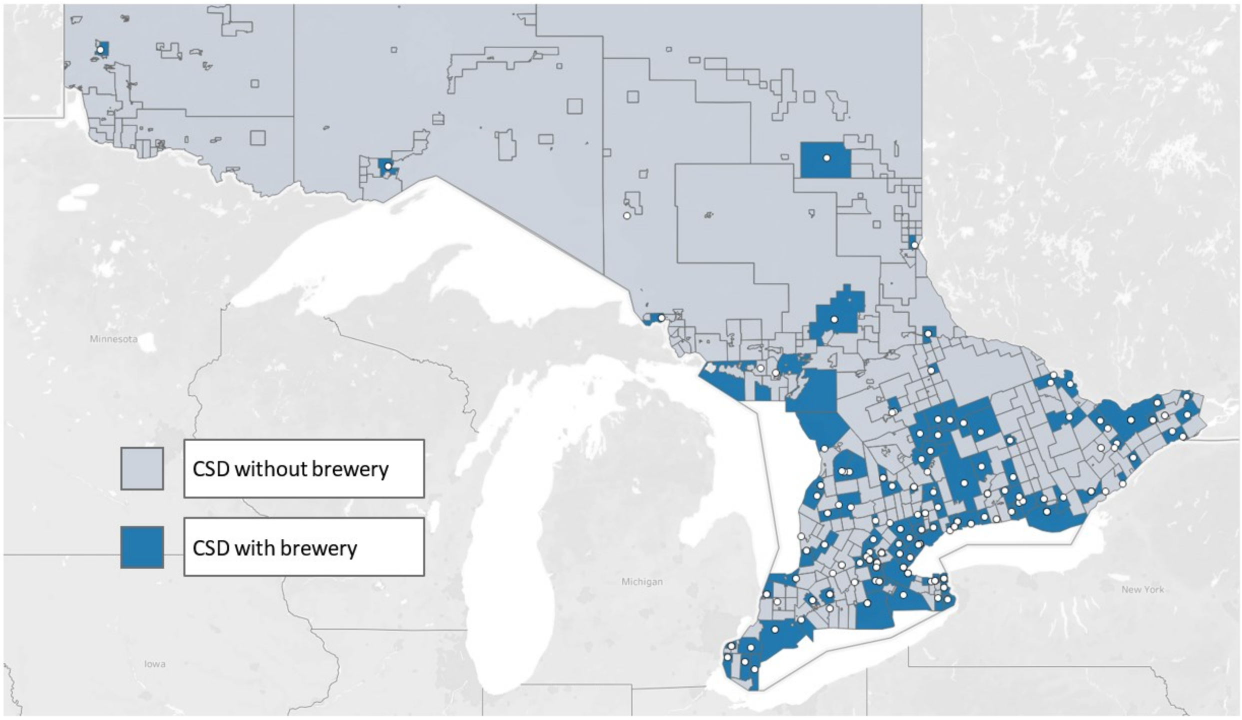



*Figure 7 Treated and Control CSDs with Craft Brewery Locations, Ontario 1984-2022*

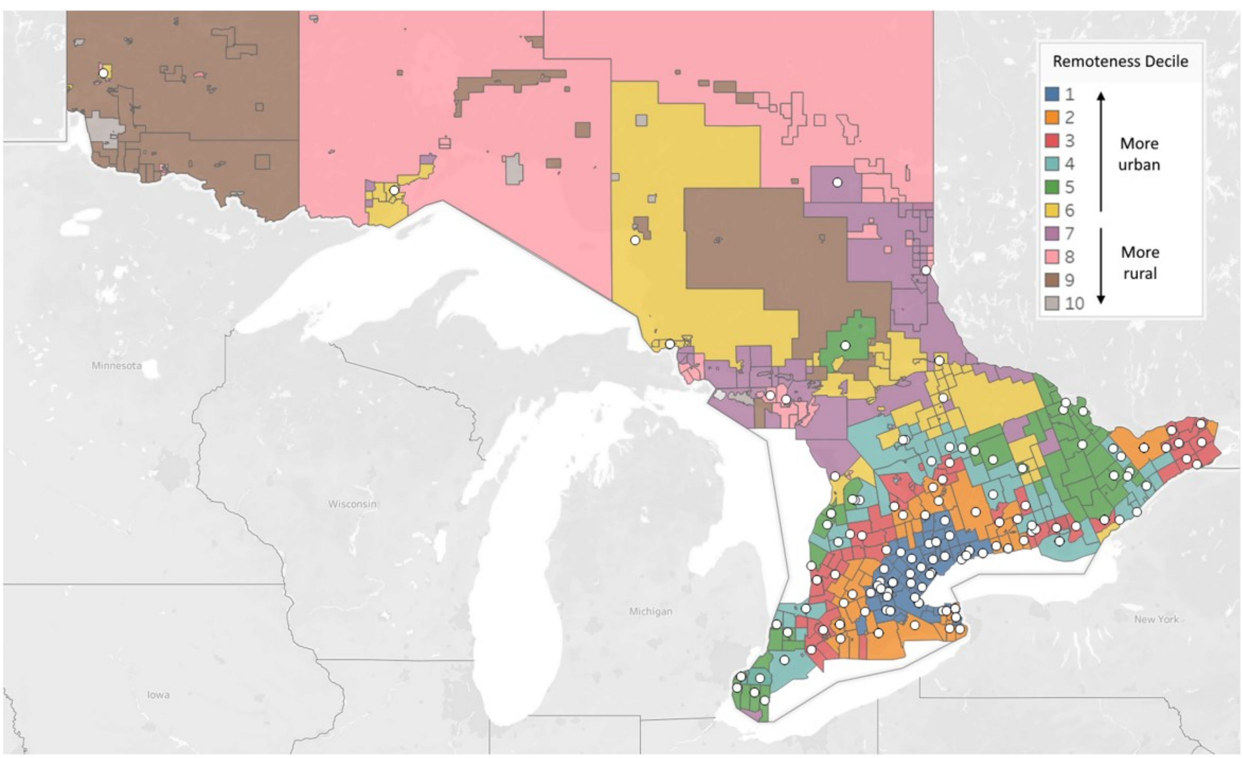



*Figure 8 Ontario CSDs by Remoteness Decile, with Craft Brewery Locations, Ontario 1984-2022*

## 4.3 Descriptive Results: Panel Dataset

Combining the two datasets into a single panel dataset makes overlaying craft breweries' locations with CSD characteristics possible. Indeed, this could be considered a visual representation of Objective 1 – though only a single point of time and without statistical causality. Figure 8 above shows CSD remoteness deciles with an overlay of the geographic location of craft breweries (white dots). It can be visually observed that there is a strong association between highly urbanized areas and the presence of a brewery.

## 4.4 Parallel Trends Assumptions Checks

Using the Sun & Abraham estimator requires investigators to argue that there is a reasonable degree of parallel trends between treated and control CSDs. However, Sun & Abraham caution that tests traditionally used to argue for parallel trends – such as the Wald pre-test – may be invalid in cohort event studies. Callaway and Sant'Anna (2021) suggest that a visual examination of the pre-treatment estimates of an event study plot can be used to argue meaningfully for the presence of parallel trends.

