Location Choices of Multi-plant Oligopolists: Theory and Evidence from the Cement Industry*

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October 2022

Abstract

I develop a quantitative model of multi-plant oligopolists where each firm decides where to locate the set of plants and how to serve each market, taking into account cannibalization and competition. In contrast to canonical trade models with multinational firms where neither spatial interdependency in production nor oligopoly is considered, the multi-plant firm here increases her markups by adding one more plants but the marginal benefit declines with more plants being built. Despite having a high-dimensional discrete choice problem, I provide an estimation toolkit for the model leveraging the solution algorithm for a combinatorial problem when the location game is submodular and aggregative. Applying the model to the cement industry in the US and Canada, I find that a carbon tax of \$50 per ton of CO_2 on cement induces 18% carbon leakage, and the taxing economy loses, especially when the industry is concentrated. Neglecting the interdependencies of plant locations within a multi-plant firm substantially biases the estimates and over-predicts the degree of carbon leakage.

Keywords: Multi-plant, oligopoly, interdependent entry, combinatorial discrete choice, submodular games, carbon leakage, Greenhouse Gas Pollution Pricing Act.

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*This paper combines the first and second chapters of my dissertation titled "Decisions of Multinational Firms: Plant Location and Sourcing". Many thanks therefore go to my advisors Keith Head, John Ries, Sanghoon Lee, Álvaro Parra, and Hiro Kasahara. I also would like to thank Paul Piveteau, Jonathan Dingel, Costas Arkolakis, seminar participants at the Canadian Economic Association annual meeting (Banff), Canadian Econometric Study Group Meetings (Montreal), Asian Development Bank Regional Conference on Mapping Value Chains (Indonesia), Singapore Management University Conference on Urban and Regional Economics, Urban Economics Association 2020 Virtual Meeting, UEA 2020 PhD Workshop in Urban Economics, and the University of British Columbia, for very helpful comments and suggestions. Support for this research from the Productivity Partnership as funded by SSHRC and SMU MOE tier 1 Grant are also gratefully acknowledged. Any remaining errors are my own.

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1 Introduction

Firm-level adjustments to regulatory changes could undermine the intended purpose of a policy and impose costs on the economy. A classic example is a regional carbon tax that increases the local operating costs relative to the unregulated rivals. Firms respond by moving production and associated emissions to jurisdictions with laxer standards, leading to employment loss in the taxing economy and limited changes in total emissions. The recurrent concerns on the issue of carbon leakage prompt a need for new analysis to understand the spatial organization of firms, especially in concentrated industries where the welfare costs can be further exacerbated.

Evaluating how firms, especially multi-plant firms, operate spatially is a complex problem. A multi-plant firm confronts trade-offs in deciding where to locate a set of plants and which plant to supply where, taking into account the competition with rival firms and cannibalization among its own plants. A firm having too sparse plants implies higher costs of transporting products to consumers. Having too many plants close to consumers incur higher fixed costs. Further, given locations differ in production costs and plants can be heterogeneous in productivity, transportation costs is not the only factor governing plants substitution. In industries where fixed costs are high and goods are tradable, the plant location decisions are interdependent of one another. The geographic distribution of plants determines the goods flow, prices, and even markups in each market. As a result, a local cost shock is likely to generate global welfare impacts.

In this paper, I study three fundamental decisions associated with multi-plant production. First, what determines the number and location of plants for multi-plant firms? Second, how do markups and prices vary by the spatial allocation of plants? Third, how important is allowing for multi-plant production and interdependent entry of plants? I develop a quantitative spatial model of oligopolists that characterizes firms' extensive and intensive margins of multi-plant production. The model accommodates rich heterogeneity in locations and firms yet generates precise mechanisms of plant locations contributing to the pricing and profitability of firms. I then provide a methodology that estimates the model's key primitives in a sequential procedure and substantially simplifies the interdependent location problem. Finally, I show that accounting for multi-plant production, namely interdependent plant locations and variable markups, has sizable effects on the spatial distribution of economic activity and welfare of the Greenhouse Gas Pollution Pricing Act (the Act) in Canada.

To shed light on the core components of firms' decisions, I set up an economy with a finite number of discrete locations that are heterogeneous in productivities and input costs. Plants at each location are potential suppliers of local consumers and those in every other locations. Firms decide how many and which locations to build plants by balancing their expectation on costs of production, costs of distribution and costs of entry, while factoring competition within and across firms given the vector of demand. When competing, plants engage in head-to-head price competition similar to Bernard et al. (2003) (hereforce BEJK) except that those owned by the same firm do not undercut each other in price. Therefore, for a multi-plant firm, there are counteracting forces in determining the optimal set of production locations: coordination in prices set by the firm improves its competitive advantage against rivals through building more and favorably located plants, whereas cannibalization between its own plants decreases the marginal benefit. Plants are strategically added until marginal payoff cannot cover fixed costs of building.

The model advances existing research in two aspects. First, firms are granular and oligopolies such that their markups vary by firm and market. Existing work has long been using constant markup derived from the workhorse model of constant elasticity of substitution (CES) with monopolistic competition. I relax those assumptions and incorporate strategic pricing among oligopolistic rivals. The model remains to be tractable with analytical expressions for firms' markup distribution and expected profit given the plant location configuration. It also conforms to a gravity trade framework, like many other canonical models in the literature.

The model predicts that a firm with more and better located plants charges higher markups and captures a larger fraction of the market. The intuition is that favorable plant bundle a firm owned lowers its average costs and improves the firm's competitive advantage over its rivals. Introduction of entry and oligopolistic competition opens up the possibility to reexamine the connection between extensive and intensive margin in the context of multi-plant or broadly multinational firms. It highlights the role of spatial distribution of plants in trade besides the usual technological differences and geographic barriers. As the geographic configuration of plants shapes the relative competency of firms, it also reinforces differences in comparative advantage across locations.

Second, the decision of plant locations is a game of strategic substitutes, and yet the model can be fully estimated.[1] Solving the interdependent entry game facing a large set of potential locations implies a hard permutation problem. When there are L number of possible production locations, a firm faces 2^L possible choices. A game with F number of players further complicates the combinatorial discrete choice (CDC) problem as it now involves 2^{FL} combinations. Due to the difficulty in tackling such a problem, some papers assume away export platform sales (Helpman et al., 2004; Irarrazabal et al., 2013) or fixed costs of entry (Ramondo and Rodríguez-Clare, 2013), treat locations as predetermined (Head and Mayer, 2019), or approximate the discrete location set as choosing continuous density of plants (Oberfield et al., 2020). I leverage two properties of the firm's profit function. One is that a firm's profit exhibits submodularity in the decision set. The other is that a firm's profit depends on its own action and an aggregate of all players' actions. These

[1] I take definitions from Jackson and Zenou (2015) p.103, where a game has *strategic complements* when "an increase in the actions of other players leads a given player's higher actions to have relatively higher payoffs compared to that player's lower actions". On the opposite, games of *strategic substitutes* are "an increase in other players' actions leads to relatively lower payoffs to higher actions of a given player".

two guarantee the existence of pure-strategy Nash equilibrium (PSNE), and also allow one to solve the game by eliminating non-optimal decision sets iteratively as in Arkolakis and Eckert (2017) and Arkolakis et al. (2021), an algorithm faster than brute force.

I estimate the model in three steps using aggregated and easily obtained data. In the first step, gravity regressions and data on bilateral trade are used to estimate a composite of local TFP and input costs that determines the competitive advantage across locations. I can also estimate the trade elasticity which regulates competition intensity among plants. In the second step, I estimate demand via generalized method of moments using data on consumption and market characteristics. In the third step, I estimate the fixed costs of building plants by fitting moments to the observed plant locations. Conditions on key parameters to guarantee the existence of a PSNE can be validated in steps prior to solving the location game. A notable advantage is that the multi-plant firm model in this paper can be estimated with minimum data requirement. Micro data on firm or plant-level market shares is not needed for this exercise.

To illustrate the policy relevance of this framework, I apply it to the cement industry in the US and Canada. As one of the largest manufacturing sources of carbon emissions, the cement industry is commonly assessed to be emissions-intensive and trade-exposed with high risk of carbon leakage (European Commission white paper, Europejska 2009). It is dominated by few giant multi-plant manufacturers with goods actively traded between locations in the US and part of Canada, making the model a well-suited and realistic characterization of the cement industry. I estimate the key costs faced by the North American cement producers, namely fixed costs of establishing a plant, the cost of production, and the cost of trade.[2] I find that the average fixed costs of building a one-million-tonne cement plant is four times the total variable cost of production. The largest cement producer has significant cost efficiency relative to the second largest producer, leading to a wider geographical span and 9% higher in gross margin. Cement plants engage a fiercer competition than other manufacturing goods found in the literature due to its homogeneous nature.

Equipped with the estimated model, I examine effects of the Greenhouse Gas Pollution Pricing Act in Canada. Three carbon pricing schemes are considered, namely carbon tax with and without border tax adjustment (BTA), and an output-based pricing system (OBPS). I find that change in plant locations is most aggressive in the case of carbon tax alone.[3] The increase in unregulated

[2]Since I apply a static model, dynamic parameters, such as sunk costs, per-period investment costs, and scrap values, are not considered in this paper. Ryan (2012) estimates that for cement, the per-period cost of investment is merely 0.5% compared to the cost of entry. He also finds that a cement plant needs to pay the environmental cleanup fee to exit which is higher than proceeds from selling off the land and infrastructure, resulting in negative scrap value which is roughly a quarter of the entry cost. Although these dynamic parameters are essential when firms decide whether to relocate plants in the next period, they are not a focus of this paper. I compare firms' adjustment in the long run under different policy scenario, considering policies such as carbon tax are not likely to be one-off or only last for a short period of time.

[3]Change in plant locations refers to different spatial allocations of plants in two steady states with and without implementing the policy, instead of transitional dynamics.

regions' emissions over domestic emission reduction (leakage rate) is 18% for a carbon tax at $50 per tonne of CO_2. BTA is most effective in fighting carbon leakage. Imposing the same level of carbon tax to imported cement decreases the leakage rate to 12% but cannot eliminate it because many Canadian plants that used to export to the US still lose their competitive advantage against the US plants. OBPS, effectively lower the carbon tax through rebates, retains the competitiveness of the domestic cement industry but only achieves one sixth of the carbon abatement using carbon tax. In terms of welfare, it is undesirable to impose a high carbon tax on a concentrated industry due to the losses from domestic market distortion and the global damages from carbon leakage.

How important is incorporating interdependent entry? I present comparisons to assuming separated plant entry. Results show that ignoring spatial interdependencies of multi-plant firms generates sizable biases in the estimates. The estimated fixed costs are one fourth of the baseline. It subsequently produces inaccurate policy predictions and could misguide the analysis. Specifically, for a carbon tax at $50 per tonne of CO_2, the carbon leakage rate without independent entry is over-predicted to be 20%.

This paper contributes to several strands of literature. First, this paper extends the existing trade models that studying oligopolists, such as BEJK and Atkeson and Burstein (2008), through distinguishing plants and firms clearly.[4] Such omission is concerning given mounting evidences that support differences between the two economic entities (i.e., Rossi-Hansberg et al., 2018; Hsieh and Rossi-Hansberg, 2019; Aghion et al., 2019; and Cao et al., 2017). My multi-plant firm model, as an extension of BEJK, derives distributions of costs and markups that nest those in single-plant setting.[5] The model, therefore, yields more generalized insights on firm-level decisions, encompassing single- or multi-plant owners.

Second, this paper adds to a vibrant area of ongoing research that explores interdependencies in multinational firms' extensive margin. An obviously important application of my model is multinational firms. Due to computational challenges, most papers in this topic speak to complementarities in firms' sourcing, production, and export decisions.[6] The closest one to mine is

[4] BEJK take different view of the world compared to the way Atkeson and Burstein (2008) modeling oligopoly in trade. In Atkeson and Burstein (2008), each firm produces a distinct good in a specific sector and firms maximize profits given imperfect substitution within a sector and across sectors. In contrast, BEJK model multiple producers producing the same good and there are a continuum of imperfectly substituted goods. I follow BEJK by assuming firms produce a homogeneous good. I acknowledge that this assumption may limit the scope of industries where the framework can be applied. However, an advantage for adopting BEJK is that it requires less firm-level data than Atkeson and Burstein (2008).

[5] Bernard et al. (2003) have markup distribution being impervious to any characteristics of market structure. Subsequent papers by Holmes et al. (2011, 2014) and De Blas and Russ (2015) generalize the model to incorporate the effects of finite number of firms in a market. My model is closer to the later development that recognizes the granularity of firms.

[6] Antras et al. (2017) features complementarity across global input sourcing because adding an extra country in the set of active importing countries reduces expected costs of the firm. The recent paper, Antràs et al. (2022), adds complementarity in both assembly and sourcing through fixed cost sharing. Jiang and Tyazhelnikov (2020) introduce

Tintelnot (2017) that studies substitutabilities in multinational production facing the potential for export platform sales. Nevertheless, his work evaluates all possibilities in a very small location set and the method is not easily scalable. I overcome the challenge by combining theoretical properties from the submodular game with a solution algorithm for combinatorial discrete choice problem. However, none of these papers allows for strategically interacted players. They all model a monopolistic competitive market and treat firms as infinitesimal with constant markups, whereas I highlight a small group of sizable firms competing oligopolistically and exploiting geographical advantages to increase markups. This key difference makes my model more suitable for analyzing policy questions in industries that are dominated by a few large firms.

Third, this paper joins a literature in the field of industrial organization that analyzes how retailers set up distribution networks in space, such as Jia (2008) and Holmes (2011). The technique to solve for combinatorial discrete choice is first introduced in Jia (2008) which focuses on positive spillover among chain stores and imposes a supermodular condition on the firm's return function. In games with strategic complements, it follows from Topkis' theorem (Topkis 1978) and Tarski's fixed point theorem (Tarski et al. 1955) that a PSNE exists. However, the existence of high dimensional spatial equilibrium when players are strategic substitutes is more theoretically demanding. The traditional method is to partially identify the parameters using a revealed preference approach (Holmes 2011). Recently, Arkolakis and Eckert (2017) make a breakthrough by offering a repetitive fixed points search algorithm to solve both supermodular and submodular problems. The algorithm is further developed in Arkolakis et al. (2021) to allow for a continuum of monopolistically competitive firms over a monotonic type space. In this paper, I adapt their solution algorithm to heterogeneous oligopolies.

Lastly, this paper addresses multi-plant firms in the environmental policy design. I show that neglecting interdependent plant relocation leads to overestimation of carbon leakage. Carbon leakage has been well studied in past research, such as Ryan (2012) and Fowlie et al. (2016). These works measure carbon leakage using an aggregated demand shift in imports without factoring in the foreign market structure or interconnection between the domestic and foreign through multi-plant firms.

The remainder of the paper is structured as follows. In Section 2, I lay out the model and propositions derived from it. In Section 3, I describe the data set and present important facts of the cement industry. The model is then estimated structurally in Section 4. In Section 5, I perform the counterfactual policy analysis on environmental policies, and then show the importance of allowing for interdependent plant locations in Section 6. Section 7 concludes.

complementarity in the production of pair of inputs. Alfaro et al. (2021) add time dimension to the combinatorial choices of export destinations.

2 A Model of Multi-plant Firms

This section sets out a theory of production locations, export and prices for multi-plant firms with market power. A firm and a plant are distinct, albeit related, economic entities. A plant can potentially serve the demand locally and elsewhere. A firm internalizes cannibalization within itself and competition with rivals by deciding where to produce, and how much each of its plants should charge. For simplicity, all that differentiates a firm from other potential entrants prior to entry are fixed costs of building plants.[7] Once fixed costs are paid, plants are differentiated by production costs and trade costs associated with their locations, and a stochastic term that indicates their productivity level. Each firm selects its optimal plant sites by maximizing total expected single-period profits. I consider a partial equilibrium environment by focusing on interdependent entry and price competition between oligopolies for one industry.

The model features a static simultaneous entry game with complete information. I identify the competition and cannibalization effects from the plants' spatial distribution pattern. This approach abstracts from a number of dynamic considerations. For example, it does not allow for preemptive entry (Igami and Yang, 2013; Zheng, 2016) nor does it allow for any learning process by firms (Arkolakis et al., 2018). One may also raise the concern about firms' additional considerations in a dynamic setting, such as how sunk costs and scrap values can deter relocation of a plant. In this regards, "relocation" decisions under a dynamic model are evaluated differently compared to "location" decisions under a static model. Since the main goal of this model is to study the interdependency in multi-plant firms' location decisions in a steady state and to compare long run equilibria under different policy regimes, incorporating transition dynamics is beyond the scope of this paper. Empirically, given the difficulty of solving the CDC problem, it is also computational challenging to extend the framework to a dynamic setting unless imposing additional assumptions.

Formally, there is a finite number of discrete geographical units, $m \in \mathcal{M}$. There is a given finite number of firms, $f \in \mathcal{F}$. A firm chooses a subset of locations $\mathcal{L}_f \subseteq \mathcal{M}$ to set up plants, where a plant is indexed by $\ell \in \mathcal{L}_f$.[8] The firm owns $N_f = |\mathcal{L}_f|$ number of plants.

I start with the description of demand and then turn to the problem of multi-plant firms.

2.1 Demand

Demand is characterized for a single product bought by a continuum of consumers $i \in \mathcal{D}_m$ on a unit interval in m. The aggregated local demand is Q_m units of the good. I assume an isoelastic

[7] The ex-ante heterogeneity across potential entrants can be extended to include firm-level productivity differences, but they are omitted for simplicity and would require additional data to be identified. I incorporate this extension in Appendix B.1.

[8] I assume a firm cannot have more than one plant at a location. Essentially, a firm choosing a set of plants is equivalent to choosing a set of locations to produce.

demand at the location level, given by

$$Q_m = A_m P_m^{-\eta}, \tag{1}$$

where $-\eta < -1$ is the price elasticity of demand to be consistent with profit maximization of monopolists. The local price index of the good is P_m, and the exogenous demand shifter is A_m. I formulate demand for each location instead of demand for each consumer because ex ante firms treat consumers in the same location identical. They only obtain knowledge on how consumers may differ and price accordingly after plants are built. Therefore, consumer-specific demand is unnecessary when constructing a firm's expected profits.[9]

2.2 The multi-plant firm's problem

A multi-plant firm decides where to establish production operations and how to serve consumers at every location. Their plants are appointed to produce the same product facing the aforementioned demand function. The timing of game is that at $t = 1$, firms simultaneously decide the set of locations to build plants in order to maximize expected profits, and pay the respective fixed costs. At $t = 2$, firms learn about the realized productivity of plants and decide to which consumer plants supply. Plants compete in price. For simplicity, I assume there is no fixed cost of exporting and every plant can be a potential supplier of every consumers across all locations.[10] I solve the model by backward induction.

2.2.1 Production decisions given plant locations

Each location $m \in \mathcal{M}$ is characterized by an exogenous productivity level T_m, as well as local equilibrium characteristics that firms take as given, namely, the demand shifter A_m and costs of input w_m. Inputs to produce the good are immobile across locations. Trade between any two locations bears an iceberg trade cost. For example, firm f has a plant in ℓ. The cost of transporting the good from ℓ to a consumer at the center of m is $\tau_{\ell m}$.

Conditional on firm f produces in a set $\mathcal{L}_f$ of locations, for each location $\ell \in \mathcal{L}_f$, the firm converts one bundle of inputs into a quantity $Z_{f\ell i}$ of the good for consumer $i \in \mathcal{D}_m$ at constant return to scale. The term $Z_{f\ell i}$ represents idiosyncratic shock specific to a plant-consumer pair.

[9] One can easily add more structure to the demand side, such as CES preferences—one special case of isoelastic demand—among goods for each consumer and then aggregate to a location. However, additional demand parameters add no benefit in solving the firm's problem but further complicate the model.

[10] Fixed costs of exporting at firm level could be incorporated, as in Tintelnot (2017), but they are omitted for simplicity and would require additional data to be identified. However, if the fixed costs of exporting are associated with the set of plants, then a firm would no longer select the lowest cost plant to serve a consumer, and the model would lose tractability.

Examples of such factors include relationship specificity and internal distance between consumers in m towards the center. Rather than dealing with each $Z_{f\ell i}$ separately, I assume that they are realizations of independently and identically distributed random draws from a Fréchet distribution. The cumulative distribution function of the productivity that firm f's plant in ℓ is

$$F_{\ell}^{draw}(z) = \Pr[Z_{f\ell i} \leq z] = \exp(-T_{\ell} z^{-\theta}).$$

Dispersion of productivity is represented by θ. The bigger θ is, the more similar are the productivity draws.

Combining productivity, input and trade costs, the marginal cost of supplying the good from a plant in ℓ to consumer i in m is therefore

$$C_{f\ell im} = \frac{w_{\ell}\tau_{\ell m}}{Z_{f\ell i}}, \forall \ell \in \mathcal{L}_f, i \in \mathcal{D}_m. \tag{2}$$

It is distributed as

$$F_{\ell m}^{c}(c) = \Pr[C_{f\ell im} \leq c] = 1 - \exp\left(-\phi_{\ell m} c^{\theta}\right),$$

where $\phi_{\ell m} = T_{\ell}(w_{\ell}\tau_{\ell m})^{-\theta}$ indicates the capability of location ℓ serving location m.

A caveat here is that plants at the same location are ex-ante identical regardless of ownership. The setup is analogous to Antras et al. (2017) that any firm-specific factors are suppressed in the productivity distribution. One may argue to include a firm's core productivity parameter to shift its plants' productivity as in Tintelnot (2017) such that more productive firm will build more productive plants on average. As I demonstrate in Appendix B.1, it is straightforward to incorporate additional firm-level heterogeneity into the benchmark model. However, estimation of the model becomes substantially more data-hungry.[11] Although firms are not endowed with core productivities, we will show later that a firm having more plants at efficient (higher T) locations implies a more productive firm overall. Therefore, the ex-ante heterogeneity across firms is fully loaded on a firm's number of plants and their locations, i.e. the extensive margin.

Plants engage in Bertrand competition in a nested structure. Every consumer in a location is served by its lowest-cost supplier. If firms are single-plant, the winning firm is constrained not to charge more than the second-lowest marginal cost, the standard setting in BEJK. In the case of multi-plant firms, the firm headquarters decide prices for all their plants instead of plant managers. The firm headquarter will internalize competition between its own plants and coordinate their pricing. As a result, the winning plant will not undercut its *sister* plants owned by the same firm, until the next lowest-cost plant is owned by a competitor. The price charged is limited by

[11] To estimate the set of firm core productivity parameters, I would need each firm's market share in every location which is not commonly available. I welcome researchers who have the relevant data to use the extended version of the model in the Appendix.

the marginal cost of the lowest-cost plant owned by the second-lowest cost firm. Instead of fully characterize cost ranking across all plants, what really matter are the lowest-cost plant within a firm and the two lowest-cost firms.

First, define the kth lowest cost among firm f's plants serving consumer i in m as $C_{k,fi(m)}$. The distribution of the lowest marginal cost can be easily derived as

$$F^c_{1,fm}(c) = \Pr[C_{1,fi(m)} \leq c] = 1 - \exp(-\Phi_{fm}c^\theta), \tag{3}$$

where $\Phi_{fm} = \sum_{\ell \in \mathcal{L}_f} \phi_{\ell m}$ refers to the capability of a firm f serving location m. The assumption of Fréchet distributed productivities becomes handy in the derivation due to its grounding in the extreme value theory. If a firm selects the best available technology from a distribution, its productivity will also follow an extreme value distribution. While technical advantages dictate this choice, empirical distributions of productivity are typically bell-shaped in the literature, which also in favor of the Fréchet specification.[12]

Based on equation (3), the firm-level expected marginal cost to consumers in m is

$$E\big[C_{1,fi(m)}\big] = \Gamma\left(\frac{\theta+1}{\theta}\right)\Phi_{fm}^{-\frac{1}{\theta}}. \tag{4}$$

More plants at favorable (high $\phi_{\ell m}$) locations lower the firm's marginal cost.[13] Intuitively, one more production location grants the firm an additional cost draw, leading to more intense competition internally and reduction in marginal cost at the firm level. More plants also imply that the average shipping distance to consumers is shorter and thus additional savings on trade costs for firms. Furthermore, the effect of an additional plant is larger when it is located somewhere cheaper to produce and closer to consumers. The properties of the minimum cost distribution for a multi-plant firm allow me to establish the following result (the proof is straightforward and omitted in the main text).

Proposition 1: *An additional production location to the firm's active location set strictly decreases its lowest cost of supplying the good to all consumers in expectation.*

Second, define $C_{1,i(m)}$ and $C_{2,i(m)}$ be the lowest and second-lowest marginal cost across all

[12] Another commonly used distribution is Pareto. Although Fréchet and Pareto distribution both have fat right tails, they are very different on the left side. The former density is bell-shaped whereas the latter density is downward-sloping throughout. Other candidate could be log normal that is very hard to be distinguished from Fréchet, or truncated distributions. However, properties in truncated distributions are more obscured and hard to applied to my model without strong support of empirical evidences. A thorough examination and comparison of distributions can be found in Head (2011) and Kotz and Nadarajah (2000).

