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

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Abstract

This paper proposes new theory and estimation method to study the spatial interdependencies in multi-plant production. I develop a quantitative model of multi-plant oligopolists, wherein each firm decides the location of its set of plants and the variable markups charged in each market. Such location decision balances two competing forces. On one hand, coordination in pricing among a large set of plants enhances the firm's competitive advantage against rivals. On the other hand, cannibalization between its own plants decreases the marginal benefit from plant expansion. Despite the high-dimensional discrete choice problem, the model can be estimated by leveraging the solution algorithm to a combinatorial problem when the location game is submodular and aggregative. I apply this framework to investigate the spatial organization of cement firms responding to environmental policy changes. I demonstrate that neglecting the interdependencies of plant locations owned by the same firm leads to significant biases that can misguide policy evaluation.

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

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1 Introduction

Firm-level adjustments to regulatory changes can 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 unregulated rivals. Firms respond by moving production and associated emissions to jurisdictions with laxer standards, leading to losses in the taxing economy and limited changes in total emissions. The recurrent concerns about 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 tradeoffs in deciding where to locate a set of plants and which market each plant will supply, taking into account the competition with rival firms and cannibalization of its own plants. A firm having too sparse plants incurs higher costs of transporting products to consumers, while having too many plants close to consumers incurs higher fixed costs. Moreover, transportation costs are not the only factor governing plant substitution, as production costs across locations and plant productivity also play a role. In industries with high fixed costs and tradable goods, plant location decisions are interdependent. As the geographic distribution of plants determines the flow of goods, prices, and markups in each market, a local cost shock will have global welfare impacts.

This paper addresses three key questions related to multi-plant production: (1) how do multi-plant firms determine the number and location of their plants, (2) how does the spatial allocation of plants affect markups and prices, and (3) what is the impact of allowing for multi-plant production and interdependent entry of plants? To answer these questions, I first develop a quantitative spatial model of oligopolists that characterizes firms' extensive and intensive margins of multi-plant production. The model generates precise mechanisms of how plant locations affect pricing and profitability of firms. Then, I propose a method to simplify the high dimensional interdependent location problem and estimate the model's key parameters. Finally, I use the model to analyse the effects of multi-plant production on the spatial distribution of economic activity and welfare under 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 consisting of a finite number of discrete and heterogeneous locations. Plants at each location are potential suppliers of local consumers and those in every other location. Firms decide where and how many plants to build by weighing the expected costs of production, distribution, and entry, while also taking into account competition within and across firms. When competing, plants engage in head-to-head price competition akin to that described by Bernard et al. (2003) (hereforce BEJK), with the exception that plants owned by the same firm do not undercut each other's prices. This framework presents multi-plant firms with countervailing forces that determine the optimal set of production locations. On one hand, coordination in pricing among a large set of plants enhances the firm's competitive advantage against rivals. On the other hand, cannibalization between its own plants decreases the marginal benefit. Thus, plants are strategically added until the marginal payoff can no longer cover the fixed costs of construction.

The model in this paper builds upon existing research in two key aspects. Firstly, by endogenizing entry and variable markups, this model offers an opportunity to reexamine the connection between extensive and intensive margins in the context of multi-plant or broadly multinational firms. A firm with more plants will be able to charge higher markups and captures a larger fraction of the market. Secondly, solving an interdependent entry game with strategic substitutes is a hard permutation problem, yet the model entails two properties such that it can be solved less computationally intensive.[1,2] 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 two properties guarantee the existence of pure-strategy Nash equilibrium (PSNE), and also allow one to solve the combinatorial discrete choice (CDC) problem by iteratively eliminating non-optimal decision sets, as in Arkolakis et al. (2021).

I estimate the model in three steps using aggregated and easily obtained data. In the first step, I use gravity regressions and data on bilateral trade to estimate a composite of local productivity and input costs that determine 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 the generalized method of moments (GMM) 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. A notable advantage is that the multi-plant firm model in this paper can be estimated with a minimum data requirement. Micro data on firm or plant-level market shares is not needed for this exercise.

To demonstrate the policy implications of the framework, I apply it to the cement industry in the US and Canada. The cement industry is one of the largest industrial sources of carbon emissions, and commonly assessed to be emissions-intensive and trade-exposed with high risk of carbon leakage (European Commission white paper, Europejska 2009). As the industry is dominated by a few giant multi-plant manufacturers with goods actively traded regionally, the model provides a realistic characterization of the cement industry. In particular, I estimate the key costs faced by

[1] When there are L possible production locations, a firm faces 2^L possible choices. A game with F number of players further complicates the combinatorial discrete choice problem, since it now involves 2^{FL} combinations.

[2] I adopt the definitions of strategic complements and strategic substitutes 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". In contrast, games of *strategic substitutes* are where "an increase in other players' actions leads to relatively lower payoffs to higher actions of a given player."

the North American cement producers, namely fixed costs of establishing a plant, the costs of production, and the costs of trade.[3] 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 a significant cost advantage relative to the second largest producer, resulting in a wider geographical span and 9 percent higher gross margin. Additionally, due to the homogeneous nature of cement, plants engage in more intense competition than other manufacturers studied in the literature.

Equipped with the estimated model, I investigate the impacts of the Greenhouse Gas Pollution Pricing Act in Canada. Three different carbon pricing schemes are evaluated, specifically a carbon tax with and without border tax adjustment (BTA), as well as an output-based pricing system (OBPS). Results demonstrate that the implementation of a carbon tax alone leads to the most significant changes in plant locations.[4] For a carbon tax of \$50 per tonne of CO_2, the carbon leakage rate—increase in unregulated regions' emissions relative to domestic emission reduction—amounts to 26 percent. BTA is the most effective strategy for combating carbon leakage, with 7.6 percent leakage rate when imposing the same level of carbon tax to imported cement. However, BTA cannot entirely eliminate leakage, as many Canadian plants that previously exported to the US still lose their competitive advantage against US plants. OBPS is effective in preserving the competitiveness of the domestic cement industry by reducing the effective carbon tax rate through rebates. Nonetheless, the carbon abatement achieved with this policy is only a quarter of that attained with a \$50 carbon tax. From a welfare standpoint, imposing a carbon tax alone on a concentrated industry is undesirable, as it exacerbates losses from domestic market distortion and generates global damages due to carbon leakage. Instead, the output-based pricing system is preferred when emissions are less damaging, while a carbon tax augmented by the border tax adjustment is more welfare-improving once the social costs of carbon hit \$59 per tonne of CO_2.

How important is incorporating interdependencies among plants when studying multi-plant firms? To address such concern, I compare baseline estimates obtained from the multi-plant model to those derived from an approximation in which each plant is assumed to enter separately. Abstracting spatial interdependencies, the estimated fixed cost of building a plant for the largest cement firm is about one third of the baseline, while that of the second-largest firm is about one fifth of the baseline. The magnitude of the bias depends on two opposing interdependencies that were omitted: building more plants against competing firms or restraining plants to reduce cannibalization. With the same \$50 carbon tax, the number of Canadian plants exiting increases

[3]Since I apply a static model, dynamic parameters, such as sunk costs, per-period investment costs, and scrap values, which are estimated for cement in Ryan (2012), are not considered in this paper. Instead, I compare firms' adjustment in the long run under different policy scenarios, considering that policies such as carbon tax are not likely to be one-off or only last for a short period of time.

[4]The term "change in plant locations" refers to the different spatial allocations of plants in two steady states with and without policy implementation, rather than transitional dynamics.

from approximately 13 percent to 22 percent, and the carbon leakage rate is over-predicted by 10 percent, exaggerating the welfare losses of the taxing economy. Therefore, ignoring spatial interdependencies in estimation leads to significant biases that can misguide policy evaluation.