The examination check is performed on a cohort event study plot like Figure 9 below. Each cohort has one chart in such a plot, totalling four charts. Each cohort is named after a year and represents CSDs that underwent treatment that year; in other words, each cohort is a collection of communities which got a new craft brewery in a particular year. The x-axis shows the passage of time within each cohort. The red marks show the pre-treatment estimates of the unemployment rate, and the blue marks are the post-treatment estimates, calculated by Equation 3 and shown on the y-axis. Each mark has a 95% confidence band, which can be used to determine statistical significance. If the band crosses the zero point of the y-axis, then the estimate should be considered equal to zero. The estimate can be considered statistically significant if the band does not cross the zero point. According to Callaway & Sant'Anna (2021), if the parallel trends assumption holds for all pre-treatment periods, the estimates should be equal to zero. Translated to the cohort event study plot, all red confidence bands (representing pre-treatment estimates) must cross the zero point on the y-axis.

In Figure 9, the 2006 cohort has no estimates for pre-treatment. Group 2011 has a single pre-treatment estimate in 2006; its confidence band crosses the zero point. The same applies to all the red pre-treatment confidence bands in Groups 2016 and 2021. Because all red pre-treatment confidence bands cross the zero point, they are equivalent to zero, and the pre-trends visual plot check can be considered as passed.

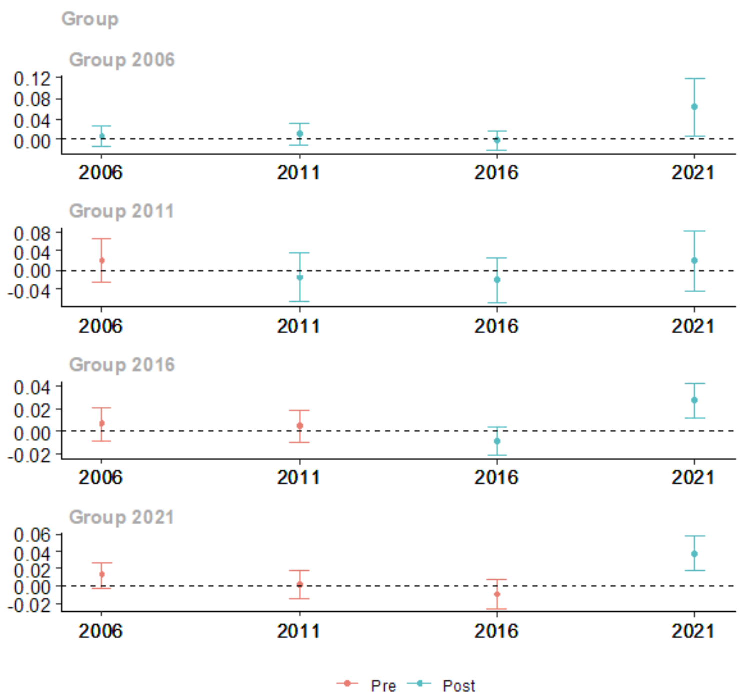



*Figure 9 Cohort Event Plot, Unemployment Rate, No Grouping.*
*As a visual plot check of the parallel trends assumption, this is an example of a pass.*

Figure 10 below is an example of the visual plot check failing. This cohort event plot examines the population percentage of immigrants in four cohorts. While the red pre-treatment confidence bands frequently cross the zero point on the y-axis, they failed to cross in 2006 for both the Group 2016 and Group 2021 cohorts. There is also a borderline situation in the confidence band in 2016 for Group 2021. Because not all red pre-treatment estimate confidence bands cross the zero mark in the event plot, there is evidence that the parallel trends argument may not hold for this analysis of immigrant populations. The practical result of a visual check is twofold: the results of that cohort can be eliminated from consideration due to a failure to argue for the presence of parallel trends conclusively, or the failing cohort can be dropped from the analysis. In this thesis when the visual plot check fails, it will be noted in the explanation of the result.

In an online tutorial on parallel trends pre-testing with the *did* R package (https://bcallaway11.github.io/did/articles/pre-testing.html), a Wald test is suggested to be combined with the visual plot check as solid evidence for the presence of parallel trends (Callaway & Sant'Anna, 2022). This additional test can help argue for the presence of parallel trends when the visual check is borderline. Therefore, a combination of a Wald test and visual plot check has been performed for each of the causal inference results in Section 4.5.

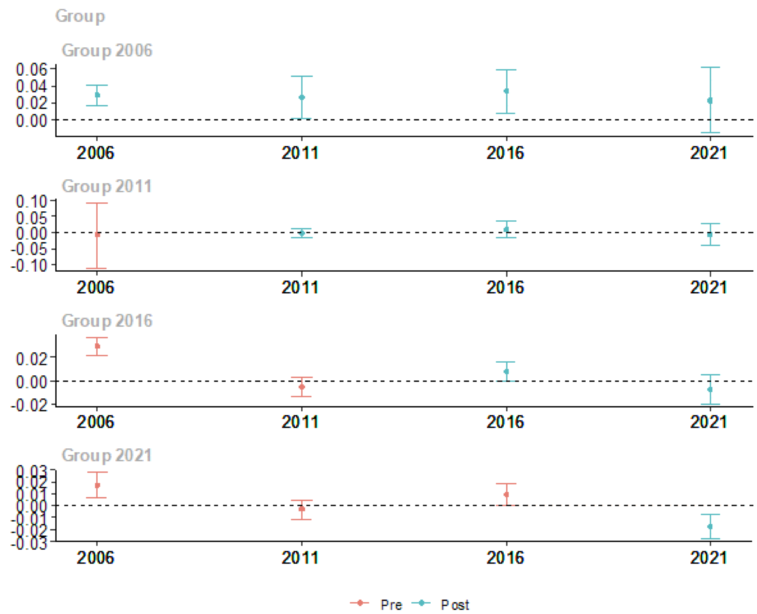



*Figure 10 Cohort Event Plot, Percent Per-Capita of Immigrants*
*As a visual plot check of the parallel trends assumption, this is an example of a failure.*

## 4.5 Causal Inference Results

Each following sub-section examines a single variable of interest according to the staggered cohort event study methodology described in Chapter 3 and the controls described in Section 4.3. Note that for all results, the following symbols apply:

*Table 9 Significance Indicators*

| Symbol | Equivalent Value | Meaning |
|---|---|---|
| | $p > 0.10$ | No statistical significance |
| . | $p \leq 0.10$ | Minimal statistical significance |
| * | $p \leq 0.05$ | Statistically significant |
| ** | $p \leq 0.01$ | Very statistically significant |
| *** | $p \leq 0.001$ | Extremely statistically significant |

The primary value of interest is the cohort average treatment effect of treated (CATT). This key metric, an estimator derived from the Sun & Abraham (2021) paper, indicates the direction of the impact associated with the presence of a brewery in a host community and the magnitude of this effect. In each graph, CATT is represented by a coloured circle with symmetrical error bars representing the two-way clustered standard errors. CATT values are graphed on a common axis within each figure. In section 4.5.1, two figures show the results for Census socioeconomic data. In the first, Figure 11, the impact of CATT is represented in the "Impact (%)" column, showing the increase or decrease in percentage per capita, and in the second, Figure 12, the increase or decrease is represented in percentage change in Canadian dollars. In section 4.5.2, Figure 13 shows the results of composite indices from the CANUE dataset regarding percentage change in the index value. Finally, in section 4.5.3 are shown the pollutant results in terms of percentage change of the pollutant in parts per billion (ppb), Figure 14.