[13] The implication is in contrast to Oberfield et al. (2020) in which they focus on the span-of-control cost and more plants will reduce a firm's efficiency. Nevertheless, we both have that favorable locations reduce the marginal costs of plants and firms.

firms for consumer i in m. Conditional on sales originating from firm f's plant at location ℓ, $C_{1,i(m)} \equiv C_{f\ell i(m)}$ and $C_{2,i(m)} \equiv \min_{g \neq f, g \in \mathcal{F}}\{C_{1,gi(m)}\}$. I show in Appendix A.1 that the conditional joint distribution of the lowest and second-lowest firm-level cost of supplying the good to a consumer at m is

$$F^c_{12,m|f}(c_1, c_2) = 1 - e^{-\Phi_m c_1^\theta} - \frac{\Phi_m}{\Phi_{fm}} \left(1 - e^{-\Phi_{fm} c_1^\theta}\right) e^{-\left(\Phi_m - \Phi_{fm}\right) c_2^\theta}, \tag{5}$$

for $c_1 \leq c_2$, where $\Phi_m = \sum_{f \in \mathcal{F}} \sum_{\ell \in \mathcal{L}_f} \phi_{\ell m}$ denotes the sourcing potential of location m over all plants. Notice that the conditional joint distribution is independent of plant-level attributes, corroborating that plants only matter in determining the minimum cost a firm can achieve.

Adding multi-plant production and firm granularity generalizes earlier models that use the BEJK framework. When the number of firms approaches to infinity, the limit distribution of equation (5) is what BEJK use for the joint distribution of two lowest costs. When firms are finite but single-plant, equation (5) takes the form of the joint distribution in Holmes et al. (2011).

I now turn to describe the price and markup distributions in this model. The competition structure implies a strategy similar to limit pricing, where the lowest-cost plant charges a minimum between the monopoly price and the lowest marginal cost of its head-to-head competitors. Mathematically, the price charged to consumer i in m is $P_{i(m)} = \min\{\bar{\mu} C_{1,i(m)}, C_{2,i(m)}\}$, where the monopoly markup $\bar{\mu} = \eta/(\eta - 1)$.

Conditional on sourcing from firm f, the firm decides its winning plant to charge consumers in location m at a price following the distribution,

$$F^p_{m|f}(p) = F^c_{12,m|f}(p, p) + \frac{\Phi_m}{\Phi_{fm}} \left(1 - e^{-\Phi_{fm} \bar{\mu}^{-\theta} p^\theta}\right), \tag{6}$$

with derivation shown in Appendix A.2. A closer look at equation (6) reveals that the first term comes from the cost ladder, while the second term is derived from the probability to charge the monopoly price. Pass-through of a firm's own cost changes into prices is zero if she always prices against the second-lowest cost. Otherwise, it is one if the monopoly price always prevails. The price-setting by multi-plant firms exhibits incomplete pass-through. Combining with Proposition 1, a firm with larger and favorably located plant set lowers its average price. The expected price charged by firm f to consumers in m is

$$E\left[P_{fm}\right] = \Gamma\left(\frac{\theta + 1}{\theta}\right) \frac{\Phi_m}{\Phi_{fm}} \left(\left(\Phi_m - (1 - \bar{\mu}^{-\theta})\Phi_{fm}\right)^{-\frac{1}{\theta}} - \left(\Phi_m - \Phi_{fm}\right) \Phi_m^{-\frac{\theta+1}{\theta}}\right), \tag{7}$$

The price distribution is the same regardless of which plant in the firm wins. It means that within a firm supplying to a destination, the souring probability from one of its plants (quantity share) is the same as expenditure share, as seen in Eaton and Kortum (2002). The property is handy empirically when one observe plant sales to every market and a standard firm-level gravity trade regression can be applied. However, we cannot draw the same conclusion at market level across different firms.

Closely related, firm f's markup in location m is realization of a random draw from a shifted Pareto distribution truncated at the monopoly level,

$$F^{\mu}_{m|f}(\mu) = \begin{cases} 1 - \frac{1}{(1-s_{fm})\mu^{\theta}+s_{fm}} & 1 \leq \mu < \bar{\mu} \\ 1 & \mu \geq \bar{\mu} \end{cases}, \tag{8}$$

where $s_{fm} = \Phi_{fm}/\Phi_m$ indicates the relative competitiveness of firm f to its rivals. It is the sole shifter of the markup distribution. See Appendix A.3 for derivation. Specifically, for $1 \leq \mu < \bar{\mu}$, a firm owning more plants in favorable locations charges higher markup. For $\mu \geq \bar{\mu}$, I compute the probability of firm f charging monopoly markup given the second-lowest cost equals to

$$\frac{1 - e^{-\Phi_{fm}(\bar{\mu}/c_2)^{-\theta}}}{1 - e^{-\Phi_{fm}c_2^{\theta}}}.$$

It implies that knowing the otherwise price charged is c_2, the firm is more likely to exploit the maximum markup if she has more plants at favorable locations (hence higher Φ_{fm}) to widen her efficiency gap to the next lowest cost rival. I also find that more dispersed plants indicated by smaller θ increase the likelihood of charging the monopoly price.

The markup distribution again generalizes what is in single-plant firm models and brings richer implications on how markups vary across firms. In the case of infinite number of firms competing head-to-head, the markup distribution converges to equation (11) in BEJK. The markup distribution in Holmes et al. (2011) is also a special case of equation (8) when firms are single-plant owners. I summarize results in the following proposition.

Proposition 2: *Holding the competitors fixed, (i) an additional production location to the firm's active location set weakly decreases its average price charged to all consumers; (ii) an additional production location to the firm's active location set weakly increases its average markup charged to all consumers.*

Lastly, I explore the implications of our model on the bilateral trade volume across locations, aggregating from firms' decisions. With firms' cost distributions in equation (3), the probability that firm f supplies to a consumer in m is

$$s_{fm} = \int_0^{\infty} \prod_{g \neq f. g \in \mathcal{F}} \left(1 - F^c_{1,gm}(c)\right) dF^c_{1,fm}(c) = \frac{\Phi_{fm}}{\Phi_m}. \tag{9}$$

Essentially, the probability equals to a firm's relative competitiveness of supplying the good compared to all other head-to-head competitors. Since all consumers are uniformly distributed on a unit interval, the probability of supplying to a consumer is the same as the expected fraction of consumers captured in m.

Proposition 3: *An additional production location to the firm's active location set strictly increases the share of consumers sourcing from it, holding the competitors fixed.*

Similarly, suppose a set $\mathcal{F}_\ell$ of firms produce at ℓ and $N_\ell = |\mathcal{F}_\ell|$, the probability that location ℓ exports to a consumer in m is

$$s_{\ell m} = \int_0^\infty \prod_{k\neq\ell, k\in\mathcal{M}} \left(1 - F^c_{1,km}(c)\right) dF^c_{1,\ell m}(c) = \frac{N_\ell \phi_{\ell m}}{\Phi_m}, \tag{10}$$

where $F^c_{1,\ell m}(c) = 1 - \exp\left(-N_\ell \phi_{\ell m} c^\theta\right)$ characterizes the distribution of the lowest-cost plant at ℓ across all firms entered. The probability represents location ℓ's competitive advantage. The more plants, the higher local efficiency, the lower input costs and the lower trade costs in a location, the larger share m sourcing from it. Different from BEJK which do not have a measure of firms, this paper shows more firms producing in a location is pro-competitive.

Recall that $\phi_{\ell m} = T_\ell(w_\ell \tau_{\ell m})^{-\theta}$, equation (10) can be transformed to resemble a standard gravity equation. The trade elasticity is shaped by the Fréchet parameter θ as in Eaton and Kortum (2002).

2.2.2 Choice of plant locations

A firm chooses the set of plant locations from a finite discrete space $\mathcal{M}$ to maximize the expected total profit summing over its plants. To complete the expected total profit function, I first present the expected variable profit, with details presented in Appendix A.4 and A.5.

$$E\left[\pi_f\right] = \kappa \sum_m A_m \left(\bar{R}_{fm} - \bar{C}_{fm}\right), \tag{11}$$

where the constant $\kappa = \Gamma\left(\frac{\theta+1-\eta}{\theta}\right)$, and

$$\bar{R}_{fm} = \left(\Phi_m - (1-\bar{\mu}^{-\theta})\Phi_{fm}\right)^{-\frac{1-\eta}{\theta}} - \left(\Phi_m - \Phi_{fm}\right)\Phi_m^{-\frac{\theta+1-\eta}{\theta}},$$

$$\bar{C}_{fm} = \Phi_{fm}\times\Bigg[(\theta+1-\eta)(\Phi_m-\Phi_{fm})\int_1^{\bar{\mu}}\mu^{-\theta-2}\left(\Phi_m-(1-\mu^{-\theta})\Phi_{fm}\right)^{-\frac{2\theta+1-\eta}{\theta}}d\mu$$
$$+\bar{\mu}^{-\theta-1}\left(\Phi_m-(1-\bar{\mu}^{-\theta})\Phi_{fm}\right)^{-\frac{\theta+1-\eta}{\theta}}\Bigg].$$

The expectation of variable profit is taken over random productivity draws for all plant-consumer pairs. It depends on the capability of supplying the good from all of the firm's plants and its competitors'. More importantly, each plant is not separately additive. Cannibalization makes the multi-plant firms' location problem to be a combinatorial optimization.

In order to have a well defined expected variable profit, I must restrict $(\eta-1)/\theta < 1$. The same restriction has been seen in the literature, such as Eaton and Kortum (2002), Eaton et al. (2011), and Bernard et al. (2003), with η representing demand elasticity and θ being the heterogeneity of suppliers in production. The condition ensures that suppliers are competitive enough such that consumption is not concentrated on a few of them. Mathematically, the condition is in need for a well-behaved κ after taking the expectation over a function of Fréchet distributed stochastic term, knowing that Gamma function is sensitive to parameter values at the negative support. One may contrast the condition to what is in Antras et al. (2017) that guarantees the supermodularity of sourcing decisions. A clear difference is mentioned in Antras et al. (2017) footnote 11 where θ in their setting is no longer heterogeneity of final good suppliers but input producers although η still remains to be demand elasticity among final varieties. The submodularity property of equation (12) will be explained in more details in Section 2.3.1.

Although the restriction on η and θ has little to do with submodularity of the profit function, discussing the comparative statics of a firm's profit with respect to these two parameters help us to understand the firm's optimal plant location strategy. Propositions 1–3 guarantee that a firm obtains positive marginal variable profit by adding one more plant to its existing active set. However, when plants are more homogeneous (high θ), the lowest cost of a firm will not reduce much after building one more plant. Furthermore, when demand is less elastic (low η), the firm's variable profit responses weaker to cost reductions and gains less.

A multi-plant firm incurs plant-specific fixed costs for setting them up, $\{FC_{f\ell}, \forall \ell \in \mathcal{L}_f\}$.[14] Fixing the same set of plant locations, firms would expect exactly same variable profits because plants at the same location are symmetric. Therefore, what drives one firm to have more plants than the other is having lower fixed costs on average. Location choices are affected by the firm's idiosyncratic fixed costs at different locations and profitability given competitors' fixed costs and

[14] There is a strand of literature concerning greenfield entry versus merger and acquisition. However, the case of M&A needs not to be fundamentally different from my benchmark model. Acquisition price can be seen as the fixed cost, except the case that the acquisition price depends on the seller's residual value that is past dependent. If then, fixed costs are also endogenous and need to be solved using a dynamic model.

location choices. A firm thus solves

$$\max_{\mathcal{L}_f \subseteq \mathcal{M}} E\big[\Pi_f(\mathcal{L}_f)\big] = E\big[\pi_f(\mathcal{L}_f)\big] - \sum_{\ell \in \mathcal{L}_f} FC_{f\ell}. \tag{12}$$

Finally, I close the model with the local price index, which is a composite of prices that all firms charge to consumers in m.

$$\begin{aligned} P_m &= \sum_{f \in \mathcal{F}} E[P_{m|f}] \times s_{fm} \qquad (13) \\ &= \Gamma\left(\frac{\theta+1}{\theta}\right) \Phi_m^{-1/\theta} \times \left[(1-N) + \sum_{f \in \mathcal{F}} \left(1 - (1-\bar{\mu}^{-\theta}) s_{fm}\right)^{-1/\theta}\right], \end{aligned}$$

where $N = |\mathcal{F}|$ is the given number of firms. The equation explains how variation on local prices is channeled through plants spatial distribution globally.

2.3 Equilibrium

So far, I have yet discussed in detail how to find the equilibrium of the interdependent production locations in this game-theoretic model. I will first show the existence of equilibrium depending on important properties of the firms' profit function. Then, I discuss how to address the issue of multiple equilibria like many other simultaneous entry games with complete information.

2.3.1 Existence of pure-strategy Nash equilibrium

In a single-agent location problem, with $|\mathcal{M}|$ number of potential production locations, a firm selects among $2^{|\mathcal{M}|}$ possible configurations. Theoretically, one can use the brute force approach to calculate firm profits for all combinations of locations and pick the set yielding the maximum profit. However, the computational cost grows exponentially when $|\mathcal{M}|$ gets large. In general, it is also not guaranteed that the optimal location set is unique for a discrete choice problem even in the case of single player. So what is the sufficient condition to ensure a global maximum and how to find the optimal in a cost-efficient way? Fortunately, Arkolakis and Eckert (2017) provide a solution that if the objective function exhibits single crossing differences, we can iteratively and repetitively refine the combinatorial discrete choice set and the process always converges to a unique equilibrium.

Noticing that equation (12) is submodular in a multi-plant firm's own strategy, meaning that the marginal value on total profit of adding location ℓ by firm f is decreasing in the number of other locations that f entered. Specifically, from the propositions, the variable profit of a firm increases from expanding its plant location set, but the marginal gain diminishes with more plants due to self-cannibalization. Submodularity in the firm's profit function is a sufficient condition for single crossing differences, suggesting that unprofitable locations will remain to be unprofitable when enlarging the set and profitable ones will remain to be profitable when shrinking the set. Leveraging the monotonicity, Arkolakis and Eckert (2017) generalize the method that is first developed in Jia (2008) to the case of submodular profit functions and further show that we can always reach a unique maximizing vector by partitioning the lattice and repetitively applying the algorithm. I will discuss how to implement the algorithm with more details in Section 4.3.

In a multi-agent location game, existence of equilibrium, and in particular a pure strategy Nash equilibrium, becomes much more challenging. There are three aspects of complexity in the game described in my multi-plant firm model: (i) discrete choices as firms decide to enter or not, (ii) multidimensional as each strategy is defined as a vector of ones and zeros, and (iii) strategic substitutes as players face competition. Attributed by the first two points, for a two-player $|\mathcal{M}|$-location game, the domain of strategies is an enormous set of $2^{2|\mathcal{M}|}$ number of configurations. Although the third point seems to be prevalent in many applications, tackling games that exhibit strategic substitutes is not as straightforward. Past literature has shown that there are substantial imbalances in existence and characterization of equilibrium between games with strategic substitutes and strategic complements (i.e. Vives, 1999; Jackson and Zenou, 2015; Jensen, 2005). An advantage of studying a game with strategic complements is that a PSNE always exists following Tarski's fixed point theorem (Tarski et al., 1955) and Topkis' monotonicity theorem (Topkis, 1978). In such case, the equilibrium set is a complete lattice and highly structured in which players benefit from coordination and typically the greatest PSNE is also Pareto optimal (Milgrom and Roberts, 1990; Zhou, 1994). However, existence of PSNE is not generally true in games with strategic substitutes.[15]

The multi-plant firm model in Section 2 is a submodular game. With multidimensional strategies, submodular games are games in which the marginal returns to any component of the player's strategy drop with increases in other components of the player himself and the competitors' strategies. I have demonstrated above that the profit function exhibits decreasing differences in a firm's own strategy due to self-cannibalization. The same holds for the marginal profit to be decreasing in the firms' joint strategy space due to competition. The model does not imply any admissible parameter setting that leads to supermodularity of the profit function. Neither does it have forces that could make plants being strategic complements to each other. For example, no agglomeration forces, such as cost sharing or knowledge sharing among nearby plants as in Jia (2008), is introduced in the model. If, however, a mixture of positive and negative spillovers coexist, the firm's optimal choice of production locations is almost impossible to characterize.

The most relevant papers in recent development of proving existence of a PSNE in submodular

[15] One can refer to Example 1 in Jensen (2005) where no equilibrium exists for a strategic substitutes game.

games are Dubey et al. (2006) and Jensen (2010). They restrict attention to aggregative games in which the payoff of a player only depends on his own strategy and an aggregate of others' strategies (or what's called "quasi-aggregative games" in Jensen (2010) when the strategy set is multidimensional). Jensen (2010) uses best-reply potential game properties and proves that a quasi-aggregative game of strategic substitutes has a PSNE, if the strategy set is compact and the payoff function is upper semi-continuous. In our context, the firm's profit, equation (12), is a function of its own location strategy $\mathcal{L}_f$ and a weighted additive aggregate of rivals' locations, Φ_m. Hence, it is a quasi-aggregative game by Definition 1 in Jensen (2010).[16] Moreover, this is a game with plants being strategic substitutes and location strategies being a finite number of zeros and ones. The multi-plant firm model satisfies all conditions for the existence of PSNE.[17] [18]

Proposition 4: *For a $|\mathcal{F}|$-player, $|\mathcal{M}|$-location game in Section 2 with profit function exhibiting submodularity for all players, the set of pure-strategy Nash equilibria is not empty.*

I will illustrate how to find the equilibrium in Section 4.3 using a duopoly game, although theoretically it can be extended to more than two players.

2.3.2 Multiple equilibria

A common concern in estimating discrete games is the existence of multiple equilibria. The fact that for a given set of parameters and covariates, there may be more than one equilibrium outcome, raises the well-known coherency problem in econometric inference (Heckman, 1978; Tamer, 2003). In the absence of interdependency across locations, for a $2\times2\times1$ (two players choosing enter one location or not) game with competition, the Nash equilibria is that either firm enters and the other stays out. With interdependency, the game would accommodate more equilibria.

Surveying the literature, there are four main approaches to deal with the multiplicity of equilibria.[19] The first is to model the probabilities of aggregated outcomes that are robust to multiplicity. For example, in the simplest $2\times2\times1$ game, the number of entrants is unique although the firm identity is undetermined (Bresnahan and Reiss, 1990; Bresnahan and Reiss, 1991; Berry, 1992).

[16] Mapping to the notation in Jensen (2010), the aggregator $g(\mathcal{L}) = \sum_{f\in\mathcal{F}} \Phi_{fm}(\mathcal{L}_f)$. The interaction functions are $\sigma_f(\mathcal{L}_{-f}) = \sum_{g\neq f, g\in\mathcal{F}} \Phi_{gm}(\mathcal{L}_g)$. The shift-functions $F_f(\sigma_f(\mathcal{L}_{-f}), \mathcal{L}_f) = \sigma_f(\mathcal{L}_{-f}) + \Phi_{fm}(\mathcal{L}_f) = g(\mathcal{L})$.

[17] According to Corollary 1 in Jensen (2010), the quasi-aggregative game has to satisfy Assumption 1 and 2 for a PSNE to exist. Assumption 1 is satisfied because the location game presented here features strategic substitutes and therefore every firm's best-reply correspondence is a decreasing selection. Assumption 2 is also satisfied through a monotonic transformation of the shift-functions.

[18] Arkolakis and Eckert (2017) impose additively separable condition to a player's profit function to prove existence of PSNE in a game exhibiting single-crossing differences, meaning that the profit function is additively separated to a player f specific part and a common part of all players' actions. This is a much stronger sufficient condition than what is needed in Jensen (2010).

[19] Ellickson and Misra (2011) provide a thorough discussion on estimating static discrete games, especially methods for dealing with the issue of multiple equilibria.

However, information on firm heterogeneity is lost. Should I use it in this paper, I would not be able to estimate the fixed costs distributions which are firm-location specific.

The second is to embrace the multiplicity and take a bounds approach (Ciliberto and Tamer, 2009; Holmes, 2011; Pakes et al., 2015). The method partially identifies parameters within a set that could be too large to be informative. Lack of point identification becomes difficult when performing counterfactual exercises. Estimating a bound also causes inference to be computationally intensive, such as placing confidence region on the set.

The third approach—the one taken here—is to choose an equilibrium by imposing certain entry sequence. Although I model the entry game as static, the assumption is convenient in avoiding multiple equilibria.[20] In principle, estimates could be sensitive to the equilibrium selected and the predetermined order of entry. Therefore, I provide robustness checks by estimating the model based on equilibria with other ordering specifications.

More recent development of the literature is around specifying a more general equilibrium selection rule that is a function of covariates and observables, as in Bajari et al., 2010. The solution requires computing all equilibria and an equilibrium selection parameter as part of the primitives to be estimated together with the model. Although this approach is more general than imposing certain sequence of entry, the computational burden to calculate all equilibria in an interdependent entry game is too high.

2.4 Welfare measures

To prepare the multi-plant firm model for policy evaluation, I specify the welfare terms and the cost of carbon emissions. Policy interventions that result in cost shocks to firms could lead to long-run adjustment in production locations after re-optimizing the profit function. Because all plants are interconnected through spillovers, a local change is likely to cause a global reshuffling if the shock is sufficiently large. Changes to production and trade costs can be summarized as a shift from $\boldsymbol{\phi}^0$ to $\boldsymbol{\phi}^1$. The new plant locations are $\mathcal{L}_f^1$ and the original ones are $\mathcal{L}_f^0$. These changes in turn affect price indices to the new level P_m^1. Therefore, effects on producer and consumer surplus are summarized as

$$\Delta PS = \sum_{f\in\mathcal{F}} \left(\pi_f(\mathcal{L}_f^1; \mathcal{L}_{-f}^1, \boldsymbol{\phi}^1, \mathbf{A}, \theta, \eta) - \pi_f(\mathcal{L}_f^0; \mathcal{L}_{-f}^0, \boldsymbol{\phi}^0, \mathbf{A}, \theta, \eta)\right) \tag{14}$$

$$\Delta CS = \frac{1}{1-\eta} \sum_{m\in\mathcal{M}} A_m \left(\left(P_m^0\right)^{1-\eta} - \left(P_m^1\right)^{1-\eta}\right). \tag{15}$$

Specifically, to evaluate the environmental policy taking into account the externalities in later

[20] The same approach has been taken by Jia (2008), **?**, Eaton et al. (2012), Edmond et al. (2015) among many others.

section, I introduce a notion as *required social costs of carbon*. I define SCC as social cost of carbon which is the long-term damage done by a tonne of CO_2 emissions in a given year measured in monetary term. Noted that carbon damages are global regardless of origin, and hence, the value of total carbon emission changes, domestic and foreign, is fully borne by every market. The social cost of carbon needs to reach the following minimum threshold for a policy to be welfare improving for the domestic market,

$$\underline{SCC_D} = \frac{\Delta PS_D + \Delta CS_D + \Delta GR_D}{\Delta e_D(1-\lambda)}, \tag{16}$$

where I define $\lambda = -\Delta e_F/\Delta e_D$, meaning the change in foreign emissions to the change in domestic emissions, as the leakage rate. Changes in domestic government revenue is ΔGR_D.

3 The Cement Industry

In this section, I bring the model to the data and draw on key institutional details about the cement industry in the contiguous US and part of Canada in 2016.[21]

3.1 Industry background

Cement is a fine mineral dust that acts as the glue after mixed with water to bind the aggregates together. It is used to form concrete, the most-used input in construction and transportation infrastructure. Cement is a rather homogeneous product.[22] According to US Geological Survey (USGS), there are more than 5000 ready-mix concrete producers who purchase cement from 121 plants in the US and part of Canada in 2016. The large number of downstream producers form the continuous measure of consumers in the model.