This paper contributes to several strands of the literature. First, it extends the existing trade models that study oligopolists, such as BEJK and Atkeson and Burstein (2008), by clearly distinguishing between plants and firms.[5] Such distinction is crucial considering the mounting evidence that highlights 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 settings.[6] As such, the model yields more generalized insights on firm-level decisions, encompassing single- or multi-plant owners.

Second, this paper adds to the growing literature that explores interdependencies in multinational firms' extensive margins. An important application of my model is to multinational firms. Due to computational challenges, most papers in this topic refer to complementarities in firms' sourcing, production, and export decisions.[7] The closest to my work is Tintelnot (2017), who studied substitutabilities in multinational production facing the potential for export platform sales. However, his work evaluated all possibilities in a very small location set, and the method is not easily scalable. I overcome these challenges by combining theoretical properties from the submodular game with a solution algorithm for a combinatorial discrete choice problem. Additionally, unlike these papers that model firms as infinitesimal with constant markups, I consider a small group of sizable firms competing oligopolistically and exploiting geographical advantages to increase markups. This key difference makes my model more suitable to analyze policy questions in industries that are dominated by a few large firms.

Third, this paper joins the literature in the field of industrial organization that analyzes how retailers establish distribution networks in space, building on the works of Jia (2008) and Holmes

[5]BEJK take a different view of the world compared to the way Atkeson and Burstein (2008) model 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 is 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 of adopting BEJK's approach is that it requires less firm-level data than Atkeson and Burstein (2008).

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

[7]Antras et al. (2017) featured 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), added complementarity in both assembly and sourcing through fixed cost sharing. Jiang and Tyazhelnikov (2020) introduced complementarity in the production of pairs of inputs. Alfaro et al. (2021) added the time dimension to the combinatorial choices of export destinations.

(2011). The technique to solve CDC problems was first introduced by Jia (2008), who focused on positive spillovers among chain stores and imposed a supermodular condition on the firm's return function. In games with strategic complements, Topkis' theorem (Topkis 1978) and Tarski's fixed point theorem (Tarski et al. 1955) ensure the existence of a PSNE. 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) developed a repetitive fixed point search algorithm to solve both supermodular and submodular problems, which was further extended by 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.

Fourth, this paper contributes to the literature on environmental policy design for multi-plant firms. It shows that neglecting interdependent plant relocation leads to an overestimation of carbon leakage. Carbon leakage has been extensively studied in previous research, such as Ryan (2012) and Fowlie et al. (2016). These works measured carbon leakage using an aggregated demand shift in imports without factoring in the foreign market structure or the interconnections between domestic and foreign markets through multi-plant firms. The proposed framework in this paper offers a more nuanced understanding of the carbon leakage phenomenon, highlighting the need to consider the strategic behavior of multi-plant firms in response to environmental policies.

The remainder of the paper is structured as follows. Section 2 presents the model and propositions derived from it. In Section 3 describes the dataset and present important facts of the cement industry. The model is structurally estimated in Section 4. Counterfactual policy analysis on different carbon pricing schemes is conducted in Section 5, followed by the importance of incorporating interdependent plant locations in Section 6. Finally, Section 7 concludes the paper.

2 A Model of Multi-plant Firms

This section presents 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, the only factor that differentiates a firm from other potential entrants prior to entry is the fixed costs of building plants.[8] Once these fixed costs are paid, plants are

[8]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 identify. I incorporate this extension in Appendix B.1.

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 regard, "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 computationally challenging to extend the framework to a dynamic setting without 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 establish plants, where a plant is indexed by $\ell \in \mathcal{L}_f$.[9] The firm owns a number $N_f = |\mathcal{L}_f|$ 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 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 as identical. They only obtain knowledge on how consumers may differ and price accordingly after plants are built. Therefore, consumer-specific demand is

[9] 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.

unnecessary when constructing a firm's expected profits.[10]

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. Its plants produce the same product facing the aforementioned demand function. The timing of the game is that at $t = 1$, firms simultaneously choose 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 choose which consumers plants will 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 all consumers across all locations.[11] 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, if a firm f has a plant at 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 producing at 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 an idiosyncratic shock specific to a plant-consumer pair. Examples of such factors include relationship specificity and internal distance between consumers at m to the center. Rather than dealing with each $Z_{f\ell i}$ separately, I assume they are realizations of independently and identically distributed random draws from a Fréchet distribution. The cumulative distribution function of the productivity of firm f's plant at 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.

[10] One can easily add more structures 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 while further complicating the model.

[11] Fixed costs of exporting at firm level can be incorporated, as in Tintelnot (2017), but they are omitted for simplicity and would require additional data identify. 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.

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

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

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. This setup is analogous to that of Antras et al. (2017), by which 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 firms 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 intensive.[12] Although firms are not endowed with core productivities, I 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 in 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 have a 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, a firm's headquarter decides prices for all its plants instead of plant managers. The 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, unless the next-lowest-cost plant is owned by a competitor. The price charged is limited by the marginal cost of the lowest-cost plant owned by the second-lowest-cost firm. Instead of fully characterizing cost ranking across all plants, what matters are the lowest-cost plant within a firm and the two lowest-cost firms.

First, I define the kth lowest-cost plant owned by firm f serving consumer i in m as $C_{k,fi(m)}$. The distribution of the lowest marginal cost can be easily derived as

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

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

[12] 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.

of Fréchet distributed productivities is 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 favors the Fréchet specification.[13]

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

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

Having more plants at favorable (high $\phi_{\ell m}$) locations lowers the firm's marginal cost.[14] Intuitively, one more production location grants the firm an additional cost draw, leading to more intense competition internally and reduction of marginal cost at the firm level. More plants also implies that the average shipping distance to consumers is shorter and thus generates additional savings of trade costs for firms. Furthermore, the effect of an additional plant is larger when it is located at a place where production is cheaper and that is 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 expected cost of supplying the good to all consumers.*

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

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

[14] The implication is in contrast to Oberfield et al. (2020), who focus on the span-of-control cost, where more plants will reduce a firm's efficiency. Nevertheless, those authors and I both establish that favorable locations reduce the marginal costs of plants and firms.

corroborating that plants only matter in determining the minimum cost a firm can achieve.

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

I now describe the price and markup distributions of my 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 charges consumers in location m a price following the distribution,

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

The derivation is 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 of charging the monopoly price. Pass-through of a firm's own cost changes into prices is zero if it 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. Combined with Proposition 1, a firm with a 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. This means that within a firm supplying a destination, the sourcing probability from one of its plants (quantity share) is the same as the expenditure share, as seen in Eaton and Kortum (2002). This property is handy empirically when one observes plant sales to every market, and a standard firm-level gravity trade regression can be applied. However, one cannot draw the same conclusion at market level across different firms.

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

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

where $s_{fm} = \Phi_{fm}/\Phi_m$ indicates the relative competitiveness of firm f versus its rivals. It is the sole shifter of the markup distribution. See Appendix A.3 for the 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 a monopoly markup given the second-lowest cost equals

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

This implies that when knowing the price otherwise charged is c_2, the firm is more likely to exploit the maximum markup if it 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 having more dispersed plants, indicated by smaller θ, increases 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 an 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 the 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; and (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 my model on the bilateral trade volume across locations, aggregated from firms' decisions. With firms' cost distributions in equation (3), the probability that firm f supplies 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 the firm's relative competitiveness of supplying the good compared to all other head-to-head competitors. Since all consumers are uniformly distributed in a unit interval, the probability of supplying 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 produces 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. The probability represents location ℓ's competitive advantage. A market m sources a larger share from a location with a higher number of plants, improved local efficiency, lower input costs, or smaller trade costs. Unlike BEJK, who do not have a measure of firms, this paper demonstrates that an increase in the number of firms producing in a location is pro-competitive.