### 4.5.1 Sociodemographic Results from the Canadian Census

Each variable examined in this thesis's causal inference results section should be considered to have a hypothesis to test (beyond the implied rejection of the statistical null hypothesis when *p* values are less than 0.10 or 0.5). Instead, logical arguments and the literature on sustainability in craft beer can help establish more precise hypotheses. Of the sociodemographic variables collected and analyzed in this thesis, the unemployment rate is perhaps the most meaningful barometer for success. Common sense dictates that opening a craft brewery would necessitate hiring employees, and therefore, it should be possible to measure a reduction in unemployment.

Common sense is more difficult to establish for the remainder of the sociodemographic variables like populations of visible minorities, indigenous people, or poverty rates. The literature discussed in Section 2.2.2 states that breweries are associated with small-town revitalization (Feeney, 2017), increased residential property values (Nilsson & Reid, 2019), and better walkability (Apardian & Reid, 2020); and are not associated with changes in crime rates (Nilsson et al., 2020). While data about residential property values were available, the other associations noted in the literature did not have corresponding data in the panel dataset for comparison.

What the remaining collected variables – ethnicity, mobility, and poverty – have in common is that they happen to be measures of gentrification (Cohen & Pettit, 2019; Firth et al., 2021). Breweries have frequently been associated with gentrification in urban areas, leading to negative sustainability impacts

(Mathews, 2022; Mathews & Picton, 2014; Walker & Fox Miller, 2018). For each variable examined, a hypothesis can be determined from the literature on gentrification and craft breweries.

To interpret the results plots, note that a single variable of interest is displayed in each shaded set of rows. The most meaningful row in each set of shaded rows is the first, with the name of the variable and the Group “All”. This row gives the results of Equation 3 and some summary statistics for comparison. Underneath the “All” row are rows showing the contribution of Urban and Rural CSDs to the overall result. Any differing impacts between Urban and Rural CSDs can be seen by comparing these contributions.

| Variable | Group | N (%) | Mean | Impact (%) | Stat. Sig. | *p* value |
|---|---|---|---|---|---|---|
| Unemployment Rate | All | 2624 (99) | 0.101 | −3.00 | ** | 0.0012 |
| | Urban | 1684 (63) | 0.075 | −1.87 | ** | 0.0030 |
| | Rural | 928 (35) | 0.135 | −4.38 | ** | 0.0029 |
| Visible Minorities | All | 2624 (99) | 0.03 | −2.32 | ** | 0.0013 |
| | Urban | 1684 (63) | 0.043 | −2.11 | ** | 0.0018 |
| | Rural | 928 (35) | 0.006 | −1.92 | *** | <0.001 |
| Indigenous People | All | 2624 (99) | 0.22 | −0.63 | ** | 0.0065 |
| | Urban | 1684 (63) | 0.099 | −0.75 | ** | 0.0012 |
| | Rural | 928 (35) | 0.45 | −3.03 | ** | 0.0058 |
| 5−year Mobility | All | 2612 (98) | 0.03 | +0.02 | None | 0.9597 |
| | Urban | 1684 (63) | 0.31 | +0.48 | None | 0.2755 |
| | Rural | 928 (35) | 0.274 | −6.93 | * | 0.0495 |
| Poverty Rate (LICOat) | All | 2303 (87) | 0.057 | +0.41 | . | 0.0839 |
| | Urban | 1608 (60) | 0.061 | +0.44 | . | 0.0660 |
| | Rural | 683 (26) | 0.05 | −0.26 | * | 0.0034 |

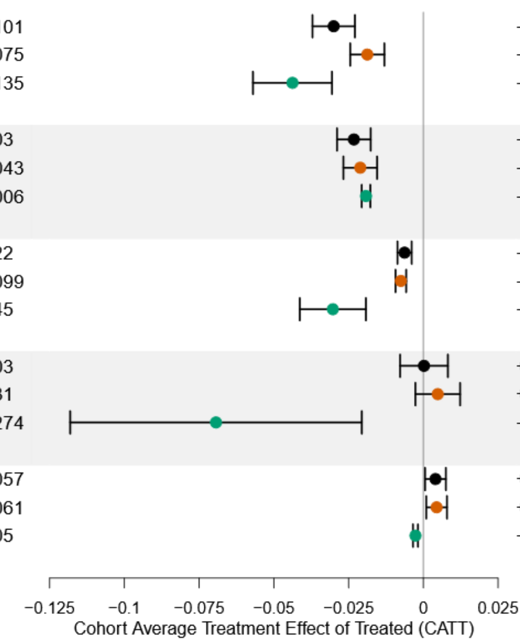



*Figure 11 Statistical Results Summary, sociodemographic variables, in percent per capita*

| Variable | Group | N (%) | Mean ($) | Impact (%) | Stat. Sig. | *p* value |
|---|---|---|---|---|---|---|
| Average Home Value | All | 2098 (79) | 284559 | −7.65 | ** | 0.0058 |
| | Urban | 1549 (58) | 326436 | −3.22 | * | 0.0372 |
| | Rural | 549 (21) | 169040 | −4.08 | None | 0.6040 |

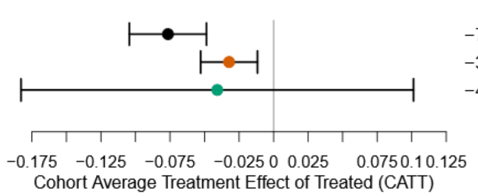



*Figure 12 Statistical Results Summary, value in Canadian dollars*

#### *4.5.1.1 Unemployment*

The variable of interest at the top of Figure 14 above is the unemployment rate. The statistical results are broadly meaningful and show that the presence of a brewery in a community is associated with a reduction in the unemployment rate of an Ontario CSD by about 3%. There is strong statistical significance with a $p$ value of 0.001 – shown by "**" in the Stat. Sig. column. Urban and rural groupings both show negative impact values of -1.87% and -4.48%. Of note is that the magnitude of effects is greater for the rural group than the urban group, suggesting that the impact on unemployment due to the presence of craft breweries differs depending on the community's remoteness.

As a test of whether the analysis techniques are capable of discerning the unemployment rate impact of Ontario craft breweries, these results appear to reject the null hypothesis (that craft brewery impacts on the unemployment rate are undistinguishable from zero) and confirm the commonsense supposition that craft breweries should reduce unemployment. A three percent reduction seems notable, though contextualization can help clarify the impact. Based on an average Ontario CSD from Table 7 and current data on unemployment, which suggests that the percent per capita labour force is 54.91% of the total population (*Labour Force Survey, May 2023*, 2023), the unemployment rate per capita would drop from 5.44% to 5.27% due to the presence of a craft brewery. Again using average figures, this represents about 22 individuals moving from unemployed to employed status in an average Ontario community that gains a craft brewery. While employment data on craft breweries in their first years of operation is scarce, published reports on employment levels indicate that 22 is a reasonable number of workers in a craft brewery (Brewers Association, 2016b; OCB, 2017). The knock-on effects of a brewery being founded could also explain a reduction in unemployment, such as jobs being needed for ingredient suppliers and beer distribution or the desire for food to accompany the beer leading to a restaurant being founded nearby.