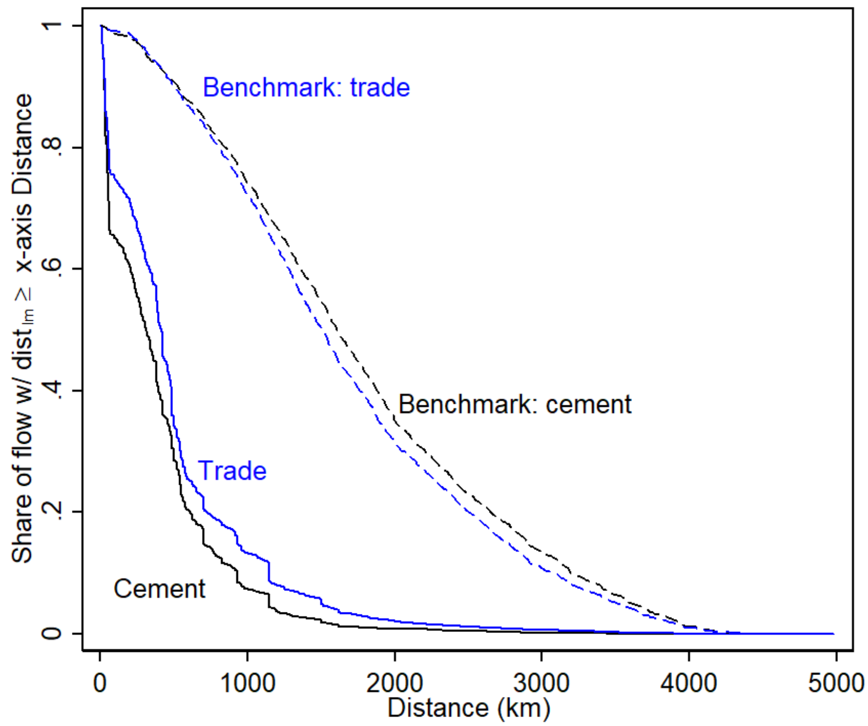
These concrete producers not only purchase cement locally, but also import cement from elsewhere. Across the US and Canada, trade in cement is comparable to other manufacturing products. Figure 1 visualizes how trade decreases with distances for cement and all manufacturing goods, and compare those with the benchmark case of frictionless trade where each origin is equally likely to export to a destination regardless of distance. Half of the cement in this region is transacted within 300 kilometers, and it extends to 420 kilometers for manufacturing goods. Furthermore, there is

[21] Some Canadian provinces and territories, namely Newfoundland and Labrador, Prince Edward Island, Northwest Territories, Nunavut, and Yukon are not included in my sample because these are tiny markets for cement and no production at all.

[22] Cement have some variation in types depending on its properties that better suits certain construction projects. For example, pozzolana cement is prepared by adding pozzolana to portland cement. It is widely used in bridges, piers and dams due to the high resistance to various chemical attacks. Rapid hardening cement attains high strength in early days and is used in road works. Sulfate resisting cement is used in construction exposed to severe sulfate action by water and soil in places like canals. These minor differences are captured by the buyer-seller idiosyncratic shock $Z_f\ell im$ in the model.

still about 10% cement trading in long distance beyond 900 kilometers, a distance equivalent to shipping from Chicago to Atlanta, or from Edmonton to the south of Idaho.

Figure 1: Distribution of distance for cement and trade in goods in the US and Canada

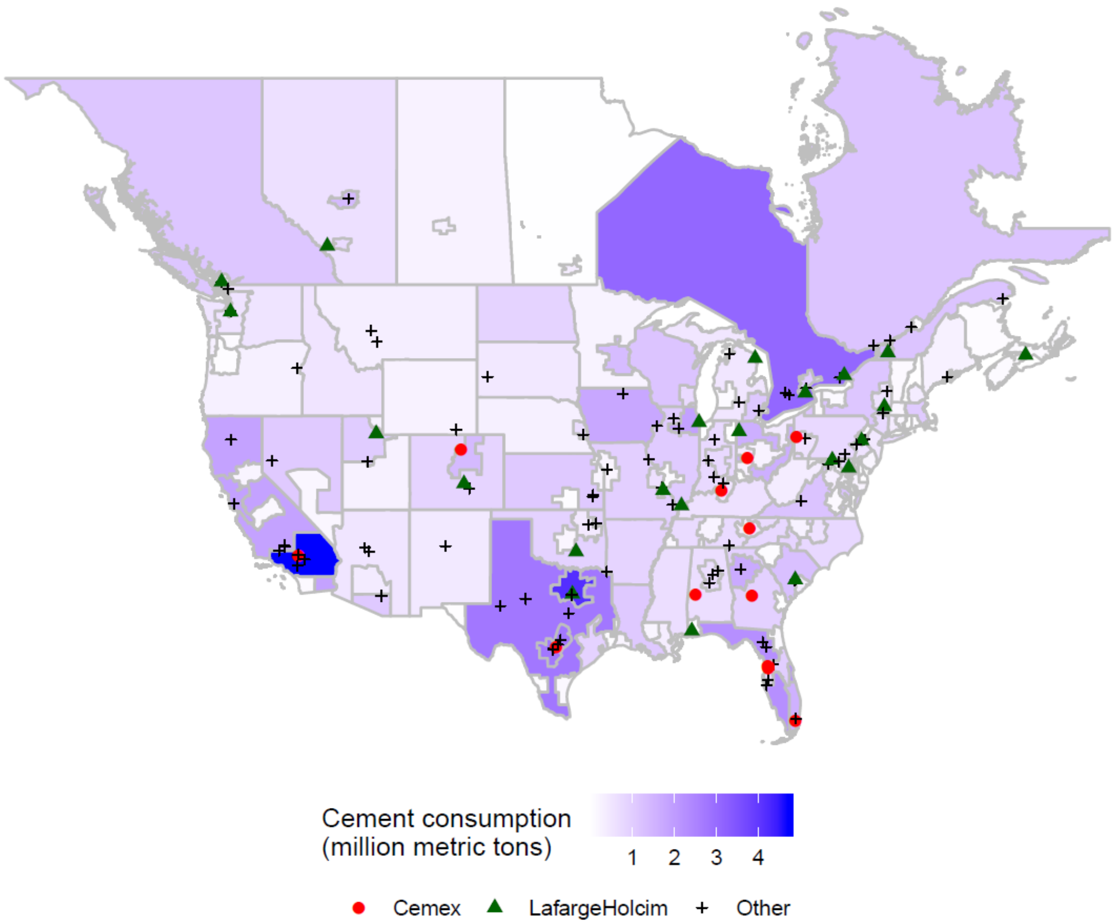


Active cement trade in this region also corresponds to the fact that cement is not produced everywhere as seen in Figure 2. The map is divided to 149 survey zones from the Freight Analysis Framework (FAF), which include census agglomerations, census metropolitan areas, and the remainder area of province/state in the US and Southern Canada. Out of the 149 FAF zones, only 73 of them have cement plants, whereas the rest entirely relies on imports. Figure 3 shows the export intensity and import penetration across the 73 FAF zones. On average, a zone exports 44% of its local production and imports 27% of its cement consumption.[23] The positive correlation between export intensity and import penetration suggests intra-industry trade in cement that can be rationalized using the multi-plant firm model with plant heterogeneity and buyer-seller idiosyncrasies.

Due to the existence of export platforms, all cement plants are potential competitors in every location. If each plant is separately owned, it is straightforward that the owner will build the plant if the expected sales from itself can recover the fixed cost. If, however, multiple plants are owned

[23] Since Canada Freight Analysis Framework is a logistics file, the origin of cement flow within Canada may not be documented as its production location. Neither is the destination of cement flow being its market for final consumption. Therefore, some Canadian FAF zone, such as Hamilton, Oshawa, and Rest of Alberta (excluding Edmonton and Calgary), could have extremely high export intensity and import penetration ratio because of re-export and re-import. I acknowledge the data limitation may cause measurement error.

Figure 2: Cement plants and consumption in 2016

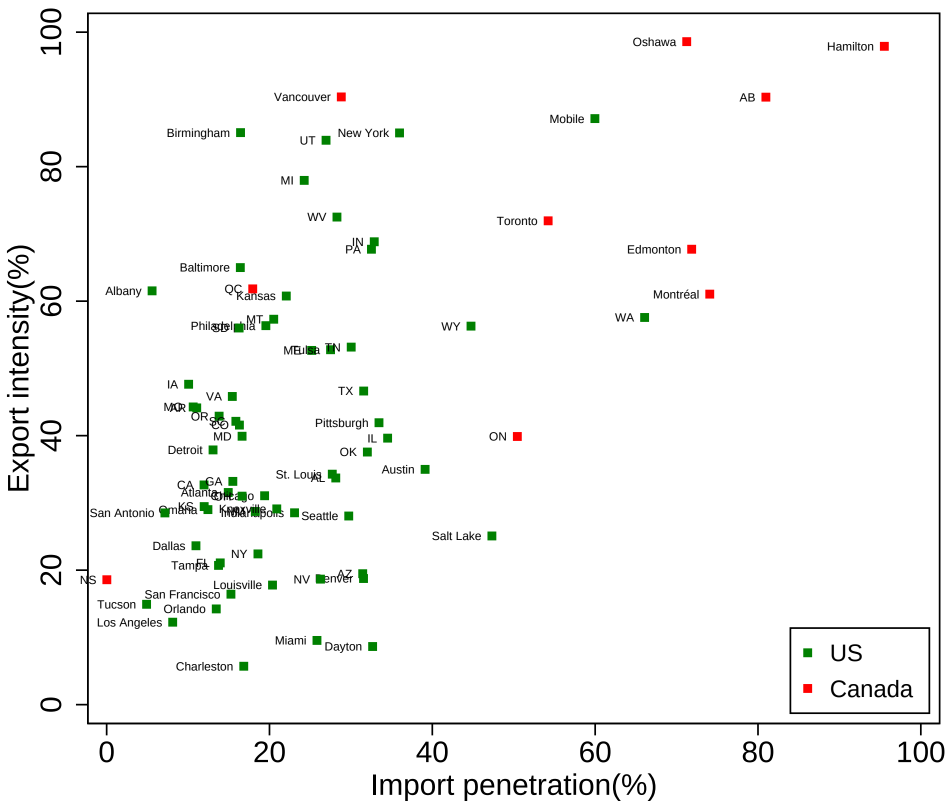


by the same entity, the owner has to decide the set of interdependent locations taking into account cannibalization. For the cement industry, most of the cases are the latter.

In the US and Canada, the cement industry is dominated by a few multi-plant oligopolists. LafargeHolcim, resulted from a merger between the world largest (Lafarge from France) and the third largest (Holcim from Switzerland) cement manufacturer, owns 20% of cement plants in the region. It is followed by Cemex, a Mexican firm, who owns another 10% of plants. Figure 2 plots a map of plants owned by these two multi-plant firms, and also a group of fringe owned by the other 24 firms. At the national level, the top four firms control 51% of the installed cement capacity in the US and 86% in Canada. The industry is even more concentrated at sub-national level: there are at most four cement plants in a single FAF zone.

How are the multi-plant firms and single-plant firms distributed spatially? In Table 1, I report joint distributions for 26 cement firms by the number of plants owned and the number of production locations entered. Panel A reports the distribution in number of firms; panel B reports the distri-

Figure 3: Cement trade intensity, 2016



bution in market share measured by capacity; panel C reports the distribution in share of plants owned. From panel A, we see that 34.6% of firms are single-plant owners producing at one location. They account for 6.5% of production capacity and 7.4% of cement plants. On the contrary, 11.5% of firms that own 11 or more plants across locations control around 41.6% of production capacity and 40.5% of plants.[24] Large cement firms produce in more locations, own more plants, and have greater production capacity at each location. Nevertheless, the group of smaller cement manufacturers is also too big to ignore.

Table 1: Distribution by number of plant and FAF zone

Panel A: Percentage of firms

	Number of FAF zones				
Number of plants	1	2-4	5-10	11+	**Total**
1	34.6	0.0	0.0	0.0	**34.6**
2-4	0.0	30.8	0.0	0.0	**30.8**
5-10	0.0	3.8	19.2	0.0	**23.1**
11+	0.0	0.0	0.0	11.5	**11.5**
Total	**34.6**	**34.6**	**19.2**	**11.5**	**100.0**

Panel B: Percentage of capacity

	Number of FAF zones				
Number of plants	1	2-4	5-10	11+	**Total**
1	6.5	0	0	0	**6.5**
2-4	0	21.5	0	0	**21.5**
5-10	0	3.6	26.7	0	**30.4**
11+	0	0	0	41.6	**41.6**
Total	**6.5**	**25.1**	**26.7**	**41.6**	**100**

Panel C: Percentage of plants

	Number of FAF zones				
Number of plants	1	2-4	5-10	11+	**Total**
1	7.4	0	0	0	**7.4**
2-4	0	19	0	0	**19**
5-10	0	4.1	28.9	0	**33.1**
11+	0	0	0	40.5	**40.5**
Total	**7.4**	**23.1**	**28.9**	**40.5**	**100**

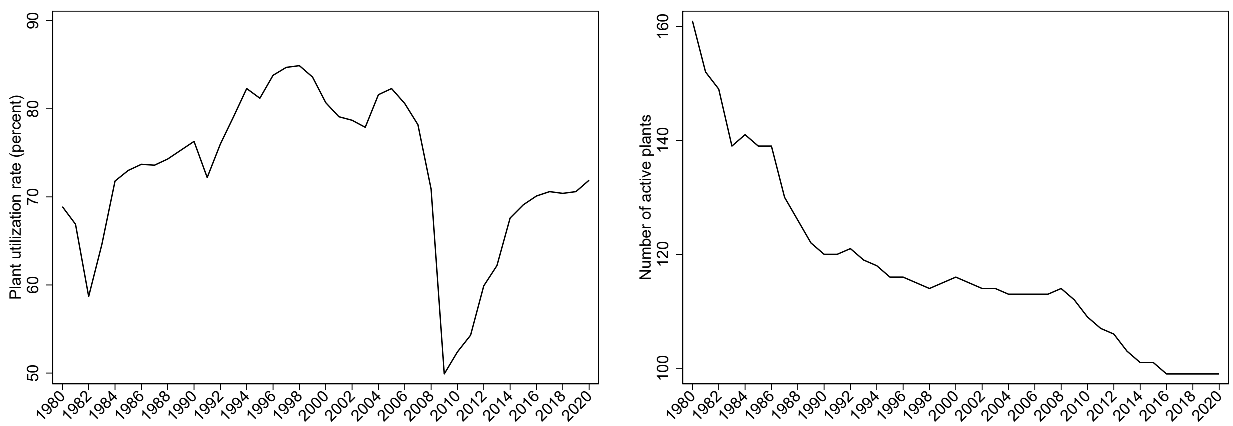
Knowing there would be competition within and across firms, what are the cost factors that a multi-plant cement firm consider in determining production and plant locations? The production cost of cement consists of equally contributed costs of materials, energy and labor.[25] The marginal

[24] There are $11.5\% \times 26 = 3$ firms in the US and Canada that owns more than 11 plants. Other than LafargeHolcim and Cemex, the third is Heidelberg. For the ease of computation, in the later estimation, I do not endogeneize the plant set selection by Heidelberg but only focus on the other two.

[25] The cost breakdown is documented in Lafarge annual report 2007 https://bib.kuleuven.be/files/

cost can be assumed to stay constant until it rises beyond 87% of the capacity due to equipment maintenance estimated in Ryan (2012). Ryan (2012) uses data from 1980 to 1999 when the utilization rate remains to be high. However, from 2008 onward, USGS shows that none of the survey region exceeds a plant utilization rate beyond the threshold, and the average has been between 50% and 70% as shown in the left panel of Figure 4. Therefore, the model without capacity constraint is still an accurate characterization of the industry in recent years.

Figure 4: Plants and plant utilization in the US cement industry



Notes: Data is for US only excluding Puerto Rico and is obtained from the US Geological Survey.

When manufacturing cement, the most important step is to heat the raw materials in a rotating kiln. A great amount of fossil fuels are burnt to increase the temperature to a peak of 1400-1450° Celsius during which a byproduct CO_2 is generated. Fuel combustion accounts for roughly half the amount of CO_2 emitted from producing cement, and the rest comes from the chemical reaction. In total, for every tonne of cement produced, around 0.8 tonne of carbon is released into the atmosphere (Van Oss and Padovani, 2003; Kapur et al., 2009). The industry is responsible for about 8% of man-made CO_2 emissions worldwide, making it a major industrial producer of greenhouse gases.

Of all the raw materials used to produce cement, limestone accounts for about 85% (Van Oss and Padovani, 2003). Given the heavy weight of limestone and high transportation cost, it is natural for one to presume that cement plant location is bound by the locations of limestone quarries. Although it is true that cement firms usually transport limestone extracted from nearby quarries using belt conveyor or truck, I show in Appendix D.3 that there are almost 3000 limestone quarries widely distributed across the US and Canada. Hence, the location of quarries is not the sole factor

`ebib/jaarverslagen/Lafarge_2007.pdf` Following this industry practice, I assume in the later estimation, the input cost w_ℓ is a composite of worker wage, material cost, and fuel cost with elasticities equal to a third.

determining where to place a cement plant.

As for the energy used in the cement production, firms and governments have been striving to deal with the associated environmental concerns. On the firm side, they have improved the kiln technology to optimize fuel usage. According to Portland Cement Association, as of 2016, around 96% of the cement capacity uses dry process kilns, a more energy efficient technic.[26] Given the standardized industry practice and technology, it is less obvious that some firms are necessarily better than the other. Hence, I can relatively safe to apply the model without ex-ante difference in firm productivity.

On the government side, most policy interventions are focused on shifting fossil fuels to more environmentally friendly alternatives by imposing carbon price on dirty fuels, such as coal. Around the world, coal provides 90% of energy consumed by cement plants.[27] In developed economies, such as the US and Canada, the share of coal is lower at 42%, but fossil fuels in total still accounts for 81% of the energy source.[28] How fast cement plants will substitute with cleaner energies is a question beyond the scope of this paper, but I will provide answers to the effects of retaining the same composition of fuels in later sections.

Other than the variable cost of production, building a cement plant involves high fixed cost investment which makes the plant location problem a nontrivial decision. Past literature as well as firm accounting records report that the fixed cost for building a one million tonne cement plant is around $200 million (Ryan, 2012; Fowlie et al., 2016; Salvo, 2010). It also contributes to the fact that cement plants being scarce and discrete as shown in Figure 2.

3.2 Data description

I collect data from four main sets. First, cement plant locations are sourced from the Global Cement Report 12th edition published by International Cement Review. The directory covers 2108 operating cement plants worldwide in 2016, out of which 104 are in the US and 17 are in Canada. For each plant, the directory lists its name, ownership, location, and capacity. With the plant ownership data, I can identify all the multi- and single-plant firms in the region. One limitation about this dataset is that without information on plant opening or closing, I have to work with the snap shot of plant data in 2016. Nevertheless, the right panel of Figure 4 provides some justifications to use 2016 as an equilibrium benchmark. There are two waves of plant closure in the history: one in 1980s due to the outdated technology, and the other in 2008 due to the housing

[26] "Wet" or "dry" refers to the moisture content of raw materials. The wet process needs more energy because the moisture needs to evaporate.

[27] Source: https://www.globalcement.com/magazine/articles/974-coal-for-cement-present-and-future-trends

[28] For a complete breakdown of fossil fuel usage and energy efficiency, please refer to Table C.17.

crisis. The industry restored to a steady state in 2016 and the number of plants has not been changing since then.

Second, bilateral cement trade flow is constructed from Freight Analysis Framework by the US Department of Transportation, Canadian Freight Analysis Framework by Statistics Canada, and US Geological Survey database (USGS). Production locations and consumption markets are zones defined by the Freight Analysis Framework, which are the smallest geographical unit available in these datasets. As mentioned earlier, it includes census agglomerations, census metropolitan areas, and the remainder area of province/state. After checking cement merger cases documented by the Federal Trade Commission, I find that metropolitan area is also the unit of assessment for competition impacts, which substantiates the definition of markets in my empirical analysis. Additionally, it is rarely seen that a cement firm would have more than one plant in a FAF zone.[29] This empirical definition of location is consistent with my model in which a firm decides whether to have a plant or not instead of how many plants for a single location.

The availability of trade data allows me to assemble a balanced panel of 73 origins shipping cement to 149 destinations from 2012 to 2016, taking into account that cement is only produced in a subset of FAF zones. Details of how to assemble the data from multiple sources and the associated assumptions are provided in Appendix D.1. The estimation is also complemented by bilateral trade in cement at the country level, and the data is obtained from UN Commodity Trade Statistics Database.

Third, bilateral trade frictions are sourced from various datasets. At the FAF-zone level, distance is measured as great-circle distance between the zone centroid. Within a zone, internal distance is measured as great-circle distance between the northeastern boundary and the southwestern boundary. The auxiliary country-level regression uses CERDI-sea-distance database and shipping days measured in Feyrer (2018). The former computes sea distance as the shortest sea route between two highest traffic ports in the respective countries, and landlocked countries are associated with the nearest foreign ports. The latter calculates round-trip shipping days between primary ports for each bilateral pair assuming an average speed of 20 knots. The country-level regression also uses tariff data from the World Integrated Trade Solution by World Bank and other gravity variables from the CEPII research center.

Lastly, to estimate demand, I collect input costs to construct instrument variables for prices, including durable goods manufacturing wage, limestone prices, natural gas and electricity prices. They are sourced from the US Energy Information Administration, US Quarterly Census of Employment and Wages, US Geological Survey, Statistics Canada, Natural Resources Canada, and Quebec Hydro. Demand shifters including population and units of building permit issued are col-

[29] Only four out of 149 locations have two plants belonged to the same firm, and one of them is Cemex at a FAF zone in Florida. In those cases, I combine plants to one.

lected from US Census and Statistics Canada. To match the consumption data, I collect all these variables from 2012 to 2016.

4 Multi-plant Firm Estimation

In this section, I lay out an estimation procedure of the multi-plant firm model. The typical dataset that econometricians observe involves a combination of aggregated data at location level and limited firm level data. Other micro data, such as prices or shipping flow for individual plant, is not necessarily available to researchers. I propose a procedure to estimate the full model with minimal data requirement. Key primitives of the model are the Fréchet dispersion parameter θ, demand elasticity η, a composite of locations' production capability $\mathbf{T}\mathbf{w}^{-\theta}$, trade costs $\boldsymbol{\tau}$, demand shifters $\mathbf{A}$, and fixed costs $\mathbf{FC}$ (vectors are bolded).

I specify trade costs as a function of observed determinants, denoted $X_{\ell m}$,

$$\tau_{\ell m} = \exp\left(\mathbf{X}_{\ell m}^{'}\beta^{\tau}\right), \tag{17}$$

where β^{τ} is a vector of the trade cost parameters. The vector $\mathbf{X_{\ell m}}$ includes the standard explanatory variables used in gravity equations: distance, contiguity, whether the dyads are located at the same state, province, or country. These variables have been shown to matter for trade flows in the past literature. Similarly, demand shifters are characterized as a function of population and the number of building permits on new privately-owned residential construction units.[30]

$$A_m = \exp\left(\mathbf{X}_{m}^{'}\beta^{A}\right), \tag{18}$$

where β^{A} is a vector of demand parameters. As for the fixed costs, instead of estimating every firm-location specific fixed costs which are impossible to be identified, I specify that they are realizations from a log-normal distribution,

$$\log\left(FC_{f\ell}\right) \sim N\left(\mathbf{X}_{f\ell}^{'}\beta^{F}, \left(\sigma^{F}\right)^{2}\right). \tag{19}$$

The distributions of fixed costs are shifted by the distance between FAF zones and the firm's North American headquarter, as well as an interaction dummy of the firm and the country where FAF zones locate. Distance is a proxy for management and communication frictions faced by multi-plant firms, while the firm-country dummy captures a firm's local knowledge that affects

[30] Cement is also widely used for non-residential, commercial construction projects. Unfortunately, data on the volume of non-residential construction activities is unavailable.

building costs of a cement plant.[31] Therefore, what left to be estimated to fully recover the model is $\{\mathbf{T}\mathbf{w}^{-\theta}, \theta, \eta, \beta^{\tau}, \beta^{A}, \beta^{F}, \sigma^{F}\}$.

The estimation is performed in three steps. First, I use a gravity-type regression to estimate the composite of locations' production capability $T_\ell w_\ell^{-\theta}$ and the Fréchet dispersion θ. The sourcing probability derived from the model provides a natural link between theoretical implication and the bilateral trade data. Next, I project local consumption on the model-consistent price index constructed using the estimates from last step and instruments, and estimate the demand elasticity $-\eta$ through Generalized Method of Moments. What has been obtained in the first two steps is critical for constructing firms' expected profit as a function of plant location configurations and fixed costs. In the final step, I match the predicted optimal plant locations to the actual ones to pin down parameters that govern the fixed cost distribution via Method of Simulated Moments. Separability in estimation allows me to reduce dimensionality of the problem and save computational cost. More importantly, I can verify that the profit function is well defined before implementing the combinatorial optimization algorithm in the last step.

4.1 Step 1: Estimation of local production capability, trade costs, and plant productivity dispersion

The first step is to estimate each location's production capability summarized by the term $T_\ell w_\ell^{-\theta}$, trade costs parameters β^{τ}, and the dispersion of plants' productivities θ. To do so, I take the plant locations as given and exploit differences in trade attributed to local endowments, such as productivity, input costs, and trade costs. Recall that equation (10) provides the probability of m sourcing from ℓ. Empirically, the model-predicted sourcing probability is associated with the trade share in volume, i.e. $s_{\ell m} = \frac{Q_{\ell m}}{Q_m}$. Transform equation (10) to its estimable version,

$$\frac{Q_{\ell m}}{Q_m} = \exp\left[\mathrm{FE}_\ell + \mathrm{FE}_m - \theta \mathbf{X}'_{\ell m}\beta^{\tau} + \epsilon_{\ell m}\right], \tag{20}$$

where the origin fixed effect $\mathrm{FE}_\ell = \ln\left(N_\ell T_\ell w_\ell^{-\theta}\right)$, and the destination fixed effect $\mathrm{FE}_m = -\ln \Phi_m$. I estimate the gravity regression via Poisson Pseudo Maximum Likelihood (PPML) due to the consistency it delivers under general conditions and its capability of incorporating zeros as clearly explained in Silva and Tenreyro (2006) and Head and Mayer (2014).