Recall that $\phi_{\ell m} = T_\ell (w_\ell \tau_{\ell m})^{-\theta}$, so 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, whose details are 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' plants. More importantly, each plant is not separately additive. Cannibalization makes the multi-plant firms' location problem a combinatorial optimization problem.

In order to have a well-defined expected variable profit, I must restrict $(\eta - 1)/\theta < 1$. The same restriction can be found 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, because the Gamma function is sensitive to changes in its parameters at the negative support, the condition is useful to construct a well-behaved κ when taking the expectation over a function of Fréchet-distributed stochastic term. One may contrast the condition to that in Antras et al. (2017), which guarantees the supermodularity of sourcing decisions. A clear difference is mentioned in Antras et al. (2017) footnote 11, where θ in their setting no longer denotes heterogeneity of final good suppliers, but rather of input producers. The submodularity property of equation (12) will be explained in more details in Section 2.3.1.

Although the restrictions on η and θ have little to do with submodularity of the profit function, discussing the comparative statics of a firm's profit with respect to these two parameters helps 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 decrease by much after building one more plant. Furthermore, when demand is less elastic (low η), the firm's variable profit responses are weaker to cost reductions and the gains are lower.

A multi-plant firm incurs plant-specific fixed costs, $\{FC_{f\ell}, \forall \ell \in \mathcal{L}_f\}$.[15] Fixing the same set of plant locations, firms would expect exactly the same variable profits because plants at the same location are symmetric. Therefore, what drives one firm to have more plants than another is having lower average fixed costs. Location choices are affected by the firm's idiosyncratic fixed costs at different locations and profitability levels given competitors' fixed costs and 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.

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

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

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

2.3 Equilibrium

So far, I have not 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 firms' profit function. Then I discuss how to address the issue of multiple equilibria, as in 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, there is is also no guarantee that the optimal location set is unique for a discrete choice problem even in the case of a single player. So what is the sufficient condition to ensure a global maximum and how can the optimal choice be found in a cost-efficient way? Fortunately, Arkolakis and Eckert (2017) provided a solution, such that if the objective function exhibits single crossing differences, one can iteratively and repetitively refine the combinatorial discrete choice set and the process always converges to a unique equilibrium.

Notice that equation (12) is submodular in a multi-plant firm's own strategy, meaning that the marginal value of total profit of adding location ℓ by firm f is decreasing with the number of other locations that f entered. Specifically, from the propositions, the variable profit of a firm increases by 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 unprofitable when enlarging the set and profitable ones will remain profitable when shrinking the set. Leveraging the monotonicity, Arkolakis and Eckert (2017) generalized the method that was first developed in Jia (2008) to the case of submodular profit functions and further showed that one 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, since firms decide to enter or not, (ii) multidimensional, since each strategy is defined as a vector of ones and zeros, and (iii) strategic substitutes, since players face competition. According to the first two points, for a two-player $|\mathcal{M}|$-location game, the domain of strategies is an enormous set of $2^{2|\mathcal{M}|}$ configurations. Although the third point seems to be prevalent in many applications, tackling games that exhibit strategic substitutes is not straightforward. Previous literature has shown 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 according to Tarski's fixed point theorem (Tarski et al., 1955) and Topkis's 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, the existence of PSNE is not generally true in games with strategic substitutes.[16]

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 decrease with increases in other components of the player itself 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 be 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 recent papers proving the existence of a PSNE in submodular 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 its own strategy and an aggregate of others' strategies (or what is called "quasi-aggregative games" in Jensen (2010) when the strategy set is multidimensional). Jensen (2010) used best-reply potential game properties and proved 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 my 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).[17] Moreover, this is a game with plants being strategic substitutes and location strategies being a finite number of zeros and ones. The

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

[17] Mapped 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 $F_f(\sigma_f(\mathcal{L}_{-f}), \mathcal{L}_f) = \sigma_f(\mathcal{L}_{-f}) + \Phi_{fm}(\mathcal{L}_f) = g(\mathcal{L})$.

multi-plant firm model satisfies all conditions for the existence of PSNE.[18] [19]

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 $2\times2\times1$ game (two players choosing whether or not to enter one location) with competition, the Nash equilibrium is that either firm enters and the other stays out. With interdependency, the game would accommodate more equilibria.

There are four main approaches in the literature to deal with the multiplicity of equilibria.[20] 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). However, information on firm heterogeneity is lost. If I used it in this paper, I would not be able to estimate the fixed cost 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 a confidence region on the set.

The third approach—the one taken here—is to choose an equilibrium by imposing a certain entry sequence. Although I model the entry game as static, the assumption is convenient to avoid

[18] According to Corollary 1 in Jensen (2010), the quasi-aggregative game has to satisfy Assumptions 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.

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

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

multiple equilibria.[21] 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.

A more recent development of the literature involves 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 a certain entry sequence, the computational burden to calculate all equilibria in an interdependent entry game is prohibitive.

2.4 Welfare measures

To prepare the multi-plant firm model for policy evaluation in later sections, 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 at the new level P_m^1. Therefore, the effects on producer and consumer surpluses are summarized as

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

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

The leakage of plants from regulated to unregulated locations is accompanied with leakage of carbon emissions. This problem is particularly acute when emissions damages are global, as in the case of carbon dioxide. Regardless of origin, the effect of overall carbon emission changes summing domestic and foreign, is fully borne by every market. To evaluate the environmental policy taking into account such externalities, one needs the monetary measure of long-term damage caused by a tonne of CO_2 emissions in a given year, social costs of carbon (SCC). The change in total surplus to the taxing economy is therefore

$$\Delta CS + \Delta PS + \Delta GR + SCC \times (1-\lambda) \times \Delta e, \tag{16}$$

[21] The same approach was taken by Jia (2008), Atkeson and Burstein (2008), Eaton et al. (2012), and Edmond et al. (2015) among many others.

where the change in government revenue is denoted by ΔGR. I define $\lambda = -\Delta e^*/\Delta e$ as the leakage rate, meaning the ratio of change in emissions of unregulated locations over the change in emissions of the regulated location.

3 The Cement Industry

In this section, I apply 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.[22]

3.1 Data description

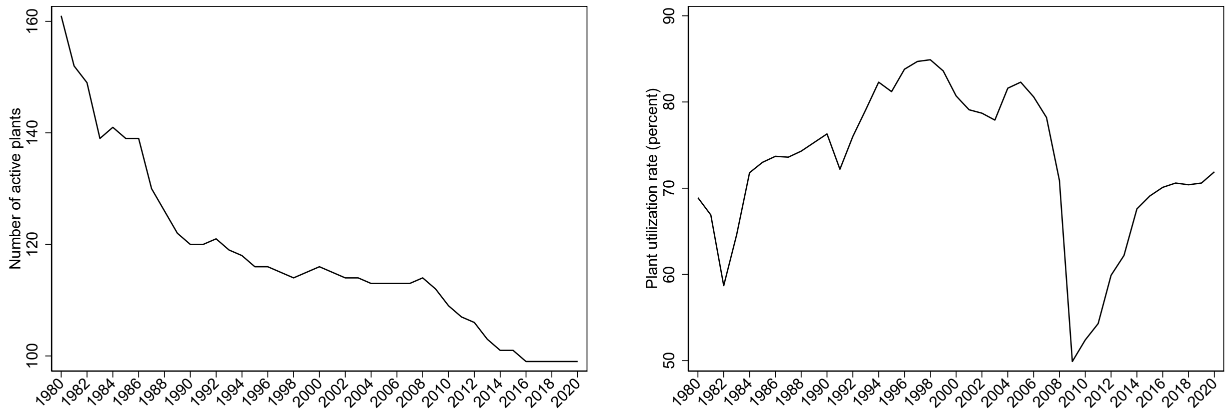
The data used in this study was obtained from four main sources. Firstly, cement plant locations were obtained from the 12th edition of the Global Cement Report, published by the International Cement Review. The report covers 2,108 operating cement plants globally in 2016, including 104 located in the US and 17 in Canada. Each plant is listed in the directory with its name, ownership, location, and capacity. Using the plant ownership data, all multi- and single-plant firms in the region were identified. However, it should be noted that this dataset is cross-sectional. To justify the use of 2016 data as the basis for partial equilibrium analysis, I checked the number of active plants in the US over time. Figure 1a shows that the US cement industry experienced two waves of plant closures in its history: one in the 1980s due to outdated technology and the other in 2008 due to the housing crisis. Since 2016, the industry has remained stable and the number of plants has not undergone any changes.