#### *4.5.1.2 Visible Minorities*

According to the Urban Institute of America, if craft breweries are associated with gentrification, it is expected that there will be an impact on the population of visible minorities (Cohen & Pettit, 2019). Specifically, gentrification tends to increase the population of white people at the expense of the population of visible minorities. Interestingly, when Statistics Canada measures gentrification in Canada, ethnicity measures are not considered (Firth et al., 2021).

The statistical findings for the impact of craft brewers on the percentage of visible minorities in Ontario communities also exhibit statistical significance. The presence of a brewery in a community is associated with a reduction in the population of visible minorities of 2.32% and a strong statistical significance. When applied to the mean value of 3% visible minority people in Ontario and an average CSD population of 24099 people (from Table 4), that would indicate breweries are associated with about 22 visible minorities leaving. It is worth noting that the CATT values for different control sets fall within a close range, suggesting a high degree of robustness in the obtained result.

#### *4.5.1.3 Indigenous People*

Populations of indigenous people are not commonly measured in gentrification studies (Cohen & Pettit, 2019; Firth et al., 2021). A hypothesis can nevertheless be made that craft breweries are likely to decrease populations of indigenous people as part of their gentrification impacts because other minority populations tend to decrease when gentrification is present.

The obtained results are once again strongly statistically significant and reveal an association between the presence of a brewery in a community and a subsequent reduction in the population of Indigenous people of 0.63%. Notably, the magnitude of this effect increases as the remoteness of the group under consideration increases. So, while the overall effect and the effect in the Urban group is less than one percent, in Rural areas, the effect is nearly five times greater.

#### *4.5.1.4 Five-Year Community Mobility*

Five-year community mobility measures the per-capita number of people who have moved to a CSD in the past five years and is a good proxy for whether a community is growing. Mobility is a standard indicator used by researchers to identify communities at risk of gentrification (Cohen & Pettit, 2019; Firth et al., 2021). Based on those guidelines, it is hypothesized that craft breweries will be associated with an increase in five-year community mobility.

The Ontario-wide results do not exhibit statistical significance. In this analysis, the parallel trends check fails for multiple cohorts, potentially due to a small sample size of the *mobility5* variable. This failure may indicate a lack of a consistent trend between treated and control groups, reducing the reliability of the analysis. Of interest is that the Rural sub-population grouping has a strongly significant result and a reasonably large magnitude of effect of –6.93%. The Urban and All groups do not have significant results, so the results for five-year community mobility can be considered evidence of substantial treatment effect heterogeneity. The rural results for five-year mobility contradict the hypothesis, showing a reduction in mobility after craft breweries appear.

#### *4.5.1.5 Poverty (low-income cutoff, after tax)*

This section describes the outcomes from the statistical analysis conducted on craft breweries' impact on Ontario's poverty rates, as measured by rates of individuals below the low-income cut-off after tax (LICOat). Gentrification literature states that areas at risk of gentrification will have higher levels of poverty, and areas that have already been gentrified will have less poverty and tend to have incomes higher than average for the region (Firth et al., 2021). This measure helps to determine the temporal contribution of craft breweries to gentrification. If craft breweries tend to result in increased poverty, it suggests that they tend to appear before gentrification takes effect. If craft breweries are associated with a reduction in poverty, that result would suggest breweries appear after gentrification has begun.

The results indicate that the presence of a craft brewery in a community is associated with an increase in the poverty rate of 0.41%, with only slight significance. The results for all Ontario and urban areas a similar but differ significantly in rural areas. There, poverty rates reduce slightly by 0.26%, with greater statistical significance.

The findings for the sub-groupings of Urban and Rural present a classic example of heterogeneous treatment effects, indicating that the influence of craft breweries on poverty rates varies among different groups within the population to the point that these effects can have opposite directions. This variability in outcomes suggests the presence of heterogeneous treatment effects, implying that specific aspects of craft breweries or their host communities that differ between urban and rural areas can result in increased or decreased poverty levels. If theories of gentrification are applied, that would indicate urban craft breweries lead gentrification and rural craft breweries lag gentrification. The limited statistical significance of these results suggests that further research is needed to explore this evidence more fully.

#### *4.5.1.6 Average Home Value*

The results for average home value are represented on a separate figure because they are presented in percent change in a dollar value. Following the literature on gentrification, it is hypothesized that craft breweries will be associated with an increase in average home value (Cohen & Pettit, 2019; Firth et al., 2021).

The results are meaningful and show that the presence of a brewery in a community is associated with a decrease in the average home value of over 7.65%. While the results for the All and Urban groups are statistically significant, a low sample size in the Rural group may not allow for a significant result.

Regarding the magnitude of CATT effects, the statistical analysis of average home values in Ontario gave the most substantial percentage impact of any variable included in this study.

Once again, the results were the opposite of the hypothesis's expected results. If the average Ontario home value is $284,559, the results indicate that the presence of a craft brewery can reduce the value of that home by over $21,000. It must be cautioned that the results obtained were aggregated due to DiD study design and use of Sun & Abraham (2021) estimators and should not be used to evaluate the home value loss for any specific dwelling.

The results seen here contrast with the work of Nilsson & Reid (2019), who found that the presence of a craft brewery tended to increase residential property values in the vicinity. That study was limited to a single city in the United States of America. Additionally, Nilsson & Reid had greater temporal precision in their analysis, observing yearly changes over eight periods for a total time range of eight years. In contrast, the panel data in this thesis observed five-yearly changes over five periods for a total time range of 20 years. The differing spatial and temporal scopes between the Nilsson & Reid (2019) analysis and the analysis used in this thesis may help to explain the opposing results.

### 4.5.2 Index Results from the Canadian Index of Multiple Deprivation

As composite indices, Residential Instability and Economic Deprivation variables obtained through the Canadian Index of Multiple Deprivation integrate multiple data variables into a single index value. Section 4.5.1 has shown that many sociodemographic variables show statistically significant impacts with both positive and negative directions of effect. Therefore, it might be best to hypothesize that the presence of a craft brewery is likely to cause either a statistically significant increase or decrease in the two index values.

| Variable | Group | N (%) | Mean Index Value | Impact (%) | Stat. Sig. | *p* value |
|---|---|---|---|---|---|---|
| Residential Instability | All | 1090 (41) | −0.399 | +1.69 | None | 0.8044 |
| | Urban | 849 (32) | −0.438 | +2.29 | None | 0.7379 |
| | Rural | 236 (9) | −0.259 | | None | |
| Economic Deprivation | All | 1090 (41) | −0.011 | −5.84 | None | 0.6248 |
| | Urban | 849 (32) | −0.159 | −5.52 | None | 0.6433 |
| | Rural | 236 (9) | 0.525 | | None | |

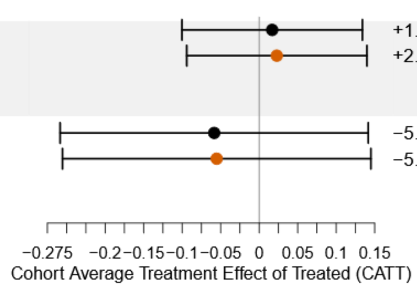



*Figure 13 Statistical Results Summary, Canadian Index of Multiple Deprivation variables, by Index value*

#### *4.5.2.1 Residential Instability Composite Index*

The results do not exhibit statistical significance. The results for the residential instability index were generated from a relatively small sample size – 1090 data points available out of 2659 rows in the panel dataset. In addition, the rural group exhibited mixed directions of effect depending on the time cohort in the OLS regression and thus did not generate a CATT result.