[31] Building a cement plant can take years to get the regulatory approval and is extremely costly in administration. A cement firm who has local knowledge and relationship may be able to reduce the regulatory costs. For example, Lafarge merged with Canada's largest cement producer, Canada Cement Company, in 1970, and then experienced unprecedented growth. Cemex, on the other hand, invested in the US market after the anti-dumping duty order on imports of gray Portland cement from Mexico went into effect on August, 1990. Cemex then shifted its strategy from export to FDI. In particular, it acquired Southdown in 2000 and RMC in 2005, which both owned assets throughout the US.

There are two caveats when estimating equation (20). One is that θ is not separately identified from β^{τ}. To deal with this issue, I supplement the FAF-zone level gravity regression with a country-level regression that exploits tariff variation to identify the trade elasticity. Tariff refers to the logarithm of one plus the bilateral tariff as an ad-valorem cost shock, of which the coefficient is an estimate of $-\theta$.[32] Distances between country pairs use measures of sea distance to reflect the fact that international trade in cement is mostly sea-borne. When using the auxiliary country-level regression, I implicitly assume that the trade elasticity is the same for trade between FAF zones and trade between countries. It is justifiable because the model provides nice aggregation properties such that the trade elasticity remains to be $-\theta$ at higher level.

The other caveat is that to obtain the component $T_\ell w_\ell^{-\theta}$ at each location, I need to separate the number of plants N_ℓ from the estimated origin fixed effects. The model presumes that local efficiency and input costs are underlying economic conditions without general equilibrium feedback of plants spatial distribution on factor markets. Consequently, I can substitute N_ℓ with the observed data on plant locations. However, in the US-Canada sample, cement is only produced in a subset of FAF zones $\mathcal{L} \subset \mathcal{M}$, which raises the issue of selection bias. The production capabilities for locations outside of $\mathcal{L}$ remain to be unknown to econometricians. Observing Figure D.16 that plots the map of limestone quarries, we see that states and provinces without cement plants are also places with almost no resources for raw materials, such as Saskatchewan, Manitoba, North Dakota, Nebraska, Wisconsin, Louisiana, and Mississippi. Therefore, I assume that the zero-production FAF zones have infinite costs such that cement firms will never build plants there in equilibrium, and it is plausible to exclude them from firms' choice sets. However, imposing the assumption could bias the fixed cost estimates if the observed zeros are ex-post realizations of stochastic shocks.

Table 2 summarizes the first-step results. Column (1) to (3) report the results for the US and Canada FAF zones, whereas column (4) and (5) are for the auxiliary sample of 144 countries. The key parameter of interest is the elasticity of trade with respect to trade costs. It maps to the negative plant productivity dispersion parameter in the multi-plant firm model, i.e. $-\theta$. Column (4) and (5) obtain similar estimates of the trade elasticity with an average of -11. Considering the homogeneous nature of cement and therefore tougher competition among cement plants, it makes sense to have θ higher than what is typically found in the literature (around -5 in Head and Mayer (2014)).

As for the trade cost parameters, the distance elasticity estimated using the country sample

[32] According to WTO, only 5 member countries specify tariff of cement in specific or other non-ad valorem formats. It accounts for 0.6% of all tariff lines in HS chapter and across all member countries. The majority uses ad-valorem tariffs. In estimating trade elasticity, I treat tariff as cost shifters rather than demand shifters, assuming tariffs are imposed before markups. Cement manufacturers are typically the one building port facilities, importing cement from abroad, clearing customs and the one selling cement domestically. Therefore, they do not have incentive to markdown price but rather report it as a cost. See Costinot and Rodríguez-Clare (2014) for more detailed discussion.

is similar to that using FAF zones. OLS overestimates the effect of distance compared to PPML in the presence of heteroskedastic gravity errors. The estimates obtained from running PPML on trade flows and trade shares are very close although the latter imposes less weight to large flows. At the FAF zone level, the effects of distance to other FAF zones and its internal distance between boundary points are separately estimated. The elasticity of distance to other zones is estimated to be around -1.2, which is consistent with what has been found in the past literature (around -1). The effect of internal distance is smaller around -0.4, suggesting that cement is more than proportionally consumed at home location, a result accords with the positive and significant home coefficient in the country-level regression. All columns show more trade if locations are adjacent. State/province and country borders also matter. Sharing common trade agreements boosts trade between countries, but not common language. For the following steps of estimation, I take $\theta = 11$ and the estimated trade costs computed from Table 2, column (3) as my benchmark.

Figure 5 plots the estimated cement production capability against the actual production volume for each location in panel (a), and combined effect with the number of plants in panel (b). The positive correlation in both figures suggests a credible ranking of the estimated location production capability. Comparing the two panels, the number of plants contributes towards explaining cement production suggested by the improvement of R-square.[33] Note that the only difference in these two plots is the number of plants at each location. If plants were always built at locations with lower input costs or higher local efficiency, we would expect a clear clock-wise rotation of panel (b) compared to panel (a). However, some locations at the upper left of the figure moves more to the right than others at the bottom right of the figure, suggesting that other factors such as fixed costs matter and vary across locations.

With the estimates of local production capability, trade costs and the degree of competition between cement plants, I now turn to estimating the price elasticity of demand $-\eta$ and parameters in demand shifters β^A.

4.2 Step 2: Estimation of demand

To estimate the demand featured in equation (1), I combine it with the local price index derived from the model. Recall in equation (13), the price index is a function of the estimates from the first step and the observed plant location data. I can construct local price index as a function of only

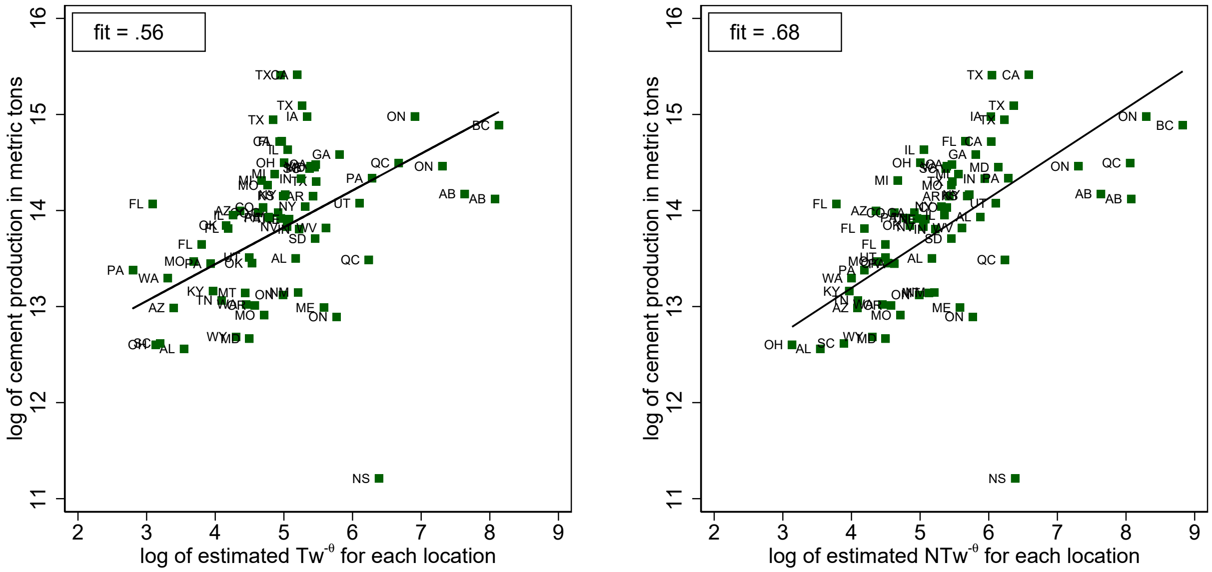
[33] The fit displayed in Figure 5 is the R-square by regressing log of production on log of location production capability and the control for average trade costs weighted by destination market size. One can derive from equation (10) that $\ln \sum_m Q_{\ell m} = \ln N_\ell T_\ell (w_\ell)^{-\theta} + \ln \sum_m \left(\frac{\tau_{\ell m}^{-\theta} Q_m}{\Phi_m} \right)$, where the second term is the average trade costs controlled for in plotting.

Table 2: Estimation of trade costs

	FAF zone sample			Country sample	
	(1)	(2)	(3)	(4)	(5)
	OLS, $\log Q_{\ell m}$	PPML, $Q_{\ell m}$	PPML, $Q_{\ell m}/Q_m$	PPML, $Q_{\ell m}/Q_m$	PPML, $Q_{\ell m}/Q_m$
log (1+ cement tariff$_{\ell m}$), $-\theta$				-10.567^a	-11.633^a
				(2.590)	(2.711)
log sea dist$_{\ell m}$				-1.359^a	
				(0.157)	
log shipping time$_{\ell m}$					-1.067^a
					(0.138)
log dist$_{\ell m, m\neq\ell}$	-2.297^a	-1.174^a	-1.198^a		
	(0.032)	(0.034)	(0.032)		
log dist$_{\ell\ell}$	-1.499^a	-0.462^a	-0.455^a		
	(0.042)	(0.037)	(0.039)		
intra-nation$_{\ell m}$	3.176^a	1.048^a	1.757^a		
	(0.134)	(0.123)	(0.239)		
intra-state$_{\ell m}$	0.393^a	0.546^a	0.414^a		
	(0.100)	(0.093)	(0.086)		
contiguity$_{\ell m}$	1.258^a	1.401^a	1.223^a	2.740^a	2.617^a
	(0.073)	(0.062)	(0.075)	(0.342)	(0.410)
language$_{\ell m}$				-0.449	-0.465
				(0.296)	(0.291)
RTA$_{\ell m}$				1.559^a	1.738^a
				(0.323)	(0.302)
home$_{\ell m}$				7.456^a	7.749^a
				(0.476)	(0.625)
Observations	25435	54385	54385	20736	20736
R^2	0.576	0.917	0.687	0.975	0.973

For the regressions using the FAF zone sample for year 2012-2016, column (1)-(3) include origin-year and destination-year fixed effects. The set of origins include 73 FAF zones across the US and Canada that have positive cement production. The set of destinations are 149 FAF zones. For the regressions using the country-level sample, column (4)-(5) include origin and destination fixed effects. Regressions use 144 countries' squared sample for year 2016. R^2 is squared correlation of fitted and true dependent variables. Robust standard errors in parentheses. Significance levels: ^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01.

Figure 5: Cement production and estimated capability by location



(a) Exclude number of firms

(b) Include number of firms

one unknown, the price elasticity η, and estimate

$$\ln Q_m = \mathbf{X}_m' \beta^A - \eta \ln P_m(\eta) + \nu_m. \tag{21}$$

Since η enters the demand function non-linearly, I apply Generalized Method of Moments (GMM) with instruments for price. I use the average of local and nearby locations' input costs as instruments, weighted by the inverse of trade costs. The input costs include durable goods manufacturing earning, limestone prices, natural gas and electricity prices. Table 3 presents the results. As expected, the estimated price elasticity in column (2) corrects the upward bias estimated using Non-linear Least Squares without instruments in column (1). The effects of two demand shifters, population and allocated building permits, are both estimated to be positive and significant.

As a robustness check, I also estimate the demand using a more "reduced-form" approach with USGS survey data on cement market prices instead of deriving it from the model primitives. The classification of price survey area in USGS is broader than FAF zones, consisting 28 clusters of states and provinces. I leverage the instruments to address the issue of measurement error and price endogeneity. Column (3) in Table 3 presents a similar "reduced-form" price elasticity to that in column (2). To verify validity of the instruments, I also present the first-stage results in Table C.16. Cost shifters are significantly correlated with the cement prices. The F-statistic of the excluded instruments on the endogenous regressor is 21.64, and the Stock-Wright S statistic is 95.59, which are all above the rule-of-thumb threshold of 10. Hence, the tests reject the weak IV concern.

Overall, I find that the price elasticity of demand for cement is -2.68. The literature studying the cement industry has yet reach a consensus about its demand elasticity. Jans and Rosenbaum (1997) estimate the US domestic demand elasticity of -0.81. Miller and Osborne (2014) estimate an aggregate demand elasticity of -0.02, using the data from southwestern United States. Ryan (2012) estimates a range between -1.99 and -3.21, and later -0.89 to -2.03 in Fowlie et al. (2016). My estimate falls along the interval where the literature has found and is close to the preferred estimate -2.96 in Ryan (2012). Estimates of $\eta = 2.68$ and $\theta = 11$ also confirm $(\eta - 1)/\theta < 1$ such that the firm's profit function is well defined for solving the multi-plant location game.

Table 3: Estimation of demand

	Model consistent		Pure empirical
	(1) NLLS	(2) GMM	(3) 2SLS
log price$_m$, $-\eta$	-1.382^a	-2.683^a	-2.117^b
	(0.323)	(0.627)	(1.014)
log building permits$_m$	0.424^a	0.399^a	0.536^a
	(0.048)	(0.051)	(0.067)
log population$_m$	0.653^a	0.628^a	0.562^a
	(0.058)	(0.059)	(0.074)
Observations	744	744	739

All regressions include year fixed effects. The dependent variable is the log of cement consumption in thousand tonnes. The last two columns use instruments, but not column (1). The set of markets include 149 FAF zones during 2012-2016. All regressions include a year fixed effect. Robust standard errors in parentheses. Significance levels: ^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01.

4.3 Step 3: Estimation of fixed costs

Having the necessary elements for constructing firms' expected payoff, the last step is to solve for the optimal plant location sets and estimate the fixed costs of establishing plants by solving a combinatorial discrete location game within a Method of Simulated Moments (MSM) estimation.

To make the problem more tractable, I restrain the location game between a duopoly, Lafarge-Holcim and Cemex, the two largest multi-plant cement producers in my sample. Since fringe firms are also important, I allow all the other firms to be incumbents competing in price, but keep their locations fixed. Essentially, the timing of events is that small firms enter without anticipating LafargeHolcim and Cemex in the later period; the spatial distribution of small firms then become covariates that LafargeHolcim and Cemex take as given when choosing locations. Opposite to many papers that study Stackelberg competition and assume large firms enter first, the timing assumption here is consistent with the background of the cement industry in the US and Canada.[34] The region was proliferated with small local firms before large multinationals entered. The unique path of development is closely tied to the historical localization of cement and improvement of the transportation technology. Any ex-post regret by the small firms is ruled out by the one-shot static game.

For a submodular game with combinatorial discrete choices over a large set of potential locations, I have shown in Section 2.3.1 that there exists a pure-strategy Nash equilibrium in the multi-plant firm model. Then, how to find it? I adopt the solution algorithm for combinatorial discrete choice problem proposed in Arkolakis and Eckert (2017) to solve for the optimal plant location set. The intuition is that with plants being substitutes, a firm would always stay out of a location if adding it to the null set incurs negative marginal profit because the location does not add value to the firm even when no other plants compete against it. Likewise, a firm would always enter a location if subtracting it from the full set incurs negative marginal profit because the location still adds value to the firm even when all other plants could steal business from it. Following this idea, we can iteratively squeeze the set to optimum if marginal profit of adding a plant location decreases with the number of existing locations. Instead of evaluating every configurations, I leverage the submodularity of the profit function to discard non-optimal location sets without having to evaluate them.

Define firm f's marginal profit of including ℓ in a location strategy $\mathcal{L}_f$ as

$$\Delta^\ell \Pi_f(\mathcal{L}_f) = \Pi_f(\mathcal{L}_f \cup \ell) - \Pi_f(\mathcal{L}_f \setminus \ell).$$

In the single-player case, starting from $\mathcal{L}_f = \mathcal{L}$ which contains all potential locations, $\ell \in \mathcal{L}_f^1$ if $\Delta^\ell \Pi_f(\mathcal{L}) > 0$. Also at the other extreme, starting from $\mathcal{L}_f = \emptyset$ which contains no entries, $\ell \notin \mathcal{L}_f^1$ if $\Delta^\ell \Pi_f(\emptyset) < 0$. The first round of mapping confirms some elements in the location vector. Now iterate the mapping until a complete equilibrium location set is reached with no more refinement can be made. When there are indefinite locations, Arkolakis and Eckert (2017) find that the set of possible vectors can be sliced to any two subsets and then operate the mapping on each of the subsets separately. Slicing and mapping is repeatedly done until a unique optimal

[34] Papers that study Stackelberg competition assume that big firms enter first and choose their prices anticipating the reactions of small firms. Next, small firms enter or exit the market and choose their prices treating big firms' choices parametrically (Etro, 2006; Etro, 2008; Anderson et al., 2020; Kokovin et al., 2017). Unlike mine, these papers endogeneize the entry and exit of fringe firms.

location vector $\mathcal{L}_f^*$ emerges. In a duopoly game, the PSNE can be found by letting firms take turns to solve the best location response, given the other player's current plant locations and fringe firms' locations. Best responses are solved iteratively until strategies of both players converge. The speed of convergence in a game with best-response potential properties is exponential derived in Swenson and Kar (2017).[35]

To deal with multiplicity of equilibria explained in Section 2.3.2, I leverage predetermined sequential entry as equilibrium selection criteria and allow for different ordering as robustness checks. As baseline, I estimate the model by selecting the equilibrium that is most profitable for LafargeHolcim, the largest player and early entrant to North America in 1950s.[36] I start from LafargeHolcim solving for her best response using the algorithm by taking Cemex enters nowhere. Then Cemex finds his best response given LafargeHolcim's initial strategy. Alternatively, I also estimate the equilibrium that is most profitable for Cemex, and another one that gives each firm regional advantage in moving first. Although I try to "solve" the coherency problem in econometric inference, it continues to raise difficulties at the counterfactual stage. For example, the moving sequence I used in estimation to characterize the data may no longer be valid under the counterfactual. There has not been an existing solution I am aware that tackles this problem. However, what can alleviate the concern is when estimates across multiple equilibria do not vary significantly. I will show later that it is exactly the case with the cement industry in this paper.

Knowing how to solve for the firms' optimal location strategy given a vector of fixed costs, I can estimate the parameters governing the fixed costs distribution via MSM. For the log-normally distributed fixed costs, I draw a 2×73-dimensional matrix of fixed costs for 300 times.[37] For each draw, firms maximize total expected profits by choosing where to build plants using the algorithm above. I then use the fraction of entry over 300 draws as the simulated approximation of entry probability for each firm in every location.[38]

Moments are to match the model-predicted and the observed values of (a) number of Lafarge-

[35] In Table A.13, I present examples of two firms choosing among different location sets. The average time of convergence for 10 potential locations is around 0.09 seconds averaging 1000 simulations. It takes a maximum of three rounds of iteration to find the best response for two firms.

[36] Lafarge (prior to the merged entity LafargeHolcim), a leading French cement producer, built its first cement plant at Richmond in western Canada as early as 1956. By the end of 1960s, Lafarge is the third largest cement producer in Canada. Lafarge's market in the US expanded after its acquisition of General Portland in 1983.

[37] For the fixed cost draws, I follow Antras et al. (2017) to use quasi-random numbers from a van der Corput sequence which have better coverage properties than usual pseudo-random draws. I use 300 simulation draws in the estimation.

[38] There is actually another level of simulation for firm markups. Notice that the expected variable profit function (12) involves numerical integration over the markup. I use a stratified random sampling method in order to obtain good coverage of the higher markup. I define intervals from 1 to $\bar{\mu} = \eta/(\eta - 1)$, [1, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 1.95, 1.97, 1.99, $\bar{\mu}$]. I then draw 5 uniform random numbers within these intervals. The draws receive a weight inversely proportional to the length of the interval. The integral part of the profit function is approximated by $\int_1^{\bar{\mu}} f(\mu) \approx \sum_{s=1}^{S} w_s f(\mu_s)$.

Holcim/Cemex plants, in the sample, in Canada and in the US;[39] (b) average distance from headquarter of LafargeHolcim/Cemex to plants;[40] (c) difference between the average production capability for locations that LafargeHolcim/Cemex produces and those that it stays out. The moments are informative about the overall magnitude of the fixed costs of entry, as well as how they vary by distance, the identity of firm, and the country of interest. Roughly, firms' entry decisions in the first two sets of moments identify the mean of fixed costs. The last set of moments helps to pin down the dispersion of fixed costs distribution. The larger the dispersion, the more entry decisions vary by fixed costs and less by local profitability. In other words, firms care more about fixed costs in deciding where to build plants and they could enter even if the local production capability is not as high.

Formally, the vector of moment functions, $g(\cdot)$, specifies the differences between the observed equilibrium outcomes and those predicted by the model. The following moment condition is assumed to hold at the true parameter value $\delta_0 = \{\beta^F, \sigma^F\}$,

$$E\big[g(\delta_0)\big] = 0.$$

MSM finds an estimate such that

$$\hat{\delta} = \arg\min_{\delta} \frac{1}{|\mathcal{L}|}\left[\sum_{\ell=1}^{|\mathcal{L}|} \hat{g}(\delta)\right]' W \left[\sum_{\ell=1}^{|\mathcal{L}|} \hat{g}(\delta)\right], \tag{22}$$

where $\hat{g}(\cdot)$ is the simulated estimate of the true moment function and W is a weighting matrix.[41] I use the identity matrix and weight the moments equally as baseline. As robustness checks, I apply the optimal weighting matrix and present the results in Table C.14.

The complexity when having spatial correlation is that the moment functions $g(\cdot)$ are no longer independent across locations. In order for the MSM estimators using a dependent cross-sectional dataset to be consistent, a sufficient condition is that the dependence between locations should die away quickly as the distance increases (Conley, 1999). In the current model setup, competition between plants becomes weaker when locations are further apart due to trade costs. To ensure the speed of dependence decay, I further segregate the 149 FAF zones to eight districts and assume

[39]Matching the number of plants in each country is relevant for the counterfactual exercises because policies are imposed at country level.

[40]For LafargeHolcim, I use its North America headquarter, which is at Chicago, Illinois, because its unlikely that plant operations is managed by its global headquarter in Switzerland given the firm size. Cemex is used as its global headquarter in Mexico.

[41]The discrete choice decisions makes the objective function non-smooth and the firm's problem not globally convex. The shortcoming is that I cannot guarantee the solution I find is the global optimum of the problem. To address this issue, I tried the particle swarm optimization algorithm to search through 100 starting points. All sets of starting points resulted in close outcomes.

that competition is negligible across them.[42] The districts are categorized by USGS as relatively separated markets. FAF zones on average export more than 88% of the cement production and import more than 82% of the consumption within the same district. More information about each district is presented in the Appendix D.2. An alternative way to restrain the geographic scope of the spillover effect is by assuming dependence only occurs for the set of locations within certain radius to each location, as in Jia (2008). However, such method does not work for the multi-plant firm model in general. Existence of overlapping across each location's catchment area causes the firm's profit function to violate the submodularity condition which is essential when solving the equilibrium.

Cluster bootstrap is used to estimate the standard errors. District vectors are re-sampled 100 times with replacement to preserve the dependence among locations.[43] Alternatively, I also estimate the asymptotic variance of the MSM estimator using either identity weight or the optimal weighting matrix, while taking the spatial dependence within each district into account. As shown in Table C.14, all estimates are close, although the optimal weighting matrix exhibits slight improvement in precision.

Estimates of the fixed costs parameters for three different equilibria are displayed in Table 4, corresponding to the scenario that is most profitable for LafargeHolcim (LFH), Cemex (CEX), or allowing LFH to have local advantage in Canada and CEX in Texas and Florida. They are not significantly different from one another, and thus, ease the generality concern of the counterfactual results. The equilibrium selection rule does not have "bite" here because the asymmetry between two oligopolists mitigates the effect of sequential move assumption in selecting equilibrium. Specifically, LafargeHolcim owns twice the number of plants than Cemex. Assuming Cemex moves first, the model must rationalize the fact that Cemex enters half the number of locations as LafargeHolcim. It does so by making Cemex to acquiesce LafargeHolcim's entry and choose to forgo some locations expecting LafargeHolcim would enter. Estimates reflect that Cemex has disadvantages in those locations. Vice versa, assuming LafargeHolcim moves first, the estimates need to be consistent with the patterns in the data and LafargeHolcim being the dominant player.

I find a location that is 10% more distant from the firm's headquarter, the average fixed costs of establishing plants will be nearly 18% higher holding everything else constant. The effect seems to be large considering communication and management cost alone, but should be interpreted with caution. First, it could reflect increasing information friction at locations further away from the firm headquarter. Second, there could be loss of productivity associated with transferring headquarter services to production locations. The model does not capture such cost of producing, and it could

[42] Districts are Mountain and Pacific North, Mountain and Pacific South, West North Central, West South Central, East North Central, East South Central, New England and Middle Atlantic, and South Atlantic.