Secondly, the bilateral cement trade flow was constructed from three sources: the Freight Analysis Framework (FAF) released by the US Department of Transportation, the Canadian Freight Analysis Framework provided by Statistics Canada, and the US Geological Survey database (USGS), from 2012 to 2016. The production locations and consumption markets are zones defined by the Freight Analysis Framework, which are the smallest geographical units available in these datasets. The 149 zones comprise census agglomerations, census metropolitan areas, and the remaining areas of provinces/states. Cross-checking with cement merger cases documented by the Federal Trade Commission, I found the FAF zones highly overlap with the market definition used by FTC to assess competition impacts as well. Furthermore, it is rare for cement firms to have more than one plant in a FAF zone.[23] This empirical definition of location is consistent with the multi-plant

[22] The Canadian provinces and territories of 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 have zero production.

[23] Only four out of 149 locations have two plants belonged to the same firm, with one of them belonging to Cemex in a Florida FAF zone. In these cases, I combined plants into one.

Figure 1: Active plants and plant utilization in the US cement industry over years



(a) Number of plants

(b) Plant utilization

Note: Data is for US only, excluding Puerto Rico, obtained from the US Geological Survey.

firm model, in which a firm decides whether or not to establish a plant, rather than determining the number of plants to have in a single location.

Thirdly, bilateral trade frictions were sourced from various datasets. At the FAF-zone level, distance was measured as the great-circle distance between zone centroids. Within a zone, internal distance was measured as great-circle distance between the northeastern and southwestern boundaries. The FAF-zone-level analysis is complemented by country-level regressions, in which I use the CERDI-sea-distance database and shipping days measured in Feyrer (2018). The former computes sea distance as the shortest sea route between the 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 regressions also use tariff data from the World Integrated Trade Solution by the World Bank and other gravity variables from the CEPII research center.

Lastly, to estimate demand, several input costs were collected to construct instrument variables for prices, including durable goods manufacturing wages, limestone prices, and natural gas and electricity prices. They were obtained from the US Energy Information Administration, US Quarterly Census of Employment and Wages, US Geological Survey, Statistics Canada, Natural Resources Canada, and Quebec Hydro. In addition to these input costs, demand shifters including population and units of building permit issued were collected from the US Census and Statistics Canada. To ensure consistency with the bilateral trade, production and consumption data, all of these variables were collected for the same period between 2012 and 2016.

3.2 Industry background

Cement is a fine mineral dust that acts as the glue after mixture with water to bind the aggregates. It is used to form concrete, the most-used input in construction and transportation infrastructure. Cement is a rather homogeneous product.[24] According to the US Geological Survey (USGS), there are more than 5000 ready-mix concrete producers that purchased 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. The active cement trade in this region is attributed to the fact that cement is not produced everywhere, as seen in Figure 2. The map shows that out of the 149 FAF zones, only 73 have cement plants, whereas the rest entirely rely on imports. Figure 3a shows the export intensity and import penetration across the 73 FAF zones. On average, a zone exports 44 percent of its local production and imports 27 percent of its cement consumption.[25] The positive correlation between export intensity and import penetration suggests intra-industry trade in cement, which is consistent with plants having buyer-seller idiosyncrasies in the multi-plant firm model.

Across the US and Canada, trade in cement is comparable to other manufacturing products. Figure 3b depicts how trade decreases with distance for cement and all manufacturing goods, and compares 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 traded within 300 kilometers, and it extends to 420 kilometers for manufacturing goods. Furthermore, about 10 percent of cement is traded at distances beyond 900 kilometers, a distance equivalent to shipping from Chicago to Atlanta, or from Edmonton to southern Idaho.

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 its expected sales can recover the fixed cost. If, however, multiple plants are owned by the same entity, the owner has to choose the set of interdependent locations taking into account cannibalization. For the cement industry, most cases are the latter.

In the US and Canada, the cement industry is dominated by a few multi-plant oligopolists.

[24] Cement has some variation of types depending on its properties, such that it 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 a few days and is used in road works. Sulfate-resisting cement is used in structures exposed to severe sulfate action by water and soil in projects like canals. These minor differences are captured by the buyer-seller idiosyncratic shock $Z_{f\ell i}$ in the model.

[25] Since Canada Freight Analysis Framework is a logistics file, the origin of cement flow within Canada may not be documented as its production location. Nor is the destination of cement flow its market for final consumption. Therefore, some Canadian FAF zones, 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 that the data limitation may cause measurement error.