#### *4.5.2.2 Economic Deprivation Composite Index*

Like the previous results, the analytical results for the economic deprivation index do not exhibit broad significance, likely due to the low sample size. In addition, the rural group exhibited mixed directions of effect depending on the time cohort in the OLS regression and thus did not generate a CATT result.

### 4.5.3 Pollutant Results

The review of literature on craft brewing and air pollution in Section 2.1 established that breweries emit significant quantities of GHGs (Olajire, 2011; Shin & Searcy, 2018), and the trace gas pollutants $NO_2$, $SO_2$, and PM2.5 (Buglass, 2010). While carbon dioxide measurements were unavailable for this thesis, CANUE provides data for $NO_2$, $SO_2$, and PM2.5 exposure. Other literature indicates that craft brewer pollutant emissions should be significant – up to six times more emissions per liter of beer brewed compared to industrial brewers (Amienyo & Azapagic, 2016; Brewers Association, 2016b; Cimini & Moresi, 2018; Koroneos et al., 2005). Therefore, the results are expected to show increases in all three gas pollutants.

As shown in the Canadian Indices of Multiple Deprivation results, when sub-groupings have a low sample size, the analysis tends to fail to produce CATT estimates. This effect should be noted for each pollutant result, where the Rural sub-groups for each of the three pollutants fail to show a result. However, unlike the Index results, the pollutant results show statistically significant impact values in most All and Urban groupings.

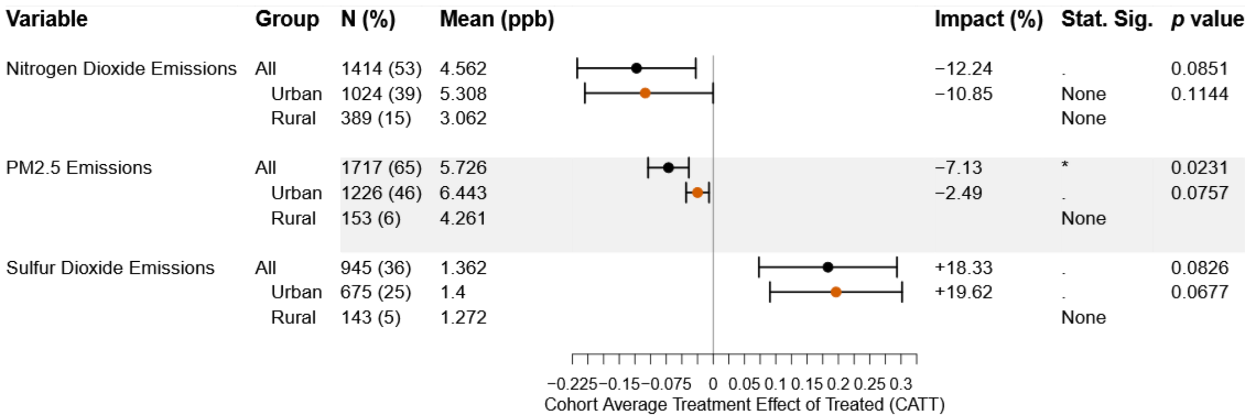



*Figure 14 Statistical Results Summary, Air Pollution variables, in ppb*

#### *4.5.3.1 Nitrogen Dioxide Emissions*

The results exhibit broad significance, showing that the presence of a brewery in a community is associated with decreases in the $NO_2$ emissions rate of 12.24%. The results are only marginally statistically significant, possibly the result of the limited availability of data on this variable, with only 1,414 out of 2,659 observations having complete $NO_2$ emissions data. Nevertheless, it can still be stated that the presence of a craft brewery in an Ontario community is associated with a reduction in $NO_2$ emissions. The average Ontario community with a brewery could see a reduction in $NO_2$ levels from 4.562 ppb to 4.004 ppb. As long-term exposure to nitrogen dioxide is associated with increased mortality in humans (Huang et al., 2021), the reduction in $NO_2$ due to craft breweries is a positive outcome for human health.

#### *4.5.3.2 Particulate Air Pollution (PM2.5)*

Once again, the results demonstrate that brewery presence is associated with lower emissions, in this case, small particulate air pollution. The magnitude of the effect is smaller than the NO2 result, but the 7.13% reduction in PM2.5 is more statistically significant with a *p* value of 0.023. The reduction in PM2.5 levels due to the presence of a craft brewery in an average Ontario community is about 0.41 ppb. Exposure to PM2.5 is associated with an increase in mortality rates, though the association was only noted when PM2.5 levels increased by 5.91 ppb (Yitshak-Sade et al., 2019).

#### *4.5.3.3 Sulfur Dioxide Emissions*

The effect of craft breweries on $SO_2$ emissions can be measured across the entire province, revealing that the presence of a brewery in a community is associated with an increase in $SO_2$ emissions of 18.33%. A relatively low sample size of 945 out of 2,659 observations – only 36% of the total panel dataset – would typically lead to a lack of statistically meaningful results. However, this study reveals significant findings, though only marginally significant ($p$ value = 0.083). A valid result suggests that the observed effect of craft breweries on $SO_2$ emissions is robust enough to stand out despite the limited sample size. Sulfur dioxide exposure in humans has been extensively shown to harm human health, even during short-term exposure events (Orellano et al., 2021). An average Ontario community with a craft brewery present can expect $SO_2$ pollution to worsen by about 0.25 ppb.

#### *4.5.3.1 Pollutant Results in Context*

The empirical findings of the pollutant results in Figure 14 do not align entirely with LCA analyses that indicate craft brewers generate notable pollutant emissions (Amienyo & Azapagic, 2016; Cimini & Moresi, 2018; Koroneos et al., 2005). Specifically, the results show that the presence of a brewery is associated with reductions in $NO_2$ and PM2.5 emissions and an increase in $SO_2$ emissions. This discrepancy with the literature could be explained by the inherent limitation of the outside-in perspective employed in this study, which cannot isolate the impact of craft breweries from other community-level changes. For example, it is common for craft brewers to occupy buildings that were previously used by factories (Feeney, 2017). Replacing an industrial factory with a small-scale craft brewery would explain why the results show a decrease in typical industrial pollutants when craft breweries are established.

The analysis reveals a measurable increase in the pollutant sulfur dioxide in communities after the founding of craft breweries. There is an implication in the sustainability literature that craft breweries will increase $SO_2$ pollution, but no systematic empirical measurements have been found. Previous research on $SO_2$ and breweries is limited to manufacturing and chemical studies (Almeida et al., 2003; Buglass, 2010; Miracle et al., 2005), as $SO_2$ can be an undesired flavour compound in beer. Hence, this study may be the first to demonstrate the significant emissions impact of $SO_2$ from craft brewers.