[43] I recognize the potential concern of bootstrap when the number of clusters is small (Cameron and Miller, 2015; MacKinnon and Webb, 2017).

Table 4: Estimation of fixed costs

	(1) Favor LafargeHolcim	(2) Favor Cemex	(3) Local advantage for two firms
β^F_{cons}	-6.631	-6.126	-5.617
	(1.616)	(1.688)	(1.559)
$\beta^F_{\text{CEX-USA}}$	-0.406	-0.363	-0.280
	(0.373)	(0.382)	(0.372)
$\beta^F_{\text{LFH-CAN}}$	-3.734	-3.475	-3.480
	(1.867)	(2.318)	(1.992)
β^F_{dist}	1.795	1.698	1.634
	(0.220)	(0.245)	(0.221)
σ^F	2.790	2.581	2.694
	(0.481)	(0.504)	(0.503)

The data shows Cemex does not have any cement plants in Canada, which makes it impossible to identify the Cemex-Canada dummy. I drop the Cemex-Canada and LafargeHolcim-US dummies and preserve the other two and a constant.

be picked up by fixed costs in estimation. With limited plant-level data, I cannot separately identify plants' ex-ante differences in variable costs from fixed costs. However, one can easily extend the model by incorporating a $h(f)\ell$-level term in the marginal cost of production. Third, the distance elasticity to fixed costs may be upward biased due to the omitted home variable. Head and Mayer (2019) find that assembly cars at the brand's home is 9.5 more likely to happen than choosing other assembly locations.

The average fixed cost is significantly lower when LafargeHolcim builds a plant in Canada, whereas Cemex does not share the country-specific advantage in fixed costs. Variance of the fixed cost distribution is rather high, suggesting that firms' entry decisions are predominantly determined by fixed costs rather than local profitability. The result is consistent with high fixed costs investment in the cement industry documented in Section 3.1. One may attempt to argue that the reason local profitability appears to matter less could be that the variable profit modeled in the multi-plant firm framework fails to capture some important aspects. To rebut the argument, I perform external validity checks to show that the estimated fixed costs align with the industry facts.

To compare the costs estimated from the model to the cement industry standard, I transform the estimates to their corresponding monetary value. Recall that in the first step of the estimation, the production capability of each location is estimated up to a scale. The normalization can be computed by comparing the predicted local price in the second step to the USGS survey data on cement prices. Since the normalization parameter enters the price index multiplicatively through Φ_m in equation (13), I run the observed cement price on the model prediction and obtain a slope of 140.575, which would then be the amount to scale up the cost estimates.

Back-of-envelope calculation reveals that the average fixed cost across the cement plants owned by LafargeHolcim is estimated to be around \$181 million and that for the Cemex plants is around \$280 million.[44] The estimated average fixed costs of building a cement plant are surprisingly close to the industry norm of \$200∼\$300 million. The cost advantage of LafargeHolcim justifies itself being the leader in the US and Canada and having twice as many plants as Cemex.

Computed from equation (4), the lowest production cost adjusted for the scaling among LafargeHolcim's plants is estimated to be \$57 per tonne of cement. At an average price of \$98 per tonne of cement based on equation (7), it implies a gross margin of 41.8% for LafargeHolcim. For Cemex, the lowest production cost adjusted for the scaling among his plants is \$65 per tonne of cement. At Cemex's average price of \$97, his gross margin is 33%. The higher efficiency and markup for LafargeHolcim than Cemex are consistent with the model implications in which a firm having more plants will gain competitive advantage and market power.

I further compare the estimated profit margins with the 2016 financial statements of the two firms to assess the plausibility of these estimates. LafargeHolcim reported a gross profit of \$11,272 million on sales of \$26,904 million, which is a profit margin of 41.9% and almost exactly matches with what has been estimated. Cemex reported a gross profit of \$4,756 millon on sales of \$13,404 million, which is a profit margin of 35.5% and again very close to the estimated value. The costs of production are also close to the engineering costs of \$60 in 2016 reported by the US Environmental Protection Agency.[45] In sum, these cross-firm comparisons corroborate the costs estimates from the multi-plant firm model.

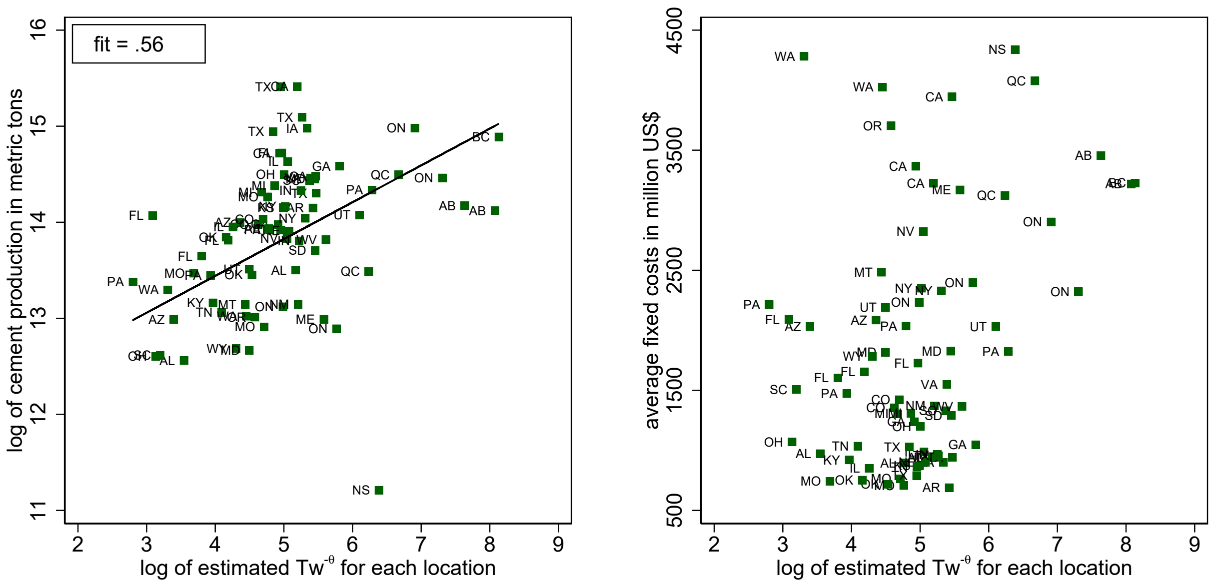
Across locations, I analyse the interaction between the estimated production capability, the estimated fixed costs and the observed cement production by FAF zones. I copied panel (a) in Figure 5 to Figure 6 to be interpreted together with the panel (b). It is clear that Nova Scotia, a province having moderate production capability, produces exceptionally small amount of cement. The inconsistency is reconciled by Nova Scotia having the highest fixed costs. On the contrary, FAF zones in Texas are as capable in producing cement as Nova Scotia but among the lowest fixed costs locations, contributing to Texas being the largest cement producer in the sample. Similar findings can be seen by comparing FAF zones in Alberta to those in Ontario. These differences in production capability and fixed costs of entry help to explain the variation across FAF zones in the number of plants located and the amount of production. Figure 6, complemented by the firm-level

[44] Since I use static data for one year, the estimated fixed costs after adjusted for the scaling also need to be computed in net present value. I use a 6% interest rate to discount.

[45] EPA reports engineering estimates of average production costs of \$50.3 per tonne of produced cement in 2005 (RTI International, 2009). I convert into 2016 dollars.

comparison, highlights the importance of heterogeneous fixed costs at plant level for matching the model to data.

Figure 6: Estimated fixed costs and production capability by location



(a) (b)

4.4 Fit of the model

To check how well the model fits the data, I start by comparing predictions of the model for the moments it is targeted to match. As shown by Table 5, the model fits the data generally well in the number of plants, total or regionally, for each firm and the average distance between plants and firm headquarters. The number of plants in Canada is slightly over-predicted and that in the US is slightly under-predicted. Since the number of plants affects a locations' competitive advantage in supplying cement to every market, I also check the fit of the model prediction to the trade data in Table 6. The predicted bilateral share of import is able to explain 64.4% of the data variation. To check to what extent the prediction is affected by the gravity errors, I regress the final prediction after solving for the endogenous plant locations on the gravity-predicted import share. The fit improves by around 20%. Restricting the sample to intra-district trade further increases the fit by another 6.7%. If comparing the import share is less convincing because it is indirectly targeted through the first-step gravity regression, I further compares the trade volume as shown in the last column of Table 6. The degree of fit does not fall.

Table 5: Model fit of plants number and distance to headquarter

	LafargeHolcim		Cemex	
	Data	Model	Data	Model
Number of plants	22	22.50	11	11.02
Number of plants, Canada	6	6.74	0	0.71
Number of plants, US	16	15.76	11	10.31
Average distance of HQ to plants (km)	369	330	271	283

The predicted number of plants is not integer because they are summations of the simulated entry probabilities.

Table 6: Model fit of trade flows

	Bilateral share of import	Gravity-predicted share of import	Gravity-predicted share of import within region	Bilateral import volume
Model prediction	0.767	0.797	0.990	0.631
	(0.005)	(0.003)	(0.008)	(0.004)
Observations	10877	10877	1437	10877
R^2	0.644	0.850	0.917	0.645

All regressions include a constant.

Other than comparing trade flow, Figure 7 plots and compares the share of trade by distance.[46] The close fit is not surprising because I estimate the distance elasticity of trade to be -1.198 to match the trade flow over distance, but it is reassuring that the estimation of fixed costs and solution for endogenous plant locations do not introduce new biases.

Having checked the model performance through plants number and trade, lastly I compare the model predicted cement consumption and production against the data. Figure 8 shows that the model fits the data reasonably well in both dimensions. The actual and predicted cement consumption across markets distribute tightly along the 45-degree line. The prediction on production, although deviates from the diagonal relationship, captures 65% of the data variation. The multiple test results establish confidence in the following counterfactual exercises.

[46]The actual trade data is used for only the dyads within the same district to be comparable with the estimation under such assumption. Same goes for the consumption and production data in Figure 8.

Figure 7: Model fit of trade flow over distance

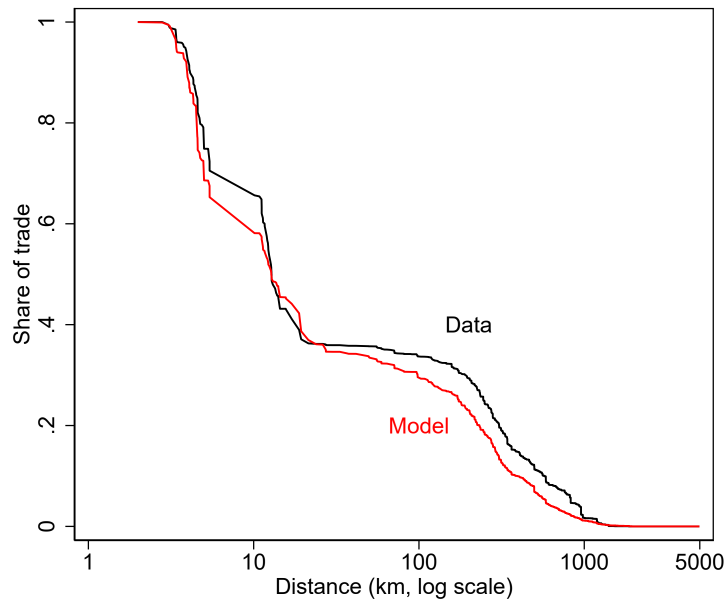
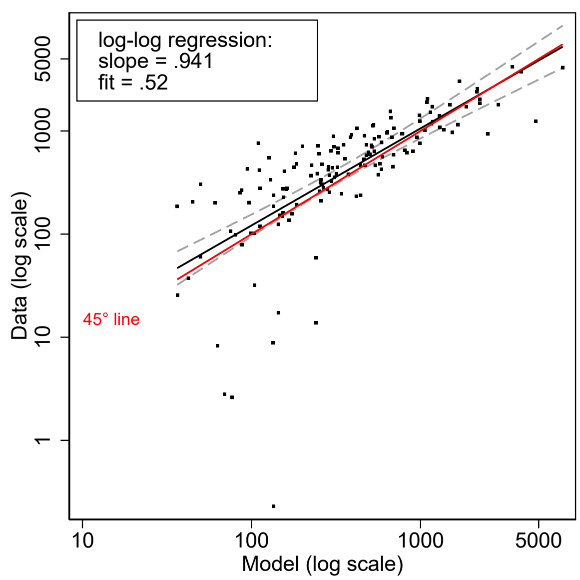
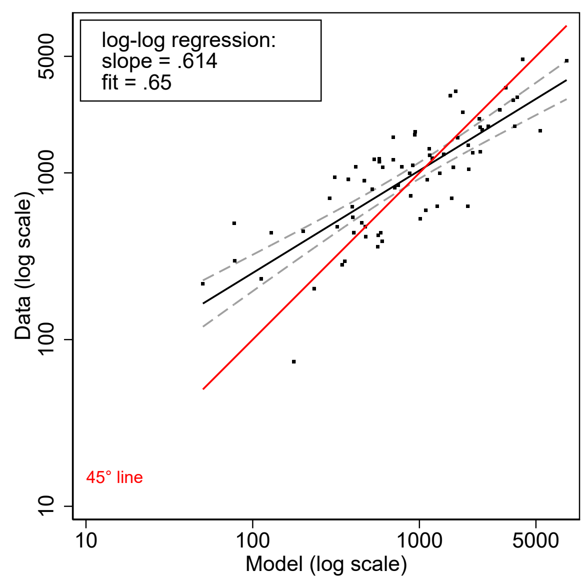


Figure 8: Model fit of cement consumption and production



(a) Consumption (thousand tonnes)



(b) Production (thousand tonnes)

4.5 Comparing determinants of plant locations

The model characterizes the decision making of plant locations for multi-plant firms. There are four main forces underlying such decision: fixed costs, local input costs, transportation costs, and strength of competition and cannibalization. How important quantitatively for each of these forces? With the estimated parameters, I let firms re-optimize their plant location sets and compare the effects on aggregated outcomes, under different scenario.

Table 7: Comparing determinants of plant locations

	Baseline model	Zero fixed costs	Infinity fixed costs	Same location input costs	$\tau = 1$ everywhere	$\theta = 5$ low competition
Number of plants (LFH & CEX)	34	146	2	36	36	61
Price (US$/tonne)	106	96	115	101	70	45
Import penetration (%)	24	17	31	20	89	58
Export intensity (%)	44	40	47	44	93	67

In the case of infinity fixed costs, I assume the firm always has a plant at its headquarter or the nearest location to its headquarter if the headquarter is out of sample. Numbers are rounded to the nearest integer. $\theta = 5$ is found in the literature as the average trade elasticity for manufacturing goods.

Table 7 tabulates the results. If there were no fixed costs for setting up plants, every firm would have built a plant in each location because the model features increasing profit with the number of plants owned. The average market price would drop with more plants competing. Trade would decrease but not vanish because intra-industry trade still persists when plants are heterogeneous. On the contrary, if fixed costs were extremely high such that all firms become single-plant owners at their headquarters, price would be higher than the observed level, and share of import and export both rise. Quantitatively, I find that the market price on average fluctuates by about 10 dollar than the baseline when having the maximum or the least number of plants. The predicted change is conservative given a large set of fringe firms competing in price, and therefore suppresses the aggregate effect on price imposed by large firms.

Next, when all locations have the same input costs at the mean value, the difference in profitability across locations drives more by transportation costs instead. The total number of plants increases slightly because plants spread out instead of agglomerating around the most efficient locations, which leads to a 5 dollar drop in price compared to the baseline. The incentive to trade would be reduced and reshuffled based on distance.

Should trade costs be eliminated, locations freely trading with one another would import from those with the lowest input costs and the highest number of plants. Import and export share would increase by two to four fold compared to the baseline. Trade liberalization induces a large drop in price by 36 dollar and a slight increase in the number of plants.

Lastly, if there is no vigorous competition across plants represented, firms would build more plants without worrying too much about their own plants cannibalize each other's market. In fact, if θ converges to its lower bound $\eta - 1$, it is equivalent to multi-plant firms make separated entry decisions. Smaller θ also silences the respond of trade to trade costs, leading to higher trade shares. Price drops the most because plants are more heterogeneous and efficient in supplying their respective consumers.

Overall, I find that all four factors are important in multi-plant firms' decisions, analytically and quantitatively. Fixed cost and competition intensity matter the most for their plant location decisions.

5 Counterfactual: The Greenhouse Gas Pollution Pricing Act

In 2018, Canada passed the Greenhouse Gas Pollution Pricing Act (the Act) which is a backstop system at the federal level that would raise the carbon price to $50 per tonne by 2022. The Framework is composed of two carbon pricing initiatives: a carbon tax on fossil fuels and an output-based pricing system (OBPS) for industrial facilities.[47] Prior to the pan-Canadian approach, provinces such as British Columbia, Alberta, or Québec have already implemented certain pricing regimes on carbon. British Columbia, for example, applies carbon tax to emissions from the combustion of fossil fuel, but not to process emissions during production such as the calcination of limestone. The primary interest is to evaluate the welfare costs of these environmental regulations for both consumers and producers by comparing what the alternative spatial allocation of plants and market structure would be in the long run.

5.1 Carbon tax on fossil fuels

I first examine the effect of carbon pricing levied on fossil fuels considering they are essential for generating energy in producing cement. The average cost of fuel to produce a tonne of cement before the carbon levy is $12.44, calculated based on the amount of energy required for production, breakdown of fuel type used, fuel prices and energy content tabulated in Table C.17.[48] The computed pre-tax unit cost of fuel is close to $13.82 in Miller et al. (2017) using the 2010 data. After the carbon levy, rates for each fuel subject to the levy is set by the Canadian Federal Carbon Pricing Backstop Technical Paper such that they are equivalent to $50 per tonne of CO_2 by 2022. The average cost of fuel for producing one tonne of cement post the levy becomes $29.37.[49] I

[47] In practice, to account for the unique circumstances across different provinces, the federal benchmark provides provinces with flexibility to implement their own carbon pollution pricing systems. Fuel charge in the backstop system is only applied to Ontario, New Brunswick, Manitoba, Saskatchewan, Alberta, Yukon and Nunavut. OBPS is applied to Ontario, New Brunswick, Manitoba, Price Edward Island, Saskatchewan, Yukon and Nunavut. Some exceptions are Nova Scotia and Québec where implement cap-and-trade systems, Alberta where has its Carbon Competitiveness Incentive Regulation, and British Columbia where implements broad-based carbon tax. However, these provincial regulations are assessed to meet the federal government's minimum stringency benchmark requirements for pricing carbon pollution. For simplification, counterfactual analysis is based on a uniform change to all Canadian provinces.

[48] Produce one tonne of cement requires energy 4.432 million BTU. Cost of fuel in 2016 $= (42\% \times 2.366 + 22\% \times 5.003 + 13\% \times 1.722 + 4\% \times 12.223) \times 4.432 =$ $12.44/tonne cement.

[49] Levy on fuel by 2022 $= (42\% \times (158.99/27.77) + 22\% \times (0.0979/0.035) + 13\% \times (0.1919/0.04) + 4\% \times (0.1593/0.036)) \times 4.432 =$ $16.93, and hence cost of fuel in 2022 will be $16.93 + 12.44 =$ $29.37/tonne cement.

assume there is no substitution of fuel to other carbon-saving sources after the policy.

As explained in Section 3.1, I specify that fuel is a third of the input costs in producing cement. Therefore, increasing the cost of fuel from \$12.44 to \$29.37 per tonne of cement is equivalent to 33% increase in the input cost w_ℓ or 96% decrease in local production capability $T_\ell w_\ell^{-\theta}$ for all FAF zones in Canada. The change in a location's competitive advantage is exacerbated by the relatively large θ. When plants are not widely differentiated, a small increase in costs of production may induce immediate losses of market share, which explains why carbon policy could be a major threat to the competitiveness of the local cement industry.

Responding to the rise in production costs, cement firms tend to move plants to "pollution havens". Figure 9 displays the comparison of spatial distribution of plants before and after the carbon tax. Combining the top two cement manufacturers, red indicates the share of plants predicted to close and green indicates the share of plants predicted to open. FAF zones other than the 73 are excluded from the potential location set and shaded in grey. The map shows that there is some degree of plants closure throughout FAF zones in Canada, with the most striking exit ratio in Québec where more than 20% of the plants will be shut down, followed by Great Vancouver metro area in British Columbia, Nova Scotia, Alberta and Ontario. As close substitutes, plants are shifted to the zones along the border in the US, near the pre-existing Canadian plants. Markets that were previously served by Canadian plants would now source from the US plants that are not too distant. On the west coast, Washington and Montana face the steepest increase in plants owned by LFH and CEX, around 16% more, whereas places in Oregon and Utah face a moderate expansion, and no plant opening in states further South. Despite similar distance to Canada, plants are built in Utah but not Nevada because Utah is more efficient and cheaper to produce cement. On the east coast, plants opening is weaker because there has already been a dense production network as shown in Figure 2.

Table 8: Counterfactual changes with \$50 carbon levy on fuel in Canada

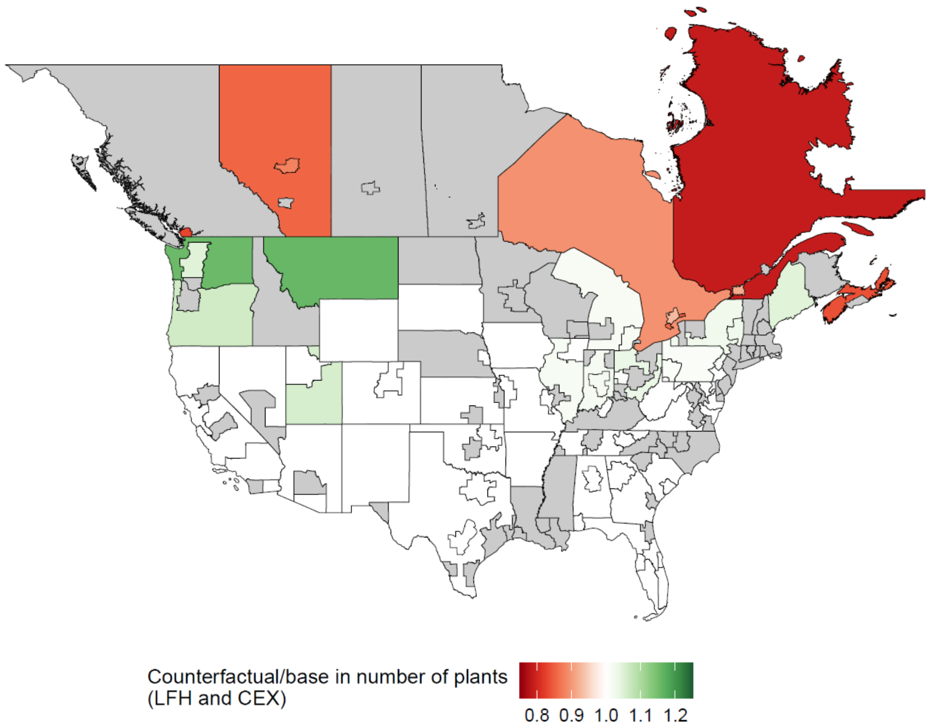
Panel A: Impacts on market outcomes

	Δ Avg entry prob(%)		Δ Price(\$)	%Δ Consum	%Δ Prod	%Δ Trade	
	LFH	CEX				Canada	US
Canada	-7.43	-2.13	26.82	-52.37	-57.63	-54.25	-94.67
US	0.13	0.19	0.73	-1.04	1.38	224.83	1.02

Panel B: Impacts on welfare and emissions

	Δ CS(\$M)	Δ PS(\$M)	Δ TaxRev(\$M)	Δ Emissions(Mt)	Leakage rate(%)
Canada	-310.50	-68.04	96.86	-5.27	17.89
US	-35.54	10.70	-	0.94	-

Figure 9: Change of plant locations with $50 carbon levy on fuel in Canada



The first two columns in Table 8, panel (a) quantify the change in average probability for building a plant in Canada or in the US, for each firm respectively. The model predicts that the probability of having a plant owned by either firm in Canada drops around 10%. In contrast, the probability of having a plant in the US barely increases, which is consistent with the fact that construction of a cement plant incurs high fixed costs. Across firms, the effect is heterogeneous. LafargeHolcim, being the dominant player in the Canadian market, is hit harder by the negative cost shock. It loses more plants in Canada and is not able to recover by building more in the US. Note that the model overpredicts the presence of Cemex in Canada, so theoretically Cemex could have benefited from having a weaker competitor after the carbon tax.

The average price in Canada for one tonne of cement is $26.82 higher (almost a third of the baseline price), out of which $16.93 is directly passed on from the increased fuel prices and the rest from the rising market concentration. The prediction is in line with Ganapati et al. (2016) and Miller et al. (2017) who find that changes of fuel cost are more than fully transmitted to cement prices. However, in the US, the impact on prices is driven by two opposing forces: downward pressure from the intensified market competition through plants entering and the upward pressure from the loss of cheap cement imported from Canada. A carbon levy as high as $50 per ton of CO_2 makes the latter slightly dominate.