Figure 2: Cement plants and consumption in 2016

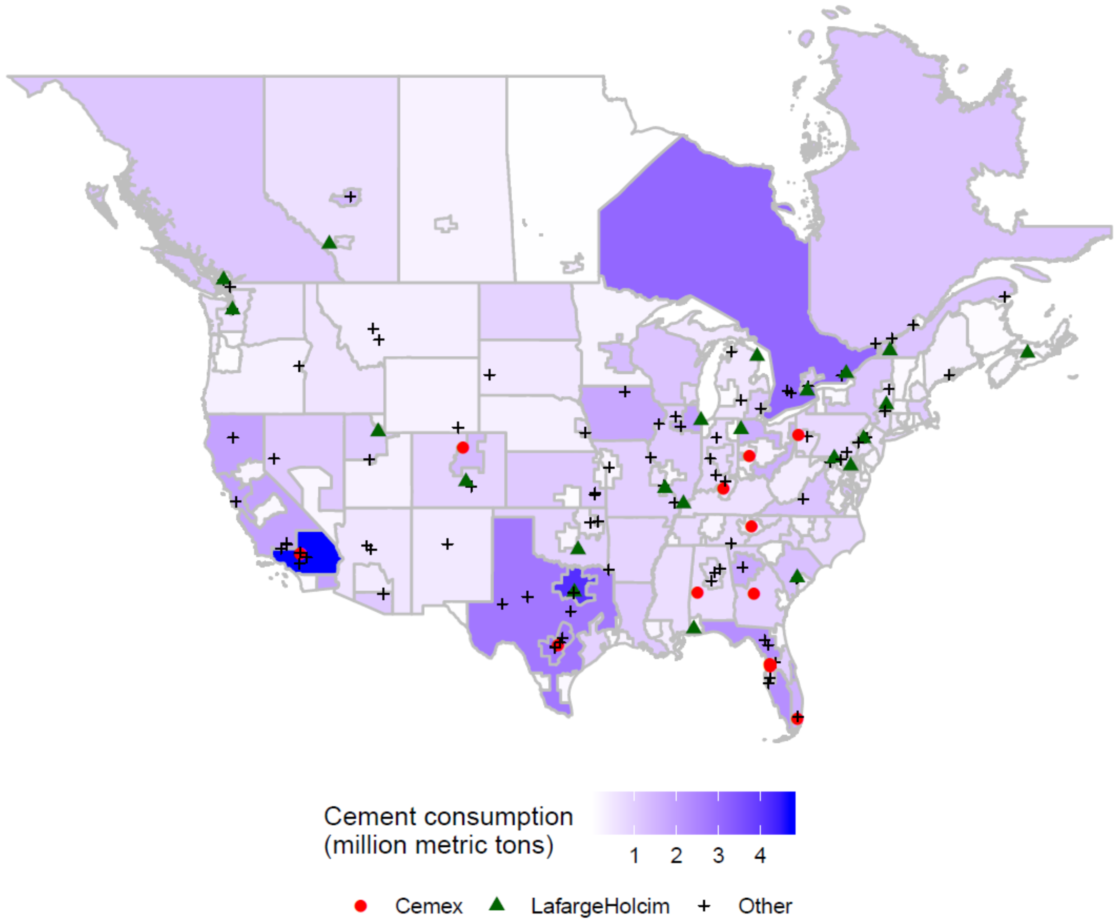
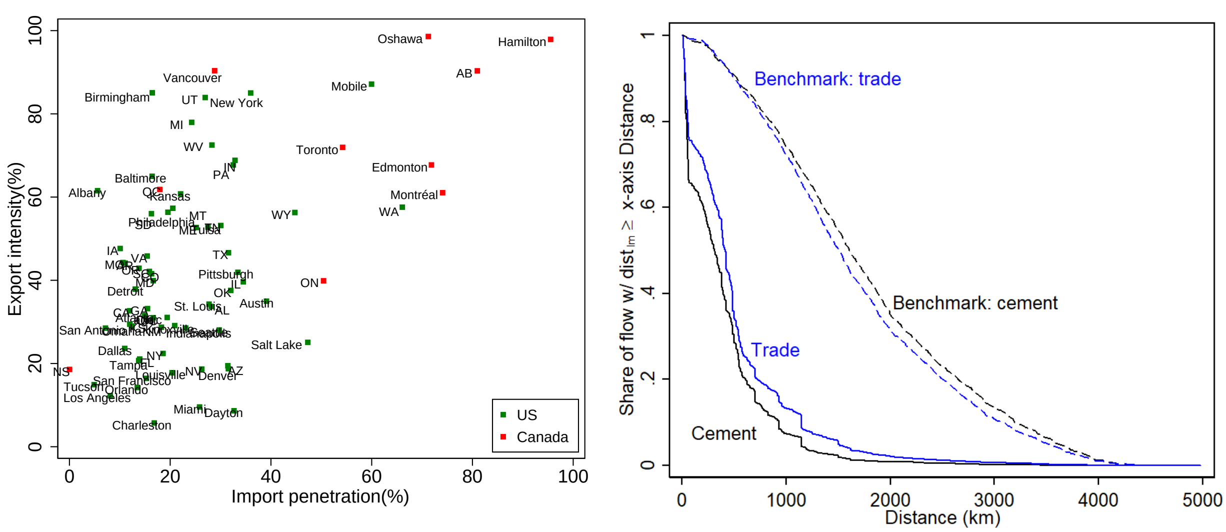


Figure 3: Cement trade across FAF zones in the US and Canada, 2016



(a) Trade intensity

(b) Trade distribution by distance

LafargeHolcim, which resulted from the merger between the world's largest (Lafarge from France) and the third-largest (Holcim from Switzerland) cement manufacturers, owns 20 percent of cement plants in the region. It is followed by Cemex, a Mexican firm, which owns another 10 percent of plants. Figure 2 plots a map of plants owned by these two multi-plant firms, as well as a group of fringe plants owned by the other 24 firms. 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 presents the distribution of the number of firms; panel B shows the distribution of the number of plants owned; and panel C reports the distribution of market share measured by capacity. From panel A, one can see that 34.6 percent of firms are single-plant owners producing at one location. They account for 7.4 percent of cement plants and 6.5 percent of the market. In contrast, 11.5 percent of firms that own 11 or more plants across locations control around 40.5 percent of plants and 41.6 percent of the market.[26] Therefore, consistent with the model's propositions, a few cement firms own a large number of plants, each having a higher market share. Nevertheless, the group of smaller cement manufacturers is also nontrivial and cannot be ignored.

Given competition within and across firms, what cost factors does a multi-plant cement firm consider in determining production and plant locations? The production cost of cement consists of costs equally contributed by materials, energy and labor.[27] The marginal cost can be assumed to remain constant until it rises beyond 87 percent of the capacity due to equipment maintenance, as estimated in Ryan (2012), who used data from 1980 to 1999 when the plant utilization rate was high. However, since 2008, USGS shows that none of the surveyed regions have had a plant utilization rate beyond this threshold, and the average has been between 50 percent and 70 percent, as shown in Figure 1b. Therefore, a model without a capacity constraint is an accurate characterization of the industry in recent years.

Of all the raw materials used to produce cement, limestone accounts for roughly 85 percent (Van Oss and Padovani, 2003). Due to the considerable weight of limestone and high transportation costs, one may presume that cement plant location is bound by the location of limestone quarries. However, in Appendix D.3, I demonstrate that there are nearly 3,000 limestone quarries dispersed across the US and Canada. While cement firms generally transport limestone from nearby quarries using belt conveyors or trucks, the location of quarries is not the sole factor determining where to establish cement plants.

As for the energy used in cement production, it mainly stems from the essential step of heating

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

[27] The cost breakdown is documented in the Lafarge annual report for 2007 https://bib.kuleuven.be/files/ebib/jaarverslagen/Lafarge_2007.pdf Following this industry practice, I assume in the subsequent estimation that the input cost w_ℓ is a composite of worker wages, material costs and fuel costs, each with elasticity of one-third.

Table 1: Distribution by number of plants and FAF zones

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 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**

Panel C: Market share

	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**

Notes: Without actual data on plants' sales, market share is proxied by the percentage of production capacity over the total installed capacity across all plants, assuming capacity is proportional to sales by a constant.

raw materials in a rotating kiln. This process requires the combustion of significant amounts of fossil fuels to increase the temperature to a peak of 1400-1450° Celsius, generating CO_2. Fuel combustion contributes to about half of the CO_2 emissions produced in cement manufacturing, with the rest arising from the chemical reaction. Overall, the production of one tonne of cement releases approximately 0.8 tonnes of carbon into the atmosphere (Van Oss and Padovani, 2003; Kapur et al., 2009). The cement industry is responsible for about 8 percent of man-made CO_2 emissions worldwide, making it a major industrial contributor of greenhouse gases.

Firms and governments are actively seeking ways to address the environmental concerns associated with cement production. To reduce the industry's carbon footprint, firms have improved kiln technology to optimize fuel usage. The Portland Cement Association reports that as of 2016, around 96 percent of cement capacity used a more energy-efficient dry process kiln.[28] Given the industry's standardized practices and technology, it is reasonable to apply the model without ex-ante differences in firm productivity.

Governments are primarily focused on shifting the industry away from fossil fuels by imposing carbon prices on dirty fuels like coal. Coal currently provides 90 percent of the energy consumed by cement plants globally.[29] In developed economies like the US and Canada, the share of coal in energy sources is lower at 42 percent, but fossil fuels in general still account for 81 percent.[30] The speed at which cement plants will adopt cleaner energies is a question beyond the scope of this paper. Nevertheless, I will provide answers to the effects of environmental policy changes on plants if they maintain the same fuel composition.

Other than the variable cost of production, the high fixed cost of building a cement plant makes the plant location problem a nontrivial decision. The relevant 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 helps to explain why cement plants are scarce and discrete, as shown in Figure 2.

4 Multi-plant Firm Estimation

In this section, I describe 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 flows for individual plants, are not always available to researchers. I propose a procedure to estimate the full model with minimal data requirements. 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 in boldface).