# Chapter 5 – Discussion and Recommendations

The results clearly illustrate that the sustainability impacts of a craft brewery in a community in Ontario can be measured and have mixed outcomes. This chapter outlines the value of the research conducted, its contribution to the literature, and lessons learned.

## 5.1 Gentrification

The sociodemographic findings in 4.5.1 showed reductions in visible minorities and indigenous people, indicating a trend toward gentrification. This unexpected discovery emerged only after examining the aggregated statistical analysis outputs. The connection between craft breweries and gentrification became well-established in the academic literature as the craft brewing movement gained momentum after 2010.

One qualitative study by Mathews & Picton (2014) shed light on the connection between craft breweries and gentrification by focusing on Mill Street Brewery, which had outlets in former industrial districts in Toronto and Ottawa. Mathews & Picton argued that craft brewers played a role in gentrification by "recalibrating industrial landscapes into spaces of consumption" (p. 337). Their sociological perspective highlighted how craft brewers' conversion of industrial spaces into commercial ones catalyzes gentrification, even as they preserve cultural heritage (Feeney, 2017).

The quantitative aspects of craft breweries and gentrification were explored in a study by Walker & Miller (2018) in Portland, Oregon. By aligning the founding dates of breweries with waves of gentrification, they established that craft breweries were "slightly more likely to open in gentrified/gentrifying neighbourhoods than not". They also found that craft brewery openings tended to occur after neighbourhoods had begun gentrifying. If the results of the Walker & Picton study apply to Ontario, it would indicate that while Ontario craft breweries tend to worsen the impacts of gentrification, they are unlikely to cause gentrification on their own.

Mathews followed up their 2014 collaboration with Picton (Mathews & Picton, 2014) in 2022 by arguing that in Saskatchewan, the magnitude of gentrification impact craft breweries have in urban areas is linked to city planning practices. Mathews' research demonstrated that when breweries adopt hyperlocal practices and are situated near residential zones, the adverse effects of gentrification are amplified. Her work provides valuable insights for urban planners seeking to mitigate some of the negative consequences that craft breweries can bring to neighbourhoods affected by gentrification. Those same urban planners can use the results of this thesis to understand the precise effect of thirteen sustainability impact variables that craft breweries might have on their communities.

## 5.2 Applicability of Study Design to Other Contexts

This thesis aims to investigate the impacts of craft breweries in Ontario; however, the methodology employed is not inherently limited to this context and can be extended to other provinces or countries. Replicating the results across all Canadian provinces and territories with craft breweries should be straightforward due to the wide availability of brewery data on the RateBeer social media platform and community data from the Canadian Census and CANUE. Alternative geographic identifiers would be required for replication in other countries since the CSDs used in this study are unique to Canada. Nevertheless, the approach of combining census data with scraped public websites and research datasets could be adapted for sourcing community data in different contexts.

## 5.3 Study Limitations and Solutions

A notable disparity exists between the results derived from the Canadian Census (section 4.5.1) and the CANUE (sections 4.5.2 and 4.5.3) data sources in this study. Compared to the Census data, CANUE data is sparser, leading to less robust statistical outcomes.

While Census data was available for 2001, 2006, 2011, 2016, and 2021, the residential instability and economic deprivation indices contained data only for 2001, 2006, and 2016. $NO_2$ and PM2.5 data were available from 2001 until 2016, and $SO_2$ was only available from 2006 to 2016. While the Census data contained a minimum of 84% of all possible data points, the availability of CANUE data ranged from 36% to 65%. These data limitations did not prevent generating statistically significant results, but they contributed to greater *p* values (which are statistically less significant) than the Census data. Furthermore, when the data was split into groups to compare urban and rural communities in Ontario, the small sample sizes in rural areas prevented the generation of statistically significant results.

Increasing the sample size is a straightforward solution to address this limitation and obtain more robust statistical results. One approach could involve awaiting the publication of updated datasets by CANUE and incorporating those revisions into future analyses. Alternatively, broadening the geographic scope of the study to include Ontario's neighbouring provinces of Quebec and Manitoba, or even expanding to all of Canada, would increase the sample size. Expanding beyond Ontario may introduce errors from treatment effect heterogeneity due to differences in alcohol laws among provinces. As established previously, modifications to the statistical approach, like new fixed effects and interaction terms, could help to mitigate the potential confounding effects.

Another limitation of this thesis is the lack of empirical measurements of $CO_2$ at the community level. The lack of $CO_2$ emissions data prevented its inclusion in the statistical analysis, thereby hindering a comparison with the ground-breaking research conducted by Shin and Searcy (2018) on GHG emissions related to Ontario craft brewing. As a result, this thesis is complementary to the existing body of knowledge on Ontario craft brewing's carbon dioxide emissions.

In Ontario, CSDs can often accommodate multiple craft breweries within their boundaries, particularly in urban areas where populations are concentrated. However, the Sun & Abraham method employed in this thesis is limited in handling multiple treatments and thus, multiple breweries. Instead, the technique only accepts "absorbing treatments" or binary interventions that begin but do not have an endpoint. Therefore, this thesis ignored multiple breweries, and the first brewery to be founded in any CSD was encoded as an absorbing treatment. The main impact of this limitation is likely to be underestimates in the magnitude of CATT results. It would be helpful for further research to measure the bias attributable to non-absorbing treatments when using Sun & Abraham (2021) estimators.

Potential solutions to the problem of multiple craft breweries in a CSD or non-absorbing treatments exist. In future studies, direct intensity measures like multiple breweries could be used as weighting measures in the OLS regressions. Like crowdsourced ratings, proxies for size and performance could also be added as exogenous controls and are already present in the panel dataset. More formal statistical methods for handling multiple treatments in cohort event studies are in development but are not mature. One proposed method was created by de Chaisemartin & D'Haultfœuille (2022) but at the time of this thesis, no implementation was available in the R coding language. As a result, it was excluded from usage.

# Chapter 6 – Conclusion

By assembling a panel dataset and analyzing it with a DiD study design using Sun and Abraham (2021) estimators, this thesis has shown how Ontario craft breweries directly affect the sustainability of their host communities. These causal impacts occur across a diverse set of social, economic, and environmental factors. A few notable impacts include a reduction in average home value and populations of visible minorities and indigenous people and increases in sulfur dioxide pollution and average household income. The analysis also indicated systemic variations in the direction and magnitude of the effects depending on the rurality or urbanity of craft breweries.

While the results of this thesis are limited to the craft brewing industry in Ontario, the mathematical approach provides new insight into how the sustainability of other types of small businesses might be measured. Further research is needed to determine the unexplained causes behind the unexpected air pollution and home value results. Replications of the methodology used in this thesis to other provinces in Canada or states in the USA could show whether these results are generalizable across North America.

The literature on econometrics has many examples of empirical DiD studies that establish causal inferences to businesses, including some works that examine the impact of craft breweries on single factors and in small geographic regions. However, this thesis is the first provincial scale attempt to measure the impact of an entire small business segment like craft breweries. This thesis, therefore, adds to the literature in both econometrics and small business by providing a methodology and results of such an analysis.

The findings of this thesis also complement the literature on gentrification. It is broadly believed that craft breweries are associated with gentrification, and findings show that craft breweries seem to add to the magnitude of some variables associated with gentrification while reducing the magnitude of others.