Associated with the price changes, consumers in both countries substitute cheaper alternatives for cement. In Canada, the amount of cement consumption drops by more than 52%. The contraction of production is even more prominent at around 58%, some of which "leak" to the US. The intensive margin in consumption and production is actually quite responsive, although on the extensive margin, the number of plants is not as flexibly adjusted. Implicitly, it indicates that the US cement plants achieve a higher utilization rate and Canadian plants will be under-utilized.[50]

The effects of the carbon tax on trade in cement are enormous. The cement export from Canada to the US almost vanishes. Instead, Canada is flooded with cement from the US, more than triple the amount before. Based on the changes in trade volume and consumption, import penetration of the US produced cement into the Canadian market rises from 6% to 41%.

As for welfare analysis, from equation (14) and (15), impacts of a \$50 carbon levy on fuel in Canada include the consumer loss around \$310 million and the producer loss around \$68 million annually.[51] Comparing to the 2016 Canadian cement industry revenue of \$7.4 billion, the combined loss is roughly 5%. Consumers bear about 82% of the tax burden, comparable to the 89% found by Miller et al. (2017) in their study of a US carbon tax. Using the carbon emission intensity from fuel combustion at 0.4 tonne of CO_2 per tonne of cement, the government revenue is around \$97 million dollars. Producers could be fully compensated by 70% of the revenue obtained from the carbon tax.

Lastly, assuming that producing one tonne of cement emits 0.8 tonne of CO_2, the leakage rate is around 18%. It implies that for a hundred tonne of CO_2 abated in Canada, approximately 20 tonne leaks. The leakage is particularly problematic when the emission damage is independent of the origin, as in the case of carbon dioxide. Therefore, evaluation of the social benefit to Canada from carbon reduction should be based on net emissions, taking into account the amount of leakage.

Summing over changes on consumer surplus, producer surplus and government revenue, the \$50/t carbon levy on fossil fuels would be welfare improving for Canada provided a minimum social cost of carbon at \$65/t.[52] At a \$50/tCO_2 carbon price set by the government, the policy generates welfare loss to Canada. There are two reasons for the carbon tax to be suboptimal. First, the market distortion is exacerbated with the presence of oligopolists, as shown by the more than complete pass-through of fuel costs. Second, the carbon pricing is incomplete and creates carbon leakage whose damages are global. In this case, welfare losses from these two channels overwhelm the gains from emissions abatement for a social cost of carbon set at the current level of the carbon

[50] Data shows that the capacity utilization rate of a US cement plant is on average 70% in 2016, which leaves room for better utilization.

[51] Producer surplus is calculated combining all firms including the small ones operating in the region. The profit change of LafargeHolcim and Cemex comes from different plant locations and adjustment in prices, whereas changes of small firms' profits are only from prices.

[52] Based on EPA Social Cost of Carbon Fact Sheet (2016), the social cost of CO_2 could range from \$14 to \$138 in 2025. To break even in welfare terms, the required minimum social cost of carbon is $(-310.50 - 68.04 + 96.86)/(-5.27 + 0.94) = \$65/tCO_2$.

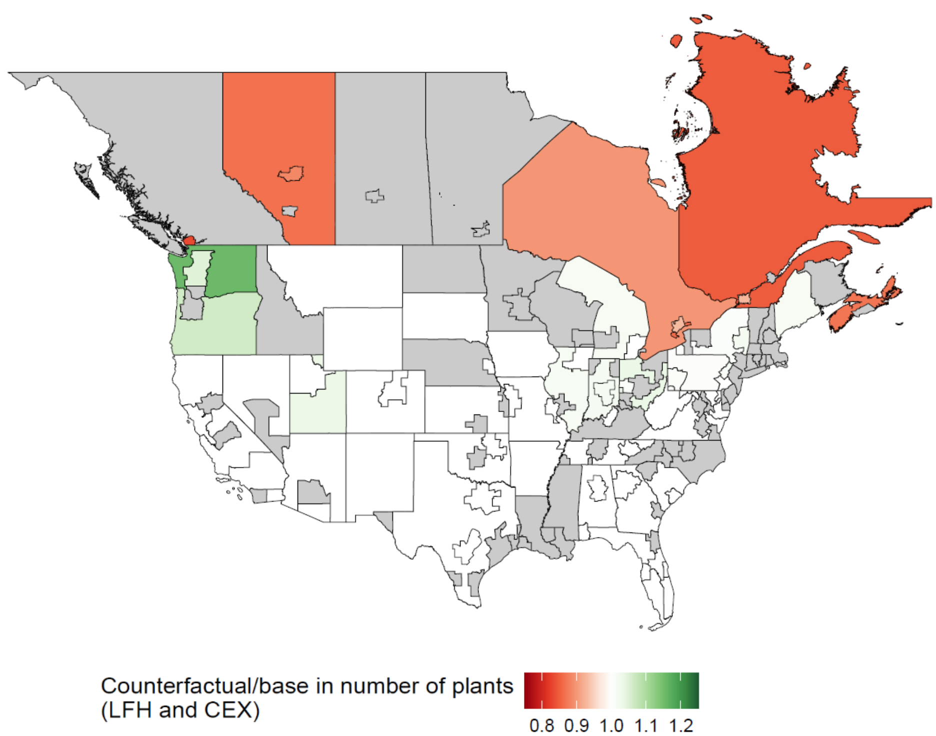
tax.

As one may expect a negative cost shock to Canada may benefit the US, the welfare evaluation shows otherwise. The US also loses around $25 million driven by higher prices faced by consumers. Just as the pollution of carbon is global, the effect of a carbon tax in one country also transmits to another through multi-plant production and trade.

5.2 Border tax adjustment

As demonstrated by the change in trade, downstream consumers turn to unregulated imports after the imposition of carbon tax. A solution to such leakage is a border tax adjustment (BTA) that raises the effective price of unregulated imports. In this section, I evaluate to what extent a BTA is effective and its welfare implications. Imposing the same level of carbon levy on fossil fuels to the imported cement from the US is equivalent to charging an *ad valorem* border tax of 33%.[53]

Figure 10: Change of plant locations with $50 carbon levy on fuel and 33% BTA in Canada



[53]Note that trade costs τ and input costs w enter the sourcing probability from a location in the same way through a power of $-\theta$. From the previous section, I've calculated that the carbon tax is equivalent to 33% increase in w, then immediately the border tax should be 33% to achieve the same level of carbon tax. Implicitly, I assume that the composition of fuel usage and related fuel prices are the same in Canada and in the US, which is an assumption has to be imposed due to limited data. 33% border tax also means that the import penetration of the US cement in Canadian consumption will be kept as the same level (6%) as before imposing the carbon tax.

Table 9: Counterfactual changes with \$50 carbon levy on fuel and 33% BTA in Canada

Panel A: Impacts on market outcomes

	Δ Avg entry prob(%)		Δ Price(\$)	%Δ Consum	%Δ Prod	%Δ Trade	
	LFH	CEX				Canada	US
Canada	-6.70	-2.00	32.24	-53.61	-57.04	-53.61	-94.65
US	0.08	0.15	0.75	-1.06	0.90	-53.61	0.99

Panel B: Impacts on welfare and emissions

	Δ CS(\$M)	Δ PS(\$M)	Δ TaxRev(\$M)	Δ Emissions(Mt)	Leakage rate(%)
Canada	-322.76	-66.27	108.90	-5.22	11.79
US	-36.30	10.93	-	0.62	-

Augmenting the carbon tax on fuel with a BTA mitigates the loss of domestic market share to foreign producers, thus slowing the change of plant sites from Canada to the US. Comparing Figure 10 to Figure 9, the exit rate for Canadian plants decreases and fewer locations in the US are seen with significant plant entry. Vancouver metro area and Québec lose the most plants of about 15%, followed by Nova Scotia, Alberta and Ontario. New plants no long enter Montana, and the fraction of new plants in Washington, Oregon, Utah and FAF zones in eastern US all decline. Table 9 also presents smaller change in entry probabilities compared to the case of carbon tax alone. Therefore, sufficient level of BTA is indeed effective in reducing production leakage. However, Canada, as a net exporter of cement, will not overturn the closure of cement plants since many of them were used to primarily serve the US markets.

Because cement consumed in Canada bears the increase of carbon price regardless of the origin, the price of cement rises by another \$5.42 for Canadian consumers and total consumption drops further. In the US, fewer plants entry besides the loss of import competition also exacerbates the price increase. The production of cement and trade both move in the expected direction, with the addition of BTA protecting domestic production and improving terms of trade. BTA, however, will not recover the loss of Canadian exports.

Finally, Canada suffers additional \$10 million loss in welfare compared to the scenario without BTA, out of which the \$2 million gain of producers cannot compensate the extra \$12 million loss of consumers. However, the government receives additional tax revenue besides the carbon tax on domestic production. Using the percentage change in trade, the border tax revenue is approximately \$10.7 million.[54]

Border tax adjustment not only works to reduce the emissions leakage rate (18% to 12%), but

[54] The 2016 export value of cement from the US to Canada is \$69.8 million according to Trade Data Online from the Government of Canada. I use the same percentage change in trade volume as trade value.

also cuts down the total emissions in level by indirectly restraining the US production through exports. However, BTA cannot eliminate carbon leakage because Canadian exporters would still shift their production to the US, and they consist a significant number of Canadian cement producers. Overall, the threshold of the social cost of carbon, in order for Canada to benefit from the policies, reduces to \$61/tCO_2.[55] The welfare loss from carbon leakage is partially mitigated by implementing BTA, although the concentrated industry is still under-producing.

5.3 Output-based pricing system

I show in the previous section that a sufficient level of BTA on top of a carbon tax is more likely to improve welfare than leaving it out. However, BTA is designed to level the playing field for domestic and foreign plants serving the Canadian market. The gain is small if the majority of Canadian plants are exporters and compete in foreign. An alternative strategy that addresses the production and carbon leakage for all Canadian plants is to impose an output-based pricing system (OBPS) as adopted by the Act. OBPS prices carbon on the basis of emission intensity, i.e. emissions per unit of output. The cement industry is subjected to an output-based standard at 95% of the sectoral average carbon intensity (0.8tCO_2/tonne of cement), which means an emitting limit of 0.76 tonne CO_2 per tonne of cement. Under OBPS, if a plant generates more emissions than 76% of her cement output, she faces a marginal rate at \$50/tCO_2 and is taxed for the portion exceeding.[56] The objective of OBPS is two fold: one is that it provides relief from fuel charge to emission-intensive and trade-exposed industries so that domestic firms still retain some level of competitiveness compared to foreign; the other is that OBPS financially incentivizes firms to reduce their emissions intensity and transit to cleaner technologies. This carbon pricing scheme comes with a notable side effect which is weaker pricing signal and smaller carbon reduction in targeted industries. It could potentially cause large distributional effects where some industries are protected at the costs of others being heavily regulated.

In this section, I model the OBPS as a output-based "rebate" following Canada Gazette (2019). Given that 95% of the sectoral emission intensity is tax-free for the cement industry, I assume 95% of the proceeds from OBPS will be returned to the sector. Due to data limitations, the sample used for this analysis does not contain information on firm- or plant-level carbon emissions intensity, nor is the static model able to accommodate endogenous technological improvement. I take a simple heuristic approach and model the cement industry as one representative firm operating at the average 0.8tCO_2 emissions intensity. The OBPS in this counterfactual exercise is effectively a

[55] To break even in welfare terms, the required minimum social cost of carbon is $(-322.76 - 66.27 + 108.9)/(-5.22 + 0.62) = \$61$/t$CO_2$.

[56] Firms that emit a quantity below their limit will obtain surplus credits that can be sold to firms that need credits for compliance. With limited firm-level data, I ignore the carbon trading aspect of OBPS in this analysis.

Figure 11: Change of plant locations with OBPS in Canada

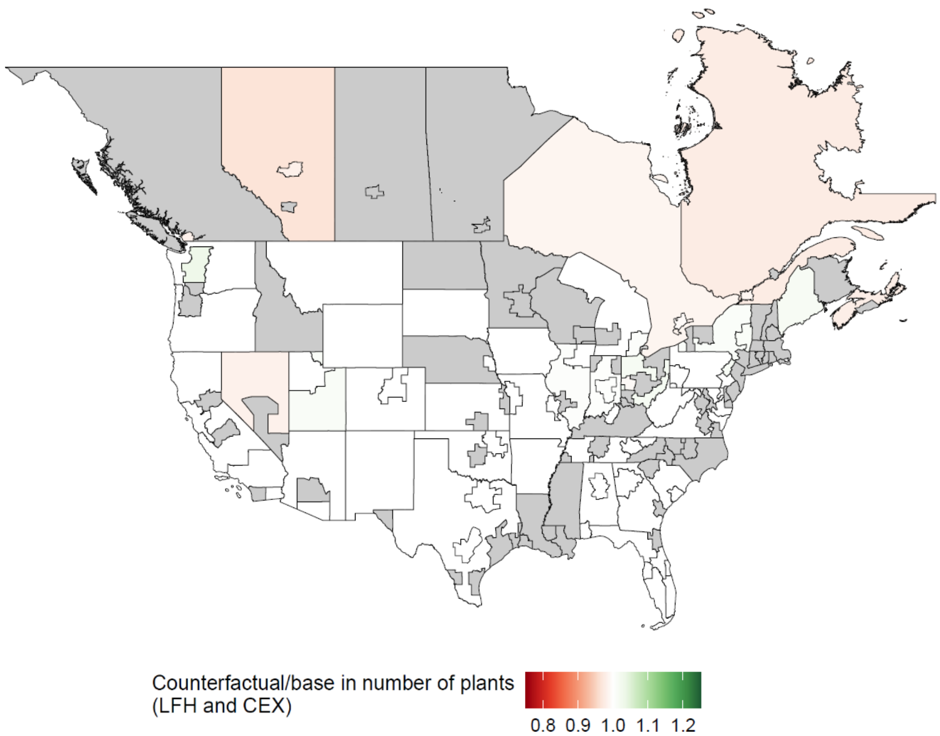


Table 10: Counterfactual changes with OBPS in Canada

Panel A: Impacts on market outcomes

	Δ Avg entry prob(%)		Δ Price($)	%Δ Consum	%Δ Prod	%Δ Trade	
	LFH	CEX				Canada	US
Canada	-1.00	-0.23	3.15	-8.65	-10.35	-8.79	-27.54
US	0.04	0.03	0.19	-0.29	0.33	11.75	0.31

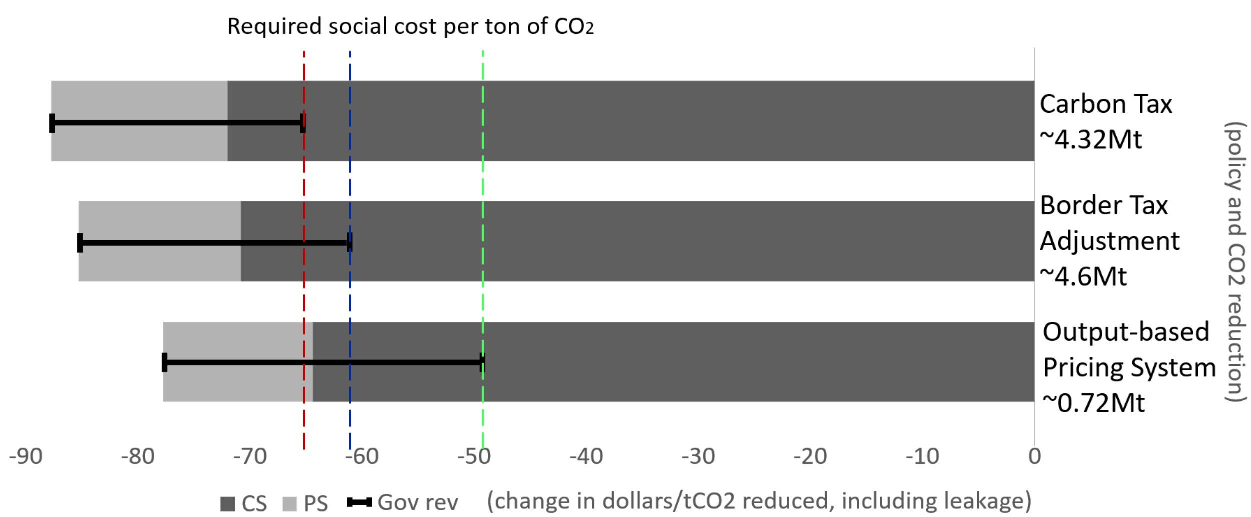
Panel B: Impacts on welfare and emissions

	Δ CS($M)	Δ PS($M)	Δ TaxRev($M)	Δ Emissions(Mt)	Leakage rate(%)
Canada	-46.36	-9.57	20.50	-0.95	23.82
US	-9.57	2.67	-	0.23	-

lower carbon tax at the average rate of $\$50 \times 0.8 \times (1-95\%) = \$2$ per tonne of cement. Compared to the 33% increase in the carbon tax case, it is equivalent to an *ad valorem* 2.76% increase in the production cost for Canadian plants.[57] Predictions under this assumption will be an upper bound of OBPS on change in plant locations and a lower bound on carbon reduction since firms are treated as passive tax payers without actively seeking cleaner production technology.

Figure 11 shows that OBPS triggers the least change in plant sites among three carbon pricing schemes. Very few locations in the US are observed with entry, and some locations such as Nevada even suffer from plants exiting due to expansion in the nearby area (Seattle). The results in Table 10 are not qualitatively different from those in Table 8, if any, smaller in magnitude. As expected, the number of plants, the amount of production, and the exports to the US, have all been restored nearer to the baseline level. Mitigation on production leakage is achieved at the sacrifice of weaker environmental targeting. Carbon emissions abatement is now 0.72 million tonne including the amount that leaks, which is around one sixth of the reduction in the case of carbon tax alone. A striking finding is that the carbon leakage rate is almost 24%, higher than any of the scenarios before. Therefore, OBPS does not curb emissions leakage in relative terms, but it indeed lessens production leakage.

Figure 12: Welfare comparison of carbon policies



Using the welfare measures to calculate the social cost of carbon for the OBPS to be welfare-enhancing for Canada, the threshold is around \$49 per tonne of CO_2.[58] Among the three scenarios,

[57]Consistent with the Act, I also adjust the calculation to cover both combustion and non-combustion emissions in OBPS, unlike only combustion for the fuel charge. The estimated average Canadian plant production cost is \$72.56 calculated from equation (4).

[58]To break even in welfare terms, the required minimum social cost of carbon is $(-46.36-9.57+20.50)/(-0.95+$

this is the only case where a \$50 carbon price will improve welfare. By giving free allowances to cement producers, OBPS essentially cuts the regulatory cost and alleviates the downward pressure on production which has already been below the socially optimal level in the concentrated cement industry. The market is not as distorted by the multi-plant firms as when charging a high carbon tax, and the consumer and producer surplus suffer smaller losses.

In summary, Figure 12 visualizes the comparison of welfare effects among the three carbon pricing schemes. Judging from these measures, OBPS is the most preferable way to price carbon in a concentrated industry like cement, supporting the actual policy design in The Act. It points to two confounding factors when internalizing pollution externality – change in market structure and emissions leakage.

6 Single-plant Approximation

Although I present in this paper a model characterizing a rich set of multi-plant firms' decisions and also provide a recipe to estimate it without sacrificing too much tractability when one has limited data, a researcher may still worry about the payoff for incorporating interdependent entry when studying multi-plant firms. In this section, I address a pressing question when applying this model: does interdependent entry matter?

In reality, a multi-plant firm could operate in a continuum degree of control over its plants, with one extreme being complete oversight of all its production locations and the other being full delegation to local managers. The latter is equivalent to treating each establishment as a single-plant firm. Although imposing single-plant (SP) assumption is inconsistent with the multi-plant (MP) firm's objective to maximize total profits, it is an empirically handy approach for researchers especially when studying discrete choice decisions because one does not need to solve combinatorial optimization. Instead of arguing which premise is correct, I present comparisons between the two.

Under the same model, now let's compute the expected profit for firm f at location ℓ. Because pricing strategy is coordinated at the firm level, the price distribution for every plant owned by the same firm is identical as shown in equation (6). Hence, the expected variable profit for a particular plant is proportional to the firm's profit based on the share of consumers sourced from this plant over all firm f's consumers. With the Fréchet distributed productivities, the sourcing probability of consumers in m from plant ℓ over the set of firm f's plants is

$$s_{f\ell m} = \frac{\phi_{\ell m}}{\Phi_{fm}}. \tag{23}$$

Multiplying the probability by equation (11) and subtracting the associated fixed costs, I obtain the

$0.23) = \$49/\mathrm{tCO_2}$.

expected profit of a plant owned by firm f at ℓ,

$$E\left[\Pi_{f\ell}\right] = E\left[\pi_{f\ell}\right] - FC_{f\ell}, \tag{24}$$

where $E\left[\pi_{f\ell}\right] = \kappa \sum_m s_{f\ell m} A_m \left(\bar{R}_{fm} - \bar{C}_{fm}\right)$.

Maintaining the same parametric assumption that fixed costs follow a log normal distribution, and then taking logs of the plant entry condition $E\left[\pi_{f\ell}\right] > FC_{f\ell}$, the empirical form of plant entry probability under single-plant approximation is

$$\Pr\left[\ell \in \mathcal{L}_f\right] = \Phi\left(\frac{1}{\sigma^F}\ln E\left[\pi_{f\ell}\right] - \mathbf{X}'_{f\ell}\frac{\beta^F}{\sigma^F}\right). \tag{25}$$

Change in the plant entry assumption will not affect estimation in the first two steps. Hence, I can use the same estimates from Section 4.2 and 4.3 to calculate the plant's expected variable profit. I estimate equation (25) via binary Probit.[59]

Table 11 summarizes and compares the estimates under SP separate entry assumption and MP interdependent entry assumption. Transforming these estimates to monetary term, the average fixed costs of building a LafargeHolcim plant is \$61 million and those of a Cemex plant is \$54 million. The estimated fixed costs without considering the interdependencies across plant locations are clearly downward biased. The reason is that in the multi-plant firm model, firms benefit from having more plants to compete against rivals. Therefore, entry to a particular location can be profitable at firm level but not at plant level. The SP approximated fixed costs need to be lower to match the observed number of plants.

Table 11: Fixed costs estimates

	Single-plant	Multi-plant
β^F_{cons}	0.338	-6.631
β^F_{dist}	0.605	1.795
σ^F	1.631	2.790

The differences in estimates cause departure in counterfactual policy evaluations. Figure 13 compares the change of plant locations using SP and MP estimates. Each dot indicates the probability of at least one player from the top two enters the location. Assuming separated plant entry generates larger deviation from 45 degree line, indicating larger exit rate in Canada and entry rate in the US with a \$50/ton carbon tax.

[59]Econometrically, the probit regression at plant level is no longer i.i.d, I use the spatial interdependent Probit models in Franzese and Hays (2008) to correct for the bias. Results are shown in Table C.18.

Figure 13: Change of plant locations with and without interdependency for \$50 carbon levy on fuel

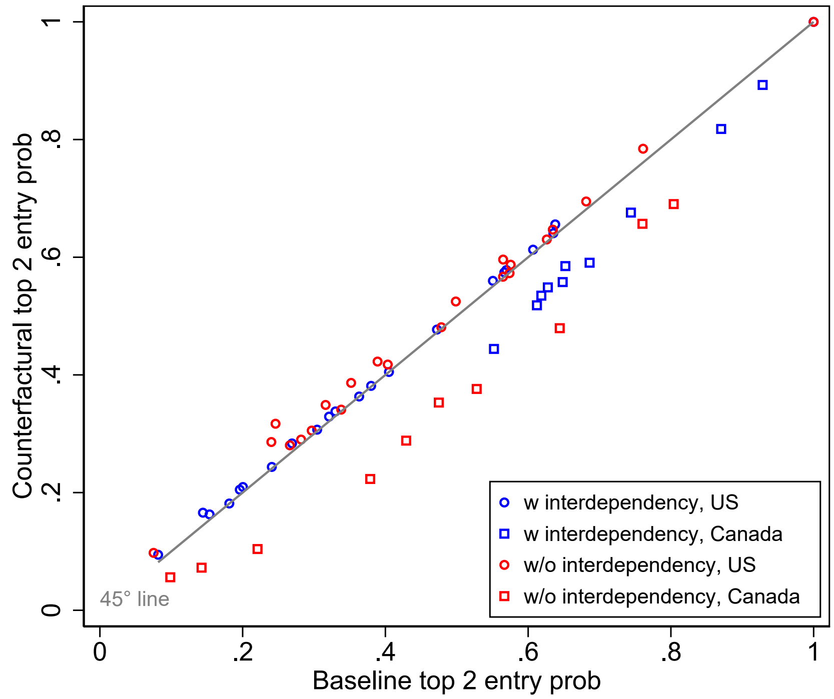


Table 12 presents the change in market outcomes. Compared to Table 8, when fixed costs are lower, plants relocate more, Canada loses more, and carbon leakage is stronger. Specifically, the carbon leakage rate is overestimated by 2 percentage points if ignoring the spatial interdependency of multi-plant firms.