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, and whether the dyads are located in the same state, province, or country. These variables have been shown to matter for trade flows in the

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

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

[30] For a complete breakdown of fossil fuel usage and energy efficiency, please refer to Table C.16.

past literature. Similarly, demand shifters are characterized as a function of population and the number of building permits for new privately-owned residential construction units,[31] according to

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

where β^A is a vector of demand parameters. As for the fixed costs, instead of estimating all specific firm-location fixed costs, which are impossible to identify, 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 each firm's North American headquarters, as well as an interaction dummy of the firm and the country where FAF zones are located. 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, which affects building costs of a cement plant.[32] Therefore, what still needs to be estimated to fully specify 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 the last step and instruments, and estimate the demand elasticity $-\eta$ using GMM. What is obtained in the first two steps is crucial 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 the method of simulated moments (MSM). 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.

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

[32] Building a cement plant can take years to obtain the regulatory approval and has extremely high administrative costs. A cement firm that has local knowledge and relationships 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 in the country. Cemex, on the other hand, invested in the US market after the anti-dumping duty on imports of gray Portland cement from Mexico went into effect in 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.

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. $s_{\ell m} = \frac{Q_{\ell m}}{Q_m}$. I 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 explained in Silva and Tenreyro (2006) and Head and Mayer (2014).

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 $-\theta$.[33] Distances between country pairs use measures of sea distance to reflect the fact that international trade in cement is mostly seaborne. 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. This is justifiable because the model provides nice aggregation properties such that the trade elasticity continues to be $-\theta$ at higher levels.

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 unknown to econometricians. Figure D.15, which plots the map

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

of limestone quarries, shows that states and provinces without cement plants are also places with almost no sources of raw materials, such as Saskatchewan, Manitoba, North Dakota, Nebraska, Wisconsin, Louisiana, and Mississippi. Therefore, I assume that the zero-production FAF zones have costs too high to build any cement firms in equilibrium, and it is plausible to exclude them from firms' choice sets.

Table 2 summarizes the first-step results. Columns (1) to (3) report the results for the US and Canada FAF zones, whereas columns (4) and (5) are pertain to 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. $-\theta$. Columns (4) and (5) obtain similar estimates of the trade elasticity, with an average of -11. Considering the homogeneous nature of cement and therefore the 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 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 applying PPML to trade flows and trade shares are very close, although the latter imposes less weight on large flows. At the FAF zone level, the effects of distance to other FAF zones and 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, at around -0.4, suggesting that cement is more than proportionally consumed in home locations, a result in accordance 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 4 plots the estimated cement production capability against the actual production volume for each location in panel (a), and the combined effect of the number of plants in panel (b). The positive correlation in both figures suggests a credible ranking of the estimated location production capability. Comparison of the two panels shows that the number of plants contributes to explain cement production, as suggested by the higher R-square.[34] 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

[34]The fit displayed in Figure 4 is the R-square by regressing log production on log 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 when plotting.

Table 2: Estimation of trade costs

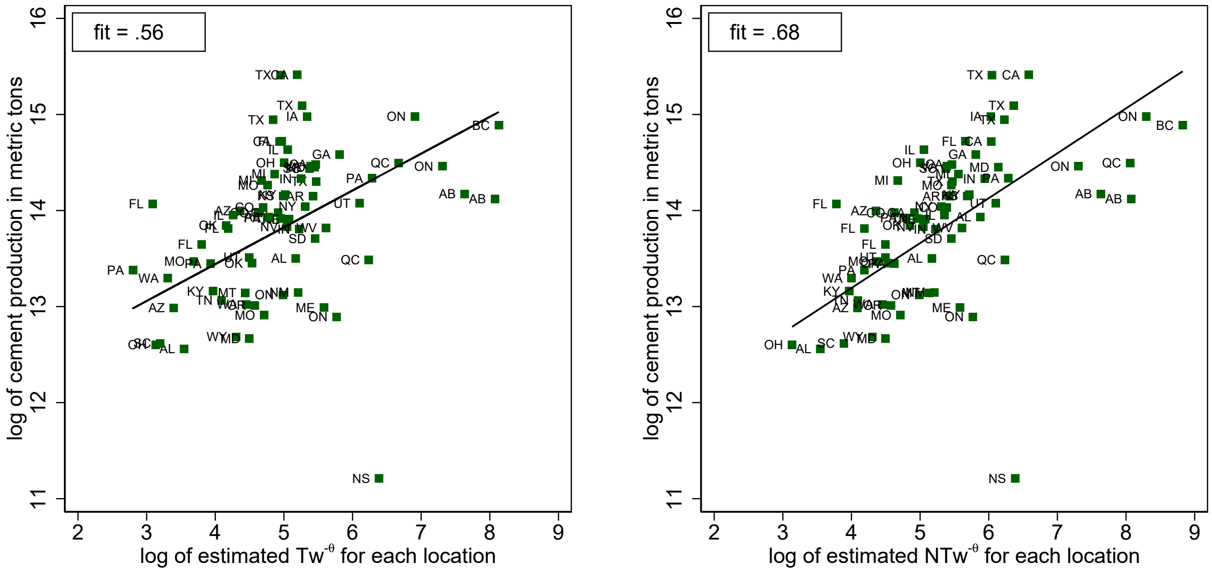
	FAF zone sample			Country sample	
	(1) OLS, $\log Q_{\ell m}$	(2) PPML, $Q_{\ell m}$	(3) PPML, $Q_{\ell m}/Q_m$	(4) PPML, $Q_{\ell m}/Q_m$	(5) PPML, $Q_{\ell m}/Q_m$
log (1+ cement tariff$_{\ell m}$), $-\theta$				-10.567^a	-11.633^a
				(2.590)	(2.711)
log sea dist$_{\ell m}$				-1.359^a	
				(0.157)	
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 2012-2016, columns (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, columns (4)-(5) include origin and destination fixed effects. Regressions use 144 countries' squared sample for year 2016. R^2 is the correlation of fitted and true dependent variables. Robust standard errors are in parentheses. Significance levels: ^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01.

lower input costs or higher local efficiency, one would expect a clear clockwise rotation of panel (b) compared to panel (a). However, some locations at the upper left of the figure move 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 of demand shifters β^A.

Figure 4: Cement production and estimated capability by location



(a) Excluding number of firms

(b) Including number of firms

4.2 Step 2: Estimation of demand

To estimate the demand indicated in equation (1), I combine it with the local price index derived from the model. Recall that 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 the local price index as a function of only one unknown, the price elasticity η, and then 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 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 wages, 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 Nonlinear 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 "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 of 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 this result. To verify validity of the instruments, I also present the first-stage results in Table C.15. Cost shifters are significantly correlated with 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. Both are 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 to reach a consensus about its demand elasticity. Jans and Rosenbaum (1997) estimated the US domestic demand elasticity as -0.81. Miller and Osborne (2014) estimated an aggregate demand elasticity of -0.02, using data from the southwestern United States. Ryan (2012) estimated a range between -1.99 and -3.21, and later Fowlie et al. (2016) estimated -0.89 to -2.03. My estimate falls within the interval of these estimates and is close to the preferred estimate of -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 cement consumption in thousand tonnes. The last two columns use instruments, but not column (1). The set of markets includes 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 MSM estimation.