Finally, this thesis complements the literature on craft brewing by presenting an outside-in empirical analysis of the craft brewing industry in Ontario. As empirical studies of craft brewing are rare, the results presented in this thesis should assist researchers and craft brewing practitioners in understanding the benefits and drawbacks of craft breweries.

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## Appendix A – Standard Error Clustering Methods

According to Abadie et al. (2022), when the number of clusters in a cohort event study constitutes a substantial proportion of the total clusters in the population, the use of clustered standard errors is likely to result in significantly overestimated or excessively conservative estimates. In this study, the number of clusters is equal to the total clusters in the population, making this issue particularly relevant. In such cases, alternative approaches to error clustering must be considered, including using simple robust standard errors, which may slightly underestimate the standard errors. Additionally, two relatively new methods of clustering errors, causal cluster variance and two-stage cluster bootstrap, are suggested by Abadie et al. but have yet to be implemented in R and were therefore excluded.

In this study, a comparison of six clustering methods was conducted to address this issue. Among the methods examined, the Conley method exhibited intriguing results because it used latitude-longitude pairs to establish geographically clustered errors. In the end, the two-way clustered standard errors method was adopted for this analysis as it has widespread usage in other DiD studies.

| Std Error Method | Heteroskedast.-rob. | | Newey-West | | Conley | | One-way (CSD) | | Two-way (CSD, Year) | | Three-way (CSD, Year, census division) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Dependent Var.:** | unemploymentRate | | unemploymentRate | | unemploymentRate | | unemploymentRate | | unemploymentRate | | unemploymentRate | |
| | Estimate | Error | Estimate | Error | Estimate | Error | Estimate | Error | Estimate | Error | Estimate | Error |
| **Year = -20** | -0.0237*** | 0.0055 | -0.0237* | 0.0054 | -0.0237*** | 0.0053 | -0.0237*** | 0.0053 | -0.0237* | 0.0077 | -0.0237. | 0.0094 |
| **Year = -15** | -0.0189*** | 0.0040 | -0.0189** | 0.0039 | -0.0189*** | 0.0043 | -0.0189*** | 0.0042 | -0.0189. | 0.0068 | -0.0189. | 0.0081 |
| **Year = -10** | -0.0142*** | 0.0042 | -0.0142* | 0.0041 | -0.0142** | 0.0044 | -0.0142** | 0.0043 | -0.0142. | 0.0054 | -0.0142. | 0.0059 |
| **Year = -5** | -0.0175*** | 0.0046 | -0.0175* | 0.0046 | -0.0175*** | 0.0049 | -0.0175*** | 0.0047 | -0.0175* | 0.0048 | -0.0175* | 0.0054 |
| **Year = 0** | -0.0270*** | 0.0046 | -0.0270** | 0.0047 | -0.0270*** | 0.0046 | -0.0270*** | 0.0045 | -0.0270** | 0.0032 | -0.0270* | 0.0060 |
| **Year = 5** | -0.0339*** | 0.0090 | -0.0339* | 0.0088 | -0.0339*** | 0.0087 | -0.0339*** | 0.0086 | -0.0339** | 0.0054 | -0.0339* | 0.0075 |
| **Year = 10** | -0.0557*** | 0.0146 | -0.0557* | 0.0164 | -0.0557*** | 0.0163 | -0.0557*** | 0.0163 | -0.0557** | 0.0116 | -0.0557* | 0.0129 |
| **CATT** | -0.0300*** | 0.0052 | -0.0300** | 0.0053 | -0.0300*** | 0.0073 | -0.0300*** | 0.0052 | -0.0300** | 0.0036 | -0.0300** | 0.0062 |

*Figure 15 Comparison of Standard Error Clustering Methods for Staggered Event Regressions*

# Appendix B – Full Results

| Variable | Group | N (%) | Mean | % Impact | Stat. Sig. | *p* value |
|---|---|---|---|---|---|---|
| Unemployment Rate | All | 2624 (99) | 0.101 | −3.00 | ** | 0.0012 |
| | Urban | 1684 (63) | 0.075 | −1.87 | ** | 0.003 |
| | Rural | 928 (35) | 0.135 | −4.38 | ** | 0.0029 |
| Poverty Rate (LICOat) | All | 2303 (87) | 0.057 | +0.41 | . | 0.0839 |
| | Urban | 1608 (60) | 0.061 | +0.44 | . | 0.066 |
| | Rural | 683 (26) | 0.05 | −0.26 | * | 0.0034 |
| Visible Minorities | All | 2624 (99) | 0.03 | −2.32 | ** | 0.0013 |
| | Urban | 1684 (63) | 0.043 | −2.11 | ** | 0.0018 |
| | Rural | 928 (35) | 0.006 | −1.92 | *** | <0.001 |
| Indigenous People | All | 2624 (99) | 0.22 | −0.63 | ** | 0.0065 |
| | Urban | 1684 (63) | 0.099 | −0.75 | ** | 0.0012 |
| | Rural | 928 (35) | 0.45 | −3.03 | ** | 0.0058 |
| White People | All | 2612 (98) | 0.956 | +2.57 | ** | 0.003 |
| | Urban | 1684 (63) | 0.942 | +2.54 | ** | 0.0029 |
| | Rural | 928 (35) | 0.98 | −3.37 | None | 0.2078 |
| 5−year Mobility | All | 2612 (98) | 0.03 | +0.02 | None | 0.9597 |
| | Urban | 1684 (63) | 0.31 | +0.48 | None | 0.2755 |
| | Rural | 928 (35) | 0.274 | −6.93 | * | 0.0495 |
| Working Age People | All | 2612 (98) | 0.643 | −0.69 | ** | 0.0039 |
| | Urban | 1678 (63) | 0.646 | −0.61 | ** | 0.0062 |
| | Rural | 934 (35) | 0.639 | −2.04 | ** | 0.0024 |
| Young Adults | All | 2612 (98) | 0.16 | −0.14 | None | 0.2886 |
| | Urban | 1678 (63) | 0.155 | −0.24 | . | 0.0771 |
| | Rural | 934 (35) | 0.168 | −0.48 | None | 0.4737 |
| Higher Educated | All | 2612 (98) | 0.363 | −0.94 | *** | 0.0007 |
| | Urban | 1684 (63) | 0.395 | −0.85 | *** | 0.0007 |
| | Rural | 928 (35) | 0.304 | −0.14 | None | 0.7171 |
| Immigrants | All | 2434 (92) | 0.079 | −0.66 | ** | 0.0046 |
| | Urban | 1637 (62) | 0.1 | −0.62 | ** | 0.0058 |
| | Rural | 797 (30) | 0.037 | −0.78 | . | 0.0926 |
| First−language English | All | 2598 (98) | 0.916 | +0.09 | None | 0.2196 |
| | Urban | 1677 (63) | 0.938 | +0.18 | . | 0.0791 |
| | Rural | 921 (35) | 0.877 | −0.85 | ** | 0.0062 |