Table 12: Counterfactual changes with \$50 carbon levy on fuel in Canada without interdependency

Panel A: Impacts on market outcomes

	Δ Avg entry prob(%)		Δ Price(\$)	%Δ Consum	%Δ Prod	%Δ Trade	
	LFH	CEX				Canada	US
Canada	-9.27	-6.93	27.91	-54.08	-59.53	-56.52	-95.09
US	0.52	0.34	0.48	-0.67	1.56	259.51	1.11

Panel B: Impacts on welfare and emissions

	Δ CS(\$M)	Δ PS(\$M)	Δ TaxRev(\$M)	Δ Emissions(Mt)	Leakage rate(%)
Canada	-316.81	-65.42	92.52	-5.44	19.49
US	-24.39	7.97	-	1.06	-

7 Conclusions

In this paper, I develop a multi-plant oligopoly model with endogenous and interdependent location decisions. On the intensive margin, the model derives multi-plant firms' pricing and markup rule in closed forms that generalize findings for single-plant firms in BEJK and others. It also characterizes the extensive margin of multi-plant production and quantitatively solves a firm's optimal set of plant locations. The two margins interact in a way such that a set of properties emerge. More and favorably located plants increase the production advantage of a firm, improve its capability to compete against rivals, and enhance the firm's market power to charge higher markup. At the same time, there are two forces against the expansion of plant set: cannibalization and fixed costs. Marginal payoff of opening up new plants diminishes because of business stealing among a firm's own plants. Hence, a firm strategically places an additional plant to the right location until the marginal payoff cannot cover its fixed costs. The framework points to the importance of spatial interdependency raised from positive and negative spillovers among plants within the same firm.

A key contribution of this paper is to overcome the empirical challenge of solving combinatorial discrete choice problem for a multi-player game. Submodularity and aggregative property of the location game underpin the methodology to solve for combinatorial optimization by eliminating many location configurations. I extend the algorithm in Arkolakis and Eckert (2017) for a game-theoretic framework and show that we can always find a pure strategy Nash equilibrium. Moreover, the model generates a gravity trade equation that can be leveraged to separately identify model primitives, which further reduces the computational cost of estimating the full model.

The framework goes quite far in matching data of the US and Canadian cement industry. The estimation reveals key costs faced by cement plants, including cost of production, trade cost and fixed cost of entry. Using the structurally estimated parameters, I quantitatively evaluate the effects of the Greenhouse Gas Pollution Pricing Act on firms and market aggregates. An increase in carbon tax causes production leakage and exacerbates market distortions in the concentrated cement industry. Moreover, it induces carbon leakage to unregulated markets where the increase in carbon emissions offsets emissions abatement and creates environmental damages in the taxing country. The welfare losses from these two channels make carbon tax a suboptimal policy. Border tax adjustment can mitigate carbon leakage, but it is not effective in reducing production leakage if plants were primarily exporters. Second, an output-based pricing system alleviates production leakage but performs poorly in cutting down carbon emissions if firms are not incentivized to adopt carbon-efficient technologies. The comparison across three carbon pricing regimes provides insights to policy makers in regulating carbon for a emission-intensive, trade-exposed and concentrated industry, like cement.

The paper goes on to show that assuming separated plant entry for multi-plant firms biases the estimates. Specifically, it would predict stronger carbon leakage and misguide us from the correct outcomes.

This paper has a broader goal that the multi-plant oligopoly framework and the associated estimation strategy I introduced can extend the reach of empirical researchers when evaluating policies and other spatial organization problems. Since multi-plant firms are prevalent in many industries, studying policy effects without a careful treatment of multi-plant production is worrisome. One caveat is that application of the model is restricted to firms producing a homogeneous good. Products such as cement, steel or paperboard are likely to be suitable candidates. It also depends on at which level the product of interest is classified.

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Appendices

A Model details

For simplicity of derivation, I invert the marginal cost and derive the following based on a plant's cost-adjusted productivity

$$\tilde{Z}_{f\ell im} = \frac{Z_{f\ell i}}{w_\ell \tau_{\ell m}}. \tag{A-1}$$

A.1 Conditional joint distribution of the lowest two cost firms

Since the conditional joint distribution of the lowest two costs is the same as that of top two productivities, the joint distribution of the first and second highest cost-adjusted productivity to market m conditional on firm f^* from ℓ^* winning the consumer is

$$\begin{aligned} F_{12,m}(z_1, z_2; \ell^*, f^*) &= \Pr\left(\tilde{Z}_{1m}(i) \le z_1, \tilde{Z}_{2m}(i) \le z_2 \mid \tilde{Z}_{1m}(i) > V\right) \\ &= \Pr\left(\tilde{Z}_{1m}(i) \le z_2 \mid \tilde{Z}_{1m}(i) > V\right) \\ &\quad + \Pr\left(z_2 \le \tilde{Z}_{1m}(i) \le z_1, \tilde{Z}_{2m}(i) \le z_2 \mid \tilde{Z}_{1m}(i) > V\right), \end{aligned} \tag{A-2}$$

where $V \equiv \max\{\tilde{Z}_{2m}(i), S\}$ and $S \equiv \max_{\ell \in \mathcal{L}_{f^*}, \ell \neq \ell^*}\{\tilde{Z}_{f^*\ell m}(i)\}$, given $z_1 > z_2$.

The distribution of S is

$$F_m^S(s; \ell^*, f^*) = \Pr(S \le s; \ell^*, f^*) = \exp\left(-\left(\Phi_{f^*m} - \phi_{\ell^*m}\right) s^{-\theta}\right).$$

And the distribution of V is

$$F_m^V(\nu; \ell^*, f^*) = \Pr(V \le \nu; \ell^*, f^*) = \exp\left(-\left(\Phi_m - \phi_{\ell^*m}\right) \nu^{-\theta}\right).$$

The first part of equation (A-2) can be simplified as

$$\begin{aligned} \Pr\left(\tilde{Z}_{1m}(i) \le z_2 \mid \tilde{Z}_{1m}(i) > V\right) &= \frac{\Pr\left(V < \tilde{Z}_{f^*\ell^*m}(i) \le z_2\right)}{\mathbb{P}_{f^*\ell^*m}} \\ &= \frac{\Phi_m}{\phi_{\ell^*m}} \int_0^{z_2} \left[\tilde{F}_{\ell^*m}^{draw}(z_2) - \tilde{F}_{\ell^*m}^{draw}(V)\right] dF_m^V(V; \ell^*, f^*) \\ &= \exp\left(-\Phi_m z_2^{-\theta}\right). \end{aligned} \tag{A-3}$$

Next, the second part of equation (A-2) is equal to

$$\frac{\Pr\left(z_2 \le \tilde{Z}_{f^*\ell^*m}(i) \le z_1, \tilde{Z}_{2m}(i) \le z_2, \tilde{Z}_{f^*\ell^*m}(i) > V\right)}{\mathbb{P}_{f^*\ell^*m}}$$
$$= \frac{\Pr\left(z_2 \le \tilde{Z}_{f^*\ell^*m}(i) \le z_1, \tilde{Z}_{2m}(i) \le z_2, \tilde{Z}_{f^*\ell^*m}(i) > S\right)}{\mathbb{P}_{f^*\ell^*m}},$$

where the equality is by definition of $\tilde{Z}_{2m}(i)$. The numerator can be further simplified as

$$\begin{aligned}
&\Pr\left(z_2 \le \tilde{Z}_{f^*\ell^*m}(i) \le z_1, \tilde{Z}_{2m}(i) \le z_2, \tilde{Z}_{f^*\ell^*m}(i) > S\right) \\
&= \Pr\left(z_2 \le S \le \tilde{Z}_{f^*\ell^*m}(i) \le z_1, \tilde{Z}_{2m}(i) \le z_2\right) + \Pr\left(S \le z_2 \le \tilde{Z}_{f^*\ell^*m}(i) \le z_1, \tilde{Z}_{2m}(i) \le z_2\right) \\
&= \int_{z_2}^{z_1} \left[\tilde{F}^{draw}_{\ell^*m}(z_1) - \tilde{F}^{draw}_{\ell^*m}(S)\right] \prod_{f \ne f^*} \tilde{F}_{1,fm}(z_2) dF^S_m(S; \ell^*, f^*) \\
&\quad + \int_{0}^{z_2} \left[\tilde{F}^{draw}_{\ell^*m}(z_1) - \tilde{F}^{draw}_{\ell^*m}(z_2)\right] \prod_{f \ne f^*} \tilde{F}_{1,fm}(z_2) dF^S_m(S; \ell^*, f^*) \\
&= \frac{\phi_{\ell^*m}}{\Phi_{f^*m}} \left(e^{-(\Phi_m - \Phi_{f^*m}) z_2^{-\theta}} e^{-\Phi_{f^*m} z_1^{-\theta}} - e^{-\Phi_m z_2^{-\theta}}\right).
\end{aligned}$$

The second part of equation (A-2) is therefore

$$\Pr\left(z_2 \le \tilde{Z}_{1m}(i) \le z_1, \tilde{Z}_{2m}(i) \le z_2 \mid \tilde{Z}_{1m}(i) > V\right) = \frac{\Phi_m}{\Phi_{f^*m}} \left(e^{-(\Phi_m - \Phi_{f^*m}) z_2^{-\theta}} e^{-\Phi_{f^*m} z_1^{-\theta}} - e^{-\Phi_m z_2^{-\theta}}\right). \tag{A-4}$$

Summing equation (A-3) and (A-4), the joint distribution of highest two cost-adjusted productivities conditional on f^* from ℓ^* selling to i in m is

$$F_{12,m}(z_1, z_2; \ell^*, f^*) = \frac{\Phi_m}{\Phi_{f^*m}} e^{-(\Phi_m - \Phi_{f^*m}) z_2^{-\theta}} e^{-\Phi_{f^*m} z_1^{-\theta}} - \frac{\Phi_m - \Phi_{f^*m}}{\Phi_{f^*m}} e^{-\Phi_m z_2^{-\theta}}.$$

The associated p.d.f. is

$$f_{12,m}(z_1, z_2; \ell^*, f^*) = \Phi_m(\Phi_m - \Phi_{f^*m}) \theta^2 z_1^{-\theta-1} z_2^{-\theta-1} e^{-(\Phi_m - \Phi_{f^*m}) z_2^{-\theta}} e^{-\Phi_{f^*m} z_1^{-\theta}}.$$

A.2 Price distribution

The price of consumer i in market m is

$$P_m(i) = \min\{\frac{1}{\tilde{Z}_{2m}(i)}, \frac{\bar{\mu}}{\tilde{Z}_{1m}(i)}\}.$$

Conditional on firm f^* serves the consumer in the market, the complement of the price c.d.f. is

$$1 - F^P_m(p; f^*) = \underbrace{\Pr\left(p \leq \frac{1}{\tilde{Z}_{2m}(i)} < \frac{\bar{\mu}}{\tilde{Z}_{1m}(i)} \mid \tilde{Z}_{1m}(i) > V\right)}_{\text{T1}} + \underbrace{\Pr\left(p \leq \frac{\bar{\mu}}{\tilde{Z}_{1m}(i)} \leq \frac{1}{\tilde{Z}_{2m}(i)} \mid \tilde{Z}_{1m}(i) > V\right)}_{\text{T2}}.$$

Derive each component, I have the firm term

$$\begin{aligned}\text{T1} &= \int_{p^{-1}}^{\infty}\int_{z_1/\bar{\mu}}^{p^{-1}} f_{12,m} dz_2 dz_1 + \int_0^{p^{-1}}\int_{z_1/\bar{\mu}}^{z_1} f_{12,m} dz_2 dz_1 \\ &= \frac{\Phi_m}{\Phi_{f^*m}} e^{-(\Phi_m - \Phi_{f^*m})p^\theta} - \frac{\Phi_m - \Phi_{f^*m}}{\Phi_{f^*m}} e^{-\Phi_m p^\theta} - \frac{\Phi_m}{\Phi_{f^*m} + (\Phi_m - \Phi_{f^*m})\bar{\mu}^\theta},\end{aligned}$$

and the second term

$$\begin{aligned}\text{T2} &= \int_0^{\infty}\int_{\bar{\mu}z_2}^{\bar{\mu}/p} f_{12,m} dz_1 dz_2 \\ &= \frac{\Phi_m}{\Phi_{f^*m}} e^{-\Phi_{f^*m}\bar{\mu}^{-\theta}p^\theta} - \frac{\Phi_m/\Phi_{f^*m}(\Phi_m - \Phi_{f^*m})\bar{\mu}^\theta}{\Phi_{f^*m} + (\Phi_m - \Phi_{f^*m})\bar{\mu}^\theta}.\end{aligned}$$

Combining the two and subtracted by one, I get the price distribution exactly equals to equation (6).

A.3 Markup distribution

The markup equals

$$\mu_m(i) = \min\left\{\bar{\mu}, \frac{C_{2m}(i)}{C_{1m}(i)}\right\}.$$

Conditional on firm f^* serves the consumer i in market m, for the range below the monopoly markup, the distribution is

$$F^\mu_m(\mu; f^*) = \Pr\left(\frac{\tilde{Z}_{1m}(i)}{\tilde{Z}_{2m}(i)} \leq \mu \mid \tilde{Z}_{1m}(i) > V\right).$$

Let's first calculate the complement of the c.d.f.,

$$\begin{aligned}1 - F_m^\mu(\mu; f^*) &= \Pr\left(\tilde{Z}_{2m}(i) \leq \mu^{-1}\tilde{Z}_{1m}(i) \mid \tilde{Z}_{1m}(i) > V\right)\\ &= \int_0^\infty \int_0^{\mu^{-1}z_1} f_{12,m}(z_1, z_2; f^*)dz_2dz_1\\ &= \frac{\Phi_m}{\Phi_{f^*m} + (\Phi_m - \Phi_{f^*m})\mu^\theta}.\end{aligned}$$

The conditional markup distribution is then

$$F_m^\mu(\mu; f^*) = 1 - \frac{1}{\mu^\theta - \frac{\Phi_{f^*m}}{\Phi_m}(\mu^\theta - 1)} = 1 - \frac{1}{(1 - s_{f^*m})\mu^\theta + s_{f^*m}},$$

where $s_{f^*m} = \Phi_{f^*m}/\Phi_m$. Given the markup $\mu \in (1, \infty)$, it's obvious that $\lim_{\mu\to 1} F_m^\mu(\mu; f^*) = 0$ and $\lim_{\mu\to\infty} F_m^\mu(\mu; f^*) = 1$.

The markup distribution is truncated at the monopoly markup,

$$F_m^\mu(\mu; f^*) = \begin{cases} 1 - \frac{1}{(1-s_{f^*m})\mu^\theta + s_{f^*m}} & 1 \leq \mu < \bar{\mu} \\ 1 & \mu \geq \bar{\mu} \end{cases}.$$

The markup increases with the number of locations a firm builds plants. Moreover, I will show below that the probability of a firm earning monopoly markup increases with its number of plants.

Define $F_m^\mu(\mu; f^*, z_2)$ as the probability that $1 \leq \frac{\tilde{Z}_{1m}(i)}{\tilde{Z}_{2m}(i)} \leq \mu$, given the second-lowest cost and firm f^* wins the consumer. It can be simplified as

$$\begin{aligned}F_m^\mu(\mu; f^*, z_2) &= \Pr\left(\tilde{Z}_{2m}(i) \leq \tilde{Z}_{1m}(i) \leq \mu\tilde{Z}_{2m}(i) \mid \tilde{Z}_{2m}(i) = z_2\right)\\ &= \frac{\int_{z_2}^{\mu z_2} f_{12,m}(z_1, z_2)dz_1}{\int_{z_2}^{\infty} f_{12,m}(z_1, z_2)dz_1}\\ &= \frac{e^{-\Phi_{f^*m}(\mu z_2)^{-\theta}} - e^{-\Phi_{f^*m}z_2^{-\theta}}}{1 - e^{-\Phi_{f^*m}z_2^{-\theta}}}.\end{aligned}$$

Therefore, the probability of firm f^* charging monopoly markup is

$$1 - F_m^\mu(\bar{\mu}; f^*, z_2) = \frac{1 - e^{-\Phi_{f^*m}(\bar{\mu}z_2)^{-\theta}}}{1 - e^{-\Phi_{f^*m}z_2^{-\theta}}}.$$

Taking first order derivative with respect to Φ_{f^*m}, we see that the probability of the firm earning monopoly markup strictly increases with its producing capability Φ_{f^*m}. Since Φ_{f^*m} increases with firm's number of plants, it implies that the more plants a firm builds, the higher likely it can charge monopoly markup.

A.4 Expected revenue

Before calculating the expected revenue and cost, it is useful to state the Gamma Lemma proved in appendix 5.1 of Holmes et al. (2011).

Gamma Lemma:

(i) For $\omega > 0$ and $\theta - \eta + 1 > 0$,

$$\int_0^\infty z^{\eta-\theta-2} e^{-\omega z^{-\theta}} dz = \omega^{\frac{\eta-\theta-1}{\theta}} \frac{1}{\theta} \Gamma\left(\frac{\theta-\eta+1}{\theta}\right)$$

(ii) For $\omega > 0$ and $2\theta - \eta + 1 > 0$,

$$\int_0^\infty z^{\eta-2\theta-2} e^{-\omega z^{-\theta}} dz = \omega^{\frac{\eta-2\theta-1}{\theta}} \left(\frac{\theta-\eta+1}{\theta^2}\right) \Gamma\left(\frac{\theta-\eta+1}{\theta}\right).$$

The conditional expected revenue is

$$E\big[R_{fm} \mid f = f^*\big] = A_m E\big[p_m(i)^{1-\eta}\big],$$

which is the expected revenue for cement sold to destination market m, conditional on sourcing from firm f^*, and fixing firm f^*'s plant locations. The expectation is taken with respect to the random price realization. The demand shifter $A_m = \exp(\alpha_m)$.

For $p_m(i) = \min\left\{\frac{1}{\tilde{Z}_{2m}(i)}, \frac{\bar{\mu}}{\tilde{Z}_{1m}(i)}\right\}$, we have the expectation

$$E\big[p_m(i)^{1-\eta}\big] = \underbrace{\int_0^\infty \int_{\frac{z_1}{\bar{\mu}}}^{z_1} \left(\frac{1}{z_2}\right)^{1-\eta} f_{12,m}(z_1, z_2) dz_2 dz_1}_{\text{T1}} + \underbrace{\int_0^\infty \int_0^{\frac{z_1}{\bar{\mu}}} \left(\frac{\bar{\mu}}{z_1}\right)^{1-\eta} f_{12,m}(z_1, z_2) dz_2 dz_1}_{\text{T2}}.$$

The first term can be simplified after changing the order of integration and applying the Gamma Lemma,

$$\text{T1} = \frac{\Phi_m}{\Phi_{f^*m}} (\Phi_m - \Phi_{f^*m}) \Gamma\left(\frac{\theta-\eta+1}{\theta}\right) \left[\left(\Phi_m - (1-\bar{\mu}^{-\theta})\Phi_{f^*m}\right)^{\frac{\eta-\theta-1}{\theta}} - \Phi_m^{\frac{\eta-\theta-1}{\theta}}\right].$$

The second term can be simplified to

$$\text{T2} = \bar{\mu}^{-\theta} \Phi_m \Gamma\left(\frac{\theta-\eta+1}{\theta}\right) \left(\Phi_m - (1-\bar{\mu}^{-\theta})\Phi_{f^*m}\right)^{\frac{\eta-\theta-1}{\theta}}.$$

Combining the two terms, I have the conditional expected revenue equals to

$$E\big[R_{fm} \mid f = f^*\big] = A_m \Gamma\left(\frac{\theta - \eta + 1}{\theta}\right) \frac{\hat{R}_{f^*m}}{s_{f^*m}},$$

where $\hat{R}_{f^*m} = \left(\Phi_m - (1-\bar{\mu}^{-\theta})\Phi_{f^*m}\right)^{\frac{\eta-1}{\theta}} - \left(\Phi_m - \Phi_{f^*m}\right)\Phi_m^{\frac{\eta-\theta-1}{\theta}}$, and $s_{f^*m} = \Phi_{f^*m}/\Phi_m$. The unconditional expected revenue is therefore,

$$E\big[R_{fm}\big] = A_m \kappa \hat{R}_{fm}, \text{ where } \kappa = \Gamma\left(\frac{\theta - \eta + 1}{\theta}\right).$$

A.5 Costs

The conditional expected cost of a firm is

$$E\big[C_{fm} \mid f = f^*\big] = A_m E\left[\frac{p_m(i)^{1-\eta}}{\mu}\right],$$

for $\mu = \frac{\tilde{Z}_{1m}(i)}{\tilde{Z}_{2m}(i)}$ when $p_m(i) = \frac{1}{\tilde{Z}_{2m}(i)}$ and $\mu = \bar{\mu}$ when $p_m(i) = \frac{\bar{\mu}}{\tilde{Z}_{1m}(i)}$. Hence,

$$E\left[\frac{p_m(i)^{1-\eta}}{\mu}\right] = \underbrace{\int_0^\infty \int_{\frac{z_1}{\bar{\mu}}}^{z_1} \left(\frac{1}{z_2}\right)^{1-\eta} \frac{z_2}{z_1} f_{12,m}(z_1, z_2) dz_2 dz_1}_{\text{T1}} + \underbrace{\int_0^\infty \int_0^{\frac{z_1}{\bar{\mu}}} \left(\frac{\bar{\mu}}{z_1}\right)^{1-\eta} \frac{1}{\bar{\mu}} f_{12,m}(z_1, z_2) dz_2 dz_1}_{\text{T2}}.$$

The simplification of the firm term is more involved. I need to replace z_1 by μz_2 and change the order of integration (refer to the appendix of Holmes et al. (2011)). The first term equals to

$$\text{T1} = \Phi_m(\Phi_m - \Phi_{f^*m})(\theta - \eta + 1)\Gamma\left(\frac{\theta - \eta + 1}{\theta}\right) \int_1^{\bar{\mu}} \mu^{-\theta-2} \left(\Phi_m - (1-\mu^{-\theta})\Phi_{f^*m}\right)^{\frac{\eta-2\theta-1}{\theta}} d\mu.$$

Unfortunately, there is no closed-form expression for the integral. Therefore, I apply the numerical approximation in the empirical section.

Applying the Gamma Lemma and taking the same steps as deriving the second term in the expected revenue function, the second term here can be simplified to

$$\text{T2} = \bar{\mu}^{-\theta-1}\Phi_m \Gamma\left(\frac{\theta - \eta + 1}{\theta}\right) \left(\Phi_m - (1-\bar{\mu}^{-\theta})\Phi_{f^*m}\right)^{\frac{\eta-\theta-1}{\theta}}.$$

Combining the two terms, I derive the conditional expected cost equals to

$$E\big[C_{fm} \mid f = f^*\big] = A_m \Gamma\left(\frac{\theta - \eta + 1}{\theta}\right) \frac{\hat{C}_{f^*m}}{s_{f^*m}},$$

where

$$\hat{C}_{f^*m} = \Phi_{f^*m}\Bigg[(\theta-\eta+1)(\Phi_m-\Phi_{f^*m})\int_1^{\bar{\mu}} \mu^{-\theta-2}\left(\Phi_m-(1-\mu^{-\theta})\Phi_{f^*m}\right)^{\frac{\eta-2\theta-1}{\theta}} d\mu + \bar{\mu}^{-\theta-1}\left(\Phi_m-(1-\bar{\mu}^{-\theta})\Phi_{f^*m}\right)^{\frac{\eta-\theta-1}{\theta}}\Bigg].$$

The unconditional expected cost is therefore

$$E\big[C_{fm}\big] = A_m \kappa \hat{C}_{fm}.$$

A.6 Best-response potential game

A best-response potential game is where potential functions infer the difference in the payoff due to unilaterally deviation of each player to the best response. It is introduced in work of Monderer and Shapley (1996) and later on developed in Voorneveld (2000). Under the condition of a finite game where the number of players is finite and each of them has a finite strategy space, a best-response potential game always has pure strategy Nash equilibrium and more interestingly, every learning process based on best-response of the players converges to an Nash equilibrium.

Moreover, starting from any arbitrary location decisions, if players simultaneously deviates to their unique best replies in each period, the process terminates in a Nash equilibrium after finite number of steps. Swenson and Kar (2017) found that the convergence rate is exponential. Table A.13 shows examples of 6 to 12 locations and two firms. Each is solved for 1000 times. The maximum number of rounds to find an equilibrium is three. When the potential number of locations is larger and therefore the strategy space is larger, it takes longer to find an equilibrium but still converges to a solution relatively fast.

Table A.13: Convergence Rate Check of Best-Response Potential Game

Number of locations	Average time (seconds)	Average number of BR rounds	Max number of BR rounds
6	0.0198	1.0830	3
7	0.0429	1.1010	2
8	0.0494	1.0190	2
9	0.0596	1.1830	3
10	0.0934	1.1230	3
11	0.0963	1.1980	2
12	0.1275	1.1130	2

B Model extensions

B.1 Adding core productivity differences at firm level

Suppose the firm's endowed core productivity also characterizes its plants' marginal cost of production,

$$C_{f\ell m}(i) = \frac{w_\ell \tau_{\ell m}}{Z_f Z_\ell(i)},$$

where $Z_\ell(i)$ are draws from the Fréchet distribution $\exp(-T_\ell z^{-\theta})$, and Z_f are firm-specific parameters.

The c.d.f. of the plant's cost-adjusted productivity $\tilde{Z}_{f\ell m}(i) = \frac{Z_\ell(i)}{w_\ell \tau_{\ell m}/Z_f}$ is then

$$\tilde{F}^{draw}_{f\ell m}(z) = \exp(-\phi_{f\ell m} z^{-\theta}),$$

where $\phi_{f\ell m} = Z_f^\theta \phi_{\ell m} = Z_f^\theta T_\ell \left(w_\ell \tau_{\ell m}\right)^{-\theta}$. The distributions of plants' productivities at the same location are shifted by firms' core productivities, although the shape parameter remains the same. Plants owned by an efficient firm are on average more productive than those owned by inefficient firms at the same location. Exploiting the properties of extreme value distribution, the distribution of a firm's highest cost-adjusted productivity in supplying the product to market m is

$$\tilde{F}_{1,fm}(z) = \exp(-\Phi_{fm} z^{-\theta}),$$

where $\Phi_{fm} = \sum_\ell \mathbb{I}_{f\ell} \phi_{f\ell m}$. The firm's capability not only depends on plants spatial setting but also its core productivity.

Other than the difference in the formulation of Φ_{fm}, what followed in completing the multi-plant firm model all remains the same. Specifically, the probability that a location exports good to a market becomes

$$s_{\ell m} = \frac{\sum_f \mathbb{I}_{f\ell} \phi_{f\ell m}}{\Phi_m}.$$

Transforming the sourcing probabilities into the gravity-type regression, one gets the same form as in equation (20), but with the location fixed effects being $\text{FE}_\ell = \ln\left(T_\ell w_\ell^{-\theta} \sum_f \mathbb{I}_{f\ell} Z_f^\theta\right)$. Therefore, one can no longer separately identify the location characteristics $T_\ell w_\ell^{-\theta}$ from the firm productivities Z_f without the help of additional firm-level data.

The gravity model, however, still holds at plant level where $s_{f\ell m} = \frac{\phi_{f\ell m}}{\Phi_m}$ conditional on firm f has a plant at location ℓ, and the estimable form is

$$E\left[\frac{Q_{f\ell m}}{Q_m} \mid \mathbb{I}_{f\ell} = 1\right] = \exp\left[\text{FE}_f + \text{FE}_\ell + \text{FE}_m - \theta \mathbf{X}'_{\ell m} \beta^\tau\right],$$

where $\text{FE}_f = \theta \ln Z_f$ and $\text{FE}_\ell = \ln \left(T_\ell w_\ell^{-\theta} \right)$. Plant-market-level trade flow in volume will be needed in performing the first step of the estimation.

C Estimation details

C.1 Asymptotic standard deviation

In the third step of the estimation, I estimate the parameters that govern the fixed costs distribution using the Method of Simulated Moments (MSM) adapted to the dependent cross-sectional data. One modification is to segregate the entire sample to eight regions to preserve the weak dependence as locations are further apart. Another modification with spatial dependence is regard to the asymptotic normality of the MSM estimators, specifically the variance covariance matrix. Following Conley (1999) and Conley and Ligon (2002), the asymptotic covariance matrix of moment functions should be

$$V_0 = \sum_{\ell' \in R_\ell} E\left[g(\delta_0; \mathbf{X}_f, \hat{\boldsymbol{\phi}}, \hat{\mathbf{A}}, \hat{\theta}, \hat{\eta}) g(\delta_0; \mathbf{X}_f, \hat{\boldsymbol{\phi}}, \hat{\mathbf{A}}, \hat{\theta}, \hat{\eta})' \right],$$

and its sample analogue is

$$\hat{V} = \frac{1}{|\mathcal{L}|} \sum_{\ell} \sum_{\ell' \in R_\ell} \left[\hat{g}(\delta) \hat{g}(\delta)' \right],$$

where R_ℓ is the set of locations belong to the same region as location ℓ.[60]

Adjusted for spatial correlation, the asymptotic distribution is

$$\sqrt{|\mathcal{L}|}(\hat{\delta} - \delta_0) \xrightarrow{d} N(\mathbf{0}, (1 + S^{-1})(G_0' W_0 G_0)^{-1} G_0' W_0 V_0 W_0 G_0 (G_0' W_0 G_0)^{-1}),$$

where the $K \times P$ gradient matrix $G_0 = E\left[\nabla_{\delta'} g(\delta_0) \right]$ and S is the number of simulation for the fixed cost draws. In practice, I take 600 simulation draws from a van der Corput sequence for a good coverage. However, in the case of small samples, the standard asymptotic reasoning may be inappropriate. I instead report the bootstrapped standard errors in the baseline estimation. Nevertheless, Table C.14 below displays the asymptotic standard errors for comparison.

Associated with the covariance matrix, one can also use the optimal weighting matrix, $W_0 = V_0^{-1}$ instead of an identity matrix. Theoretically, using a consistent estimator of the optimal weighting matrix, the MSM estimates are asymptotically efficient, with the asymptotic variance being

$$\text{Avar}(\hat{\delta}) = (1 + S^{-1})(G_0' V_0^{-1} G_0)^{-1} / |\mathcal{L}|.$$

[60] The variance covariance estimator is not always positive semidefinite. I follow Jia (2008) and use a numerical device to weight the moment by 0.5 for all the neighbors.

I show in the Table C.14 column (3), (6) and (9) the 2-step estimators, where the first step is performed using identity weight on moments and then compute the optimal weight using the first-step estimates to be fed in the second-step estimation. In most cases, the 2-step estimates are more efficient than the identity weighted estimates. The estimates themselves are consistent and close.

Table C.14: Robustness check: estimation of fixed costs

	Favor LafargeHolcim			Favor Cemex			Local advantage for two firms		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β^F_{cons}	-6.631	-6.631	-6.643	-6.126	-6.126	-6.038	-5.617	-5.617	-5.616
	(1.616)	(1.048)	(0.209)	(1.688)	(1.268)	(0.138)	(1.559)	(0.621)	(0.165)
$\beta^F_{\text{CEX-USA}}$	-0.406	-0.406	-0.313	-0.363	-0.363	-0.303	-0.280	-0.280	-0.234
	(0.373)	(1.707)	(0.180)	(0.382)	(0.661)	(0.145)	(0.372)	(0.318)	(0.158)
$\beta^F_{\text{LFH-CAN}}$	-3.734	-3.734	-3.698	-3.475	-3.475	-3.430	-3.480	-3.480	-3.587
	(1.867)	(0.724)	(1.702)	(2.318)	(1.046)	(0.255)	(1.992)	(1.133)	(1.616)
β^F_{dist}	1.795	1.795	1.803	1.698	1.698	1.700	1.634	1.634	1.648
	(0.220)	(0.130)	(0.018)	(0.245)	(0.073)	(0.021)	(0.221)	(0.080)	(0.025)
σ^F	2.790	2.790	2.568	2.581	2.581	2.437	2.694	2.694	2.591
	(0.481)	(0.472)	(0.159)	(0.504)	(1.342)	(0.105)	(0.503)	(0.411)	(0.104)

Column (1), (4) and (7) are baseline estimates in Table 4 using identity weighting matrix and bootstrapped standard errors. Column (2), (5), and (8) are estimates using identity weighting matrix and asymptotic standard errors. Column (3), (6) and (9) are 2-step estimates using optimal weighting matrix and asymptotic standard errors.

C.2 Additional tables

Table C.15 provides alternative specifications for the first-step gravity-type regression using the country-level sample. Table C.16 presents the first-stage results of the demand estimation using the price survey data. Table C.17 provides details in computing fuel costs for the carbon tax on fossil fuel counterfactual exercise. Table C.18 is the binary Probit regression results in the single-plant approximation,

Table C.15: Estimation of Trade Costs at Country Level

	Great circle distance			Sea distance			Shipping time		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS, $\log Q_{\ell m}$	PPML, $Q_{\ell m}$	PPML, $Q_{\ell m}/Q_m$	OLS, $\log Q_{\ell m}$	PPML, $Q_{\ell m}$	PPML, $Q_{\ell m}/Q_m$	OLS, $\log Q_{\ell m}$	PPML, $Q_{\ell m}$	PPML, $Q_{\ell m}/Q_m$
log (1+ cement tariff$_{\ell m}$)	2.808	-10.980^a	-10.749^a	1.451	-12.635^a	-10.567^a	1.460	-13.648^a	-11.633^a
	(3.716)	(3.248)	(2.736)	(3.712)	(3.475)	(2.590)	(3.787)	(3.441)	(2.711)
log dist$_{\ell m}$	-2.160^a	-1.997^a	-2.083^a	-1.471^a	-1.201^a	-1.359^a	-1.321^a	-1.097^a	-1.067^a
	(0.259)	(0.285)	(0.254)	(0.170)	(0.121)	(0.157)	(0.182)	(0.134)	(0.138)
contiguity$_{\ell m}$	3.916^a	1.685^a	2.255^a	4.005^a	2.286^a	2.740^a	3.609^a	1.693^a	2.617^a
	(0.423)	(0.362)	(0.420)	(0.427)	(0.286)	(0.342)	(0.497)	(0.368)	(0.410)
language$_{\ell m}$	0.296	-0.380	-0.462	0.361	-0.340	-0.449	0.424	-0.377	-0.465
	(0.354)	(0.285)	(0.300)	(0.356)	(0.277)	(0.296)	(0.360)	(0.282)	(0.291)
RTA$_{\ell m}$	0.293	0.972^a	1.224^a	0.801^b	1.231^a	1.559^a	0.829^b	1.261^a	1.738^a
	(0.421)	(0.272)	(0.323)	(0.397)	(0.268)	(0.323)	(0.396)	(0.270)	(0.302)
home$_{\ell m}$	8.306^a	6.323^a	5.893^a	9.823^a	7.895^a	7.456^a	9.547^a	7.394^a	7.749^a
	(0.869)	(0.711)	(0.733)	(0.744)	(0.441)	(0.476)	(0.836)	(0.543)	(0.625)
Observations	1100	20736	20736	1100	20736	20736	1100	20736	20736
R^2	0.719	0.999	0.973	0.715	0.999	0.975	0.709	0.999	0.973

All regressions include origin and destination fixed effects. Regressions use 144 countries' squared sample and for year 2016. R^2 is squared correlation of fitted and true dependent variables. Robust standard errors in parentheses. Significance levels: ^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01.

Table C.16: First-Stage Regression for Demand Estimation

	log price$_m$
log ($\sum_{\ell \neq m}$natural gas$_\ell / d_{\ell m}$)	0.410^a
	(0.073)
log ($\sum_{\ell \neq m}$electricity$_\ell / d_{\ell m}$)	-0.159
	(0.125)
log ($\sum_{\ell \neq m}$wage$_\ell / d_{\ell m}$)	1.238^a
	(0.146)
log ($\sum_{\ell \neq m}$limestone$_\ell / d_{\ell m}$)	-0.046
	(0.067)
log natural gas$_m$	-0.037^a
	(0.012)
log electricity$_m$	-0.032^c
	(0.017)
log wages$_m$	0.099^a
	(0.031)
log limestone$_m$	0.022^b
	(0.009)
log building permits$_m$	0.025^a
	(0.006)
log population$_m$	-0.038^a
	(0.006)
F test of excluded instruments	21.64
Stock-Wright LM S statistic	95.59
Observations	739

First-stage regression for the column (3) in Table 3. Price is from the data based on survey regions and then assigned to the 149 FAF zones. $d_{\ell m}$ is the distance between a location-market pair. The regression include year fixed effects from 2012 to 2016. Variables other than the number of building permits and population are excluded instruments. Robust standard errors in parentheses. Significance levels: ^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01.

Table C.17: Fuel Costs and Energy Content

	Energy Source Breakdown (%)	Energy Content	Price, 2016 ($/mBTU)	Levy, 2022
Coal (coke)	42	27.77 mBTU/t	2.366	$158.99/t
Natural gas	22	0.035 mBTU/m^3	5.003	$0.0979/$m^3$
Petroleum coke	13	0.04 mBTU/L	1.722	$0.1919/L
Heavy fuel oil	4	0.036 mBTU/L	12.223	$0.1593/L

Based on the Portland Cement Association's US and Canadian Portland Cement Labor-Energy Input Survey, the amount of energy required to produce one tonne of cement is **4.432** million BTU. The rest of 11% energy is provided by electricity and 7% by other sources which will not be accounted in computing cost of fuels, and neither covered by carbon tax on fossil fuels.
Source: Energy Consumption Benchmark Guide: Cement Clinker Production, Energy Fact Book 2019-2020 (Natural Resources Canada), Technical Paper on The Federal Carbon Pricing Backstop, US Energy Information Administration energy conversion calculators.

Table C.18: Estimation of entry without interdependency

	Probit
constant	-0.207
	(1.494)
ln distance to $HQ_{f\ell}$	-0.371^b
	(0.188)
ln variable $\text{profits}_{f\ell}$	0.613^a
	(0.171)
Observations	146
R^2	0.136

Robust standard errors in parenthesis.

D Data appendix

D.1 Implied trade across FAF zones

There are three groups of trade to consider, across Canada-FAF flow, across US-FAF flow and US-FAF-Canada-FAF flow. For the first group, the cement trade across Canadian FAF zones are directly provided by the Canadian FAF survey. The drawback of using Canadian Freight Analysis Framework is that it is a logistics file built upon a carrier survey where the origins and destinations are not necessarily the points of production or final consumption. The US Freight Analysis Framework, on the other hand, is based on the US Commodity Flow Survey (CFS) and collects data on shipments from the point of production to the point of consumption. As for the second group, the limitation of obtaining across US-FAF flow is that the commodities in the US FAF survey is classified at 2-digit level of Standard Classification of Transported Goods (SCTG). Cement is a subcategory belongs to nonmetallic mineral product. To derive US-FAF cement trade, I assume that the cement trade is proportional to nonmetallic mineral trade by the fraction of cement consumed in nonmetallic mineral consumption by destination FAF zone. Because the US Geological Survey only provides cement consumption by state but not by FAF zone, I further assume that the consumption ratio of cement over nonmetallic mineral is the same for every FAF zone within the same state.

Table D.19: Trade Estimates for Cement and Nonmetallic Minerals

	Great circle distance	Sea distance	Shipping time
log dist$_{\ell m}$	-2.105^a	-1.255^a	-1.095^a
	(0.090)	(0.051)	(0.068)
log dist$_{\ell m} \times$ industry	-0.032	-0.056	-0.022
	(0.078)	(0.053)	(0.077)
contiguity$_{\ell m}$	1.072^a	1.668^a	1.186^a
	(0.160)	(0.139)	(0.196)
contiguity$_{\ell m} \times$ industry	0.100	0.074	0.082
	(0.184)	(0.171)	(0.222)
language$_{\ell m}$	0.437^a	0.675^a	0.735^a
	(0.143)	(0.133)	(0.143)
language$_{\ell m} \times$ industry	0.083	0.084	0.086
	(0.161)	(0.159)	(0.170)
RTA$_{\ell m}$	0.540^a	0.838^a	0.939^a
	(0.131)	(0.129)	(0.135)
RTA$_{\ell m} \times$ industry	0.237	0.204	0.244
	(0.188)	(0.194)	(0.205)
industry	0.008	0.219	-0.207
	(0.639)	(0.459)	(0.210)
Observations	33842	33842	33842
R^2	0.397	0.398	0.325

The dependent variable is share of export volume. All regressions include origin and destination fixed effects and are performed using PPML. Sample is for year 2016 and 144 countries. Trade with own is dropped in the sample since the data is unavailable in the nonmetallic mineral products. Different columns use different measurement of distance. R^2 is squared correlation of fitted and true dependent variables. Robust standard errors in parentheses. Significance levels: ^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01.

Calculating cement trade between a Canadian FAF and a US FAF zone is more complicated.

From Statistics Canada, I obtain the cement trade between Canadian provinces and US states. How to allocate the trade from the state/province level to the each FAF zone? The implied trade is computed by utilizing Canadian FAF zone-US cement trade, US FAF zone-Canada cement trade and the distance between each US-Canada FAF zone pair. One key variable given by the US Commodity Flow Survey is the distance band between origin and destination where there is positive cement shipment. Comparing the distance between each US-Canada FAF zone dyads with the distance band and considering the zones with positive cement production, I significantly reduce the sample of pairs to those that are likely to have positive cement trade. The next step is to compute trade in this restricted sample. Trade between each FAF zone pair is derived by proportioning the state-province trade where the zones locate by total export and import of the originating zone and the destination zone. The assumption is that within the same state-province pair, one zone cannot export to a destination more than its nearby zone if its total export is smaller. I acknowledge the restrictiveness of the assumption due to data limitation.

Since some parts of cement trade data is implied from trade in nonmetallic minerals, I validate that the trade coefficients are not significantly different between this two group using country-level data as shown in Table D.19. Other products included in the nonmetallic minerals category are glass, bricks, and ceramic products. The result is not unreasonable given that product characteristics of cement and other nonmetallic minerals are similar, such as both being heavy to trade.

D.2 Districts

Map in Figure D.14 and Table D.20 shows the division of sample to 8 districts and an overview of cement market. The area greyed out in the districts map are FAF zones without cement production. Consumption and production are roughly the same for each district, indicating smaller share of trade with outside. Explicitly, Figure D.15 shows the distribution of FAF zones trading within the same district. Out of the 73 producing zones, all of them export at least 50% to other FAF zones within the same district and more than three quarters export more than 80% within the same district. As for the importing cement markets, the distribution is a little dispersed. But still, three quarters of the 149 markets import more than 80% from FAF zones located within the same district and more than 90% of the markets import at least half of their cement consumption within the district. Trade flow validates my assumption of districts being relatively separated from one another. The competition among plants across districts is negligible.

Table D.20: Summary Statistics of Districts

	Consumption (million ton)	Production (million ton)	Number of markets	Number of locations	Number of plants
Mountain and Pacific North	10.2	10.4	20	10	13
Mountain and Pacific South	13.9	14.2	13	9	16
West North Central	8.8	8.8	13	7	11
West South Central	16.5	16.1	17	7	15
East North Central	15.8	16.5	22	12	19
East South Central	4.3	4.1	11	6	8
New England and Middle Atlantic	10.9	10.5	28	10	18
South Atlantic	16.2	16.1	25	12	17

Figure D.14: Districts Map

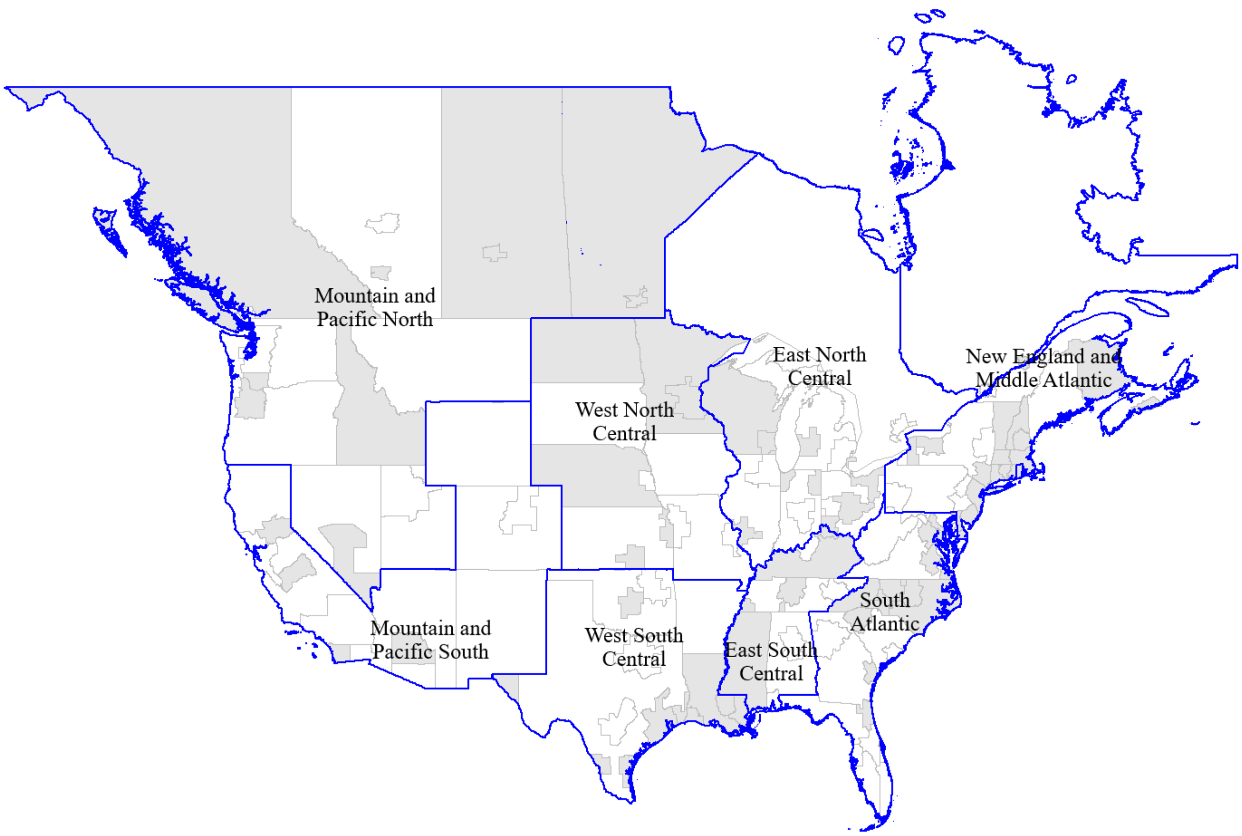
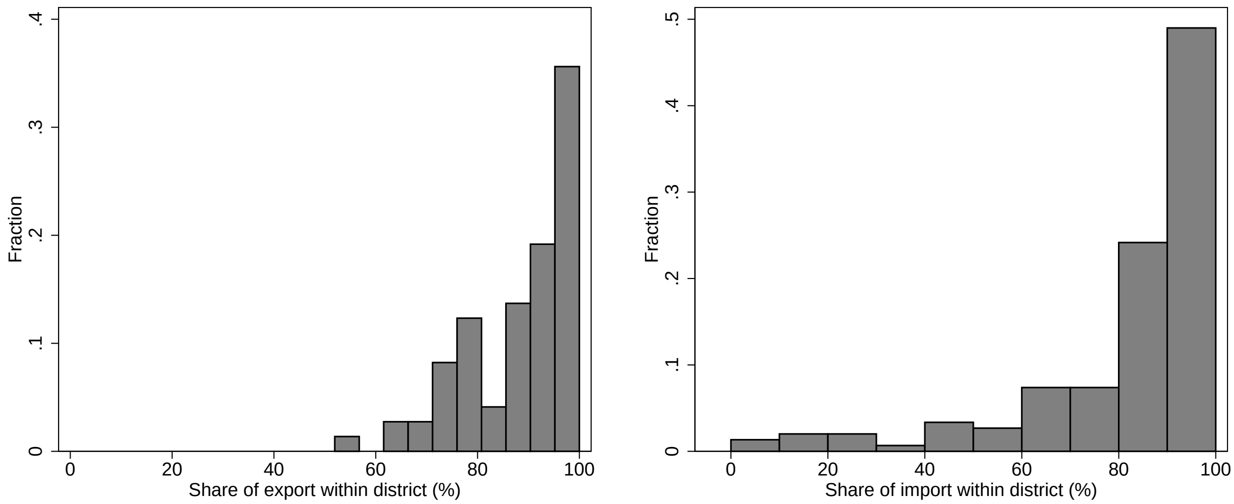


Figure D.15: Trade within the Same District



(a) Exports

(b) Imports

D.3 Locations of limestone deposits and cement plants

Figure D.16 maps the distribution of cement plants versus limestone resources. The information is obtained from US Geological Survey. There are 2909 limestone quarries in the US and 40 in Canada. Most of the FAF zones studied in my sample have at least one limestone quarry available. Obvious exceptions are Saskatchewan and North Dakota where no limestone is available and neither cement plants. These locations where access to limestone is limited are out of the potential set of locations to set up cement plants in my study.

Another issue is that large cement firms such as LafargeHolcim and Cemex typically use limestone mined from their own quarries, process and transport it to their cement plants right after extraction. The vertical integration of limestone quarries and cement plants is not a focus of this paper. Since the cement plants are usually few kilometers away from the limestone quarries, the location choice of cement plants studied in this chapter can be regarded as decisions for an integrated set of facilities, including mining activities and further processing.

Figure D.16: Cement and limestone resources location distribution