To make the problem more tractable, I restrain the location game to a duopoly, LafargeHolcim 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 entered without anticipating LafargeHolcim and Cemex in the later period. The spatial distribution of small firms then defines covariates that LafargeHolcim and Cemex take as given when choosing locations. Unlike other papers that assume large firms enter first, the timing assumption here is consistent with the background of the cement industry in the US and Canada.[35] The region had many small local firms before large multinationals entered. 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. I adopt the solution algorithm for combinatorial discrete choice problems proposed in Arkolakis and Eckert (2017) to solve for the optimal plant location set. The intuition is that with plants being substitutes, a firm will 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 will 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, I can iteratively squeeze the set to the optimum if the marginal profit of adding a plant location decreases with the number of existing locations. Instead of evaluating every configuration, 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 of the location vector. Now I iterate the mapping until a complete equilibrium location set is reached with no possibility of further refinement. When there are indefinite locations, Arkolakis and Eckert (2017) found that the set of possible vectors can be sliced to any two subsets, followed by mapping each of the subsets separately. Slicing and mapping is repeatedly done until a unique optimal location

[35] Papers that have studied 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 by treating big firms' choices parametrically (Etro, 2006; Etro, 2008; Anderson et al., 2020; Kokovin et al., 2017). Unlike my setup, these papers endogeneize the entry and exit of fringe firms.

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, proved in Swenson and Kar (2017).[36]

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 an early entrant in North America in the 1950s.[37] I start from the solution of LafargeHolcim for its best response using the algorithm by assuming Cemex does not enter anywhere. Then Cemex finds its 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 by moving first. Although I try to "solve" the coherency problem in econometric inference, it continues to pose 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. I am not aware of any solution that tackles this problem. However, this concern can be alleviated when estimates across multiple equilibria do not vary significantly. I show later that this 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 cost distribution via MSM. For the log-normally distributed fixed costs, I draw a 2×73-dimensional matrix of fixed costs 300 times.[38] 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.[39]

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

[36] In Table A.12, I present examples of two firms choosing among different location sets. The time of convergence for 10 potential locations is around 0.09 seconds when averaging across 1000 simulations. It takes a maximum of three rounds of iteration to find the best response for two firms.

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

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

[39] 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 $\int_1^{\bar{\mu}} f(\mu) \approx \sum_{s=1}^{S} w_s f(\mu_s)$.

fargeHolcim/Cemex plants in Canada and the US;[40] (b) the average distance from headquarters of LafargeHolcim/Cemex to plants;[41] and (c) the difference between the average production capability for locations where LafargeHolcim/Cemex produces and those where it is absent. 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 firms, and the country of interest. Roughly, firms' entry decisions in the first two sets of moments identify the mean fixed costs. The last set of moments helps to pin down the dispersion of the fixed cost distribution. The larger the dispersion is, 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

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

where $\hat{g}(\cdot)$ is the simulated estimate of the true moment function and W is a weighting matrix.[42] 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.13.

The complexity in the presence of 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 fade 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 into eight districts

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

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

[42] 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 that my solution 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.

and assume that competition is negligible across them.[43] The districts are categorized by USGS as relatively separate 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 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 a certain radius to each location, as in Jia (2008). However, this method does not work for the multi-plant firm model in general. Existence of overlaps 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.[44] 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.13, all estimates are close, although the optimal weighting matrix exhibits slightly greater 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), that is most profitable for Cemex (CEX), and that where LFH has a 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 as 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 acquiesce to 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 whereby LafargeHolcim is 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's headquarter. Second, there could be loss of productivity associated with transferring

[43] 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.

[44] I recognize the potential concern regarding 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.

headquarter services to production locations. The model does not capture such cost of producing, and it could 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) found that car assembly is 9.5 more likely to occur at the brand's home than other 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 cost investment in the cement industry documented in Section 3.2. One may 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 values. 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.

A back-of-envelope calculation reveals that the average fixed cost across the cement plants owned by LafargeHolcim is estimated at around \$181 million and that for the Cemex plants around \$280 million.[45] The estimated average fixed costs of building a cement plant are surprisingly close to the industry norm of \$200$\sim$\$300 million. The cost advantage of LafargeHolcim justifies it 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 based on equation (7), this implies a gross margin of 41.8% for LafargeHolcim. For Cemex, the lowest production cost adjusted for the scaling among its 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 my estimate. Cemex reported a gross profit of \$4,756 million 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.[46] In sum, these cross-firm comparisons corroborate the cost estimates of the multi-plant firm model.

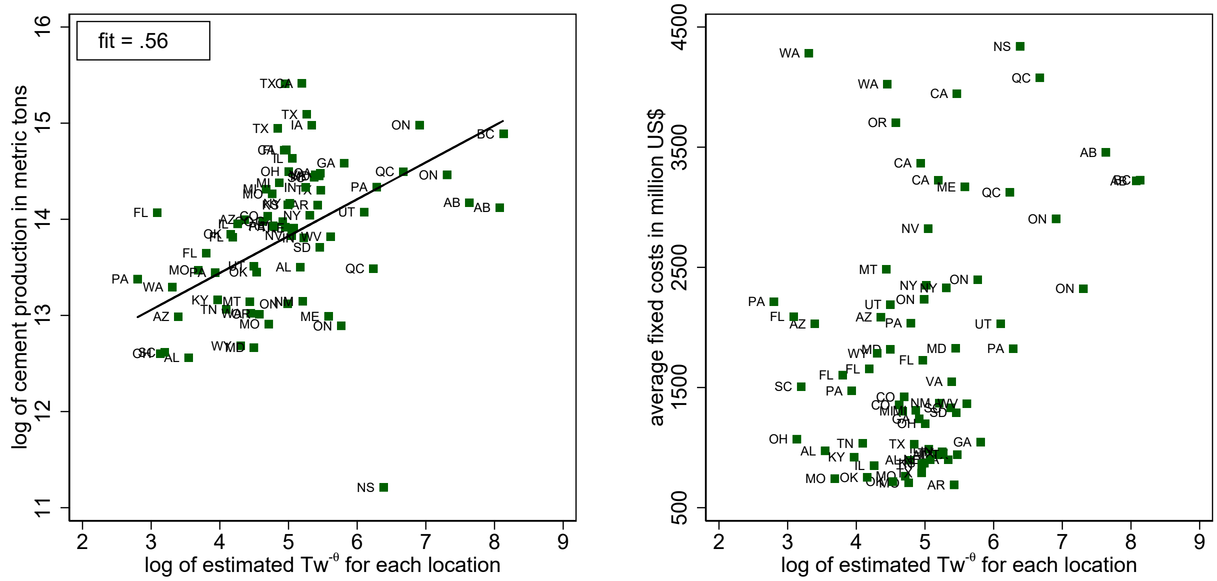
Across locations, I analyze the interaction between the estimated production capability, the estimated fixed costs and the observed cement production by FAF zones. I copied panel (a) in Figure 4 to Figure 5 to be interpreted together with the panel (b). It is clear that Nova Scotia, a province having moderate production capability, produces an 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 of producing cement as Nova Scotia, but are 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

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

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

zones in the number of plants located and the amount of production. Figure 5, complemented by the firm-level comparison, highlights the importance of heterogeneous fixed costs at the plant level for matching the model to the data.

Figure 5: 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 location's 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 imports 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%. Since the import share is indirectly targeted through the first-step gravity regression, I further compare the trade volume as shown in the last column of Table 6. The degree of fit does not fall.

Table 5: Model fit of plant number and distance to headquarters

	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 numbers of plants are not integers 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.

Besides comparing trade flow, Figure 6 plots and compares the share of trade by distance.[47] 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 the solution for endogenous plant locations do not introduce new biases.

Having checked the model performance through plant number and trade, lastly I compare the model-predicted cement consumption and production against the data. Figure 7 shows that the model fits the data reasonably well in both dimensions. The actual and predicted cement consumption across markets are distributed tightly along the 45-degree line. The prediction on production, although deviating from the diagonal relationship, captures 65% of the data variation. The multiple test results establish confidence in the following counterfactual exercises.

[47]The actual trade data are used for only the dyads within the same district to be comparable with the estimation under such assumption. The same goes for the consumption and production data in Figure 7.

Figure 6: Model fit of trade flow over distance

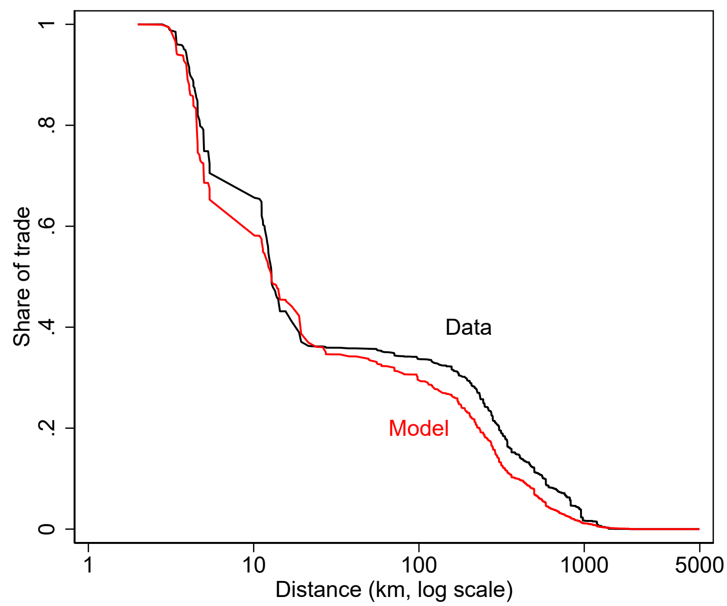
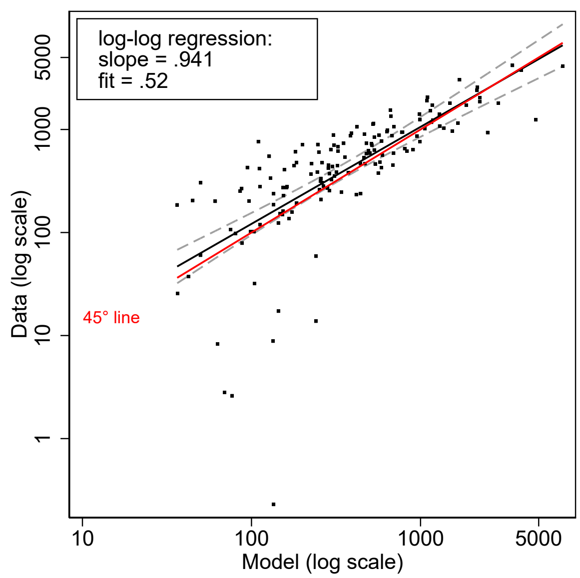
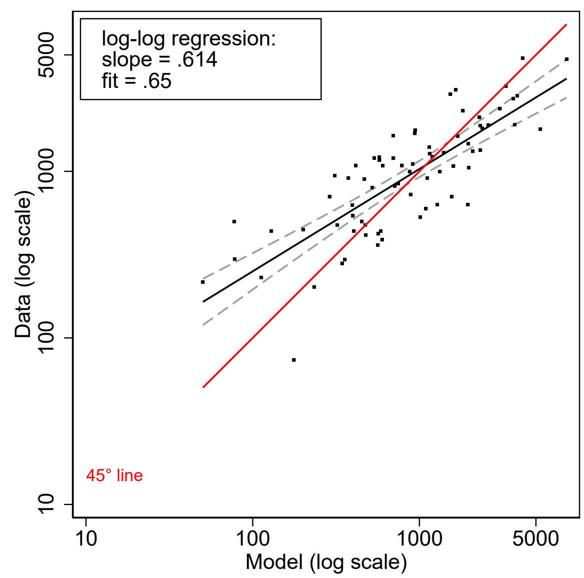


Figure 7: Model fit of cement consumption and production



(a) Consumption (thousand tonnes)



(b) Production (thousand tonnes)

5 Counterfactual: The Greenhouse Gas Pollution Pricing Act

In 2018, Canada enacted the Greenhouse Gas Pollution Pricing Act, which established a federal backstop system to increase the carbon price to \$50 per tonne by 2022. The framework includes two carbon pricing initiatives: a carbon tax on fossil fuels and an output-based pricing system for industrial facilities.[48] My primary interest is to evaluate the welfare costs of these environmental regulations for both consumers and producers by examining the alternative spatial allocation of plants and market structure in the long run.

5.1 Carbon tax on fossil fuels

In this section, I examine the effect of a carbon tax levied on fossil fuels, which are essential for generating energy to produce 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, as shown in in Table C.16.[49] The pre-tax unit cost of fuel is close to \$13.82, as found by Miller et al. (2017) using 2010 data. After the carbon levy, rates for each fuel subject to the levy are set based on the Canadian Federal Carbon Pricing Backstop Technical Paper, such that they are equivalent to \$50 per tonne of CO_2 by 2022. Assuming that there is no substitution of fuel to other carbon-saving sources after the policy, the average cost of fuel for producing one tonne of cement after the levy becomes \$29.37.[50]

Since fuel accounts for one-third of the input costs to produce cement as mentioned in Section 3.2, increasing the cost of fuel from \$12.44 to \$29.37 per tonne of cement is equivalent to a 33 percent increase in the input cost w_ℓ, or a 96 percent 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 high θ. When plants are not widely differentiated, a small increase in production costs can lead to immediate losses of market share. This explains why carbon policy could be a significant threat to the competitiveness of the local cement industry.

[48] In practice, the federal benchmark allows provinces to implement their own carbon pollution pricing systems to account for their unique circumstances. Fuel charges under the backstop system apply in Ontario, New Brunswick, Manitoba, Saskatchewan, Alberta, Yukon and Nunavut. OBPS is applied in Ontario, New Brunswick, Manitoba, Prince Edward Island, Saskatchewan, Yukon and Nunavut. Prior to the pan-Canadian approach, provinces such as British Columbia, Alberta, Nova Scotia, and Quebec had already implemented certain carbon pricing regimes. For example, British Columbia has applied a carbon tax on emissions from the combustion of fossil fuels, but not to process emissions during production such as the calcination of limestone. Alberta has its own Carbon Competitiveness Incentive Regulation. Nova Scotia and Quebec have implemented cap-and-trade systems. All of these provincial regulations meet the federal government's minimum stringency benchmark requirements for pricing carbon pollution. For simplification, counterfactual analysis in this paper assumes a uniform change in all Canadian provinces.

[49] Producing one tonne of cement requires an energy of 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.

[50] The 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 the cost of fuel in 2022 will be $16.93 + 12.44 =$ \$29.37/tonne cement.

In response to the increase in production costs, cement firms tend to relocate their plants to "pollution havens". Figure 8 compares the spatial distribution of plants before and after the carbon tax, combining the top two cement firms. Red indicates the share of plants predicted to close, while 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 plant closures are spread across FAF zones in Canada, with the most notable exit ratio in Quebec where over 20 percent of the plants will be shut down. Cement plants are relocated to zones along the US border, near the original Canadian locations, as they serve as close substitutes. Markets that were previously served by Canadian plants would now source from US plants that are not too distant. On the west coast, Washington and Montana experience the highest increase in plants owned by LafargeHolcim and Cemex, around 16 percent more, while areas in Oregon and Utah show moderate expansion, with no plants opening in states further south. Despite similar distance to Canada, plants are built in Utah but not Nevada because it is more efficient and cheaper to produce cement in Utah. On the east coast, plant openings are weaker because there is already a dense production network, as shown in Figure 2.

Figure 8: Change of plant locations with $50 carbon levy on fuel in Canada