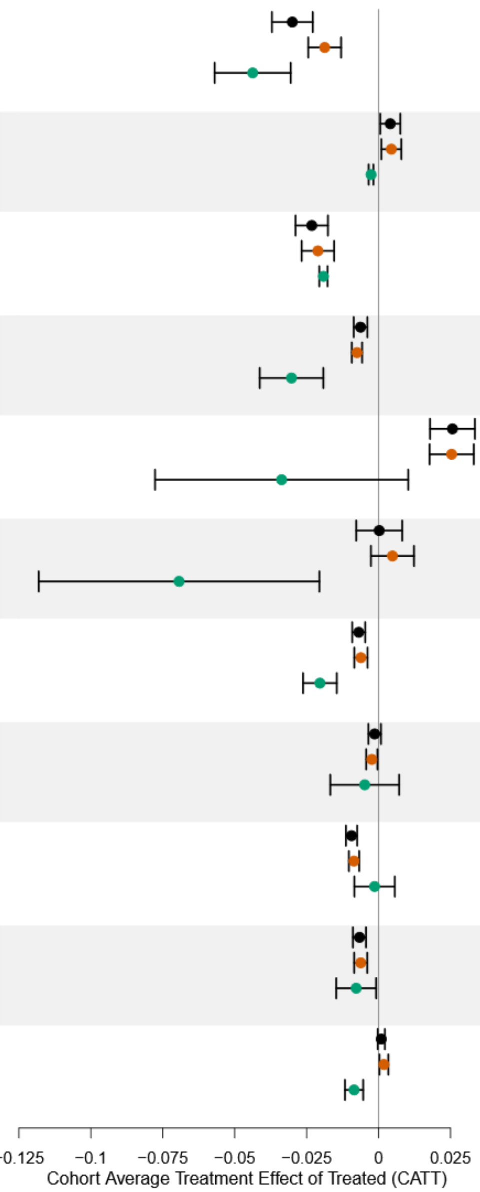


*Figure 16 Statistical Results Summary, sociodemographic and economic variables, in percent per capita*

| Variable | Group | N (%) | Mean (CA$) | % Impact | Stat. Sig. | *p* value |
|---|---|---|---|---|---|---|
| Household Income (median) | All | 2377 (89) | 56422 | +1.71 | ** | 0.0043 |
| | Urban | 1640 (62) | 59313 | +1.26 | *** | 0.0009 |
| | Rural | 229 (9) | 49986 | +5.66 | ** | 0.0057 |
| Average Home Value | All | 2098 (79) | 284559 | −7.65 | ** | 0.0058 |
| | Urban | 1549 (58) | 326436 | −3.22 | * | 0.0372 |
| | Rural | 549 (21) | 169040 | −4.08 | None | 0.604 |

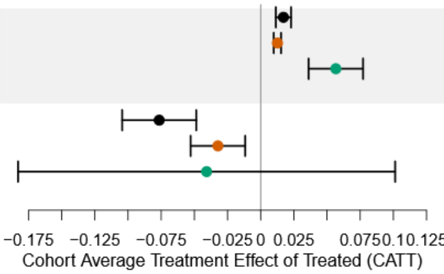


*Figure 17 Statistical Results Summary, sociodemographic and economic variables, in Canadian dollars normalized to 1992 values*

| Variable | Group | N (%) | Mean Index Value | % Impact | Stat. Sig. | *p* value |
|---|---|---|---|---|---|---|
| Residential Instability | All | 1090 (41) | −0.399 | +1.69 | None | 0.8044 |
| | Urban | 849 (32) | −0.438 | +2.29 | None | 0.7379 |
| | Rural | 236 (9) | −0.259 | | None | |
| Economic Deprivation | All | 1090 (41) | −0.011 | −5.84 | None | 0.6248 |
| | Urban | 849 (32) | −0.159 | −5.52 | None | 0.6433 |
| | Rural | 236 (9) | 0.525 | | None | |

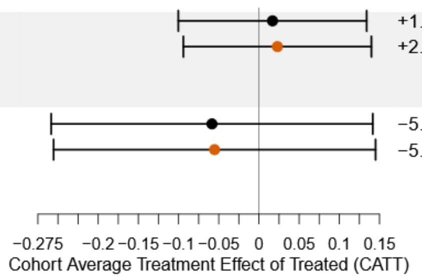


*Figure 18 Statistical Results Summary, Canadian Index of Multiple Deprivation variables, by Index value*

| Variable | Group | N (%) | Mean (ppb) | % Impact | Stat. Sig. | *p* value |
|---|---|---|---|---|---|---|
| Nitrogen Dioxide Emissions | All | 1414 (53) | 4.562 | −12.24 | . | 0.0851 |
| | Urban | 1024 (39) | 5.308 | −10.85 | None | 0.1144 |
| | Rural | 389 (15) | 3.062 | | None | |
| PM2.5 Emissions | All | 1717 (65) | 5.726 | −7.13 | * | 0.0231 |
| | Urban | 1226 (46) | 6.443 | −2.49 | . | 0.0757 |
| | Rural | 153 (6) | 4.261 | | None | |
| Sulfur Dioxide Emissions | All | 945 (36) | 1.362 | +18.33 | . | 0.0826 |
| | Urban | 675 (25) | 1.4 | +19.62 | . | 0.0677 |
| | Rural | 143 (5) | 1.272 | | None | |
| Ozone Emissions | All | 1715 (64) | 34.522 | −2.47 | . | 0.0921 |
| | Urban | 1225 (46) | 36.422 | −0.35 | None | 0.274 |
| | Rural | 490 (18) | 30.19 | −0.87 | None | 0.1122 |

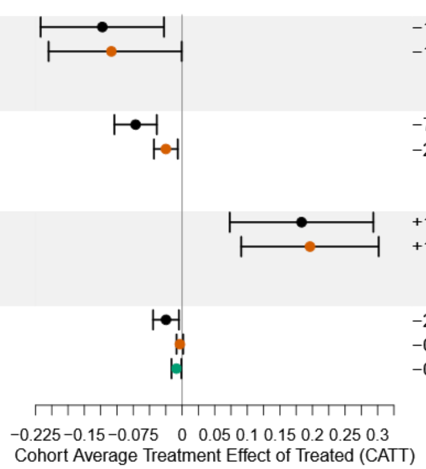


*Figure 19 Statistical Results Summary, Environmental Air Pollution variables, in ppb*

| Variable | Group | N (%) | Mean | % Impact | Stat. Sig. | *p* value |
|---|---|---|---|---|---|---|
| Climate Zone: Natural | All | 1716 (65) | 0.782 | +4.88 | None | 0.2791 |
| | Urban | 1226 (46) | 0.76 | +2.97 | None | 0.4848 |
| | Rural | 490 (18) | 0.838 | | None | |
| Green−ness (normalized difference vegetation index) | All | 1716 (65) | 0.526 | +3.06 | . | 0.0544 |
| | Urban | 1226 (46) | 0.53 | +4.14 | * | 0.0217 |
| | Rural | 490 (18) | 0.517 | | None | |

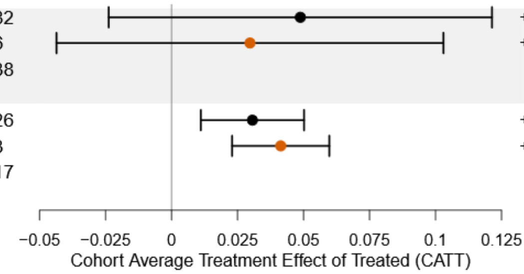


*Figure 20 Statistical Results Summary, Environmental Local Climate variables, in percent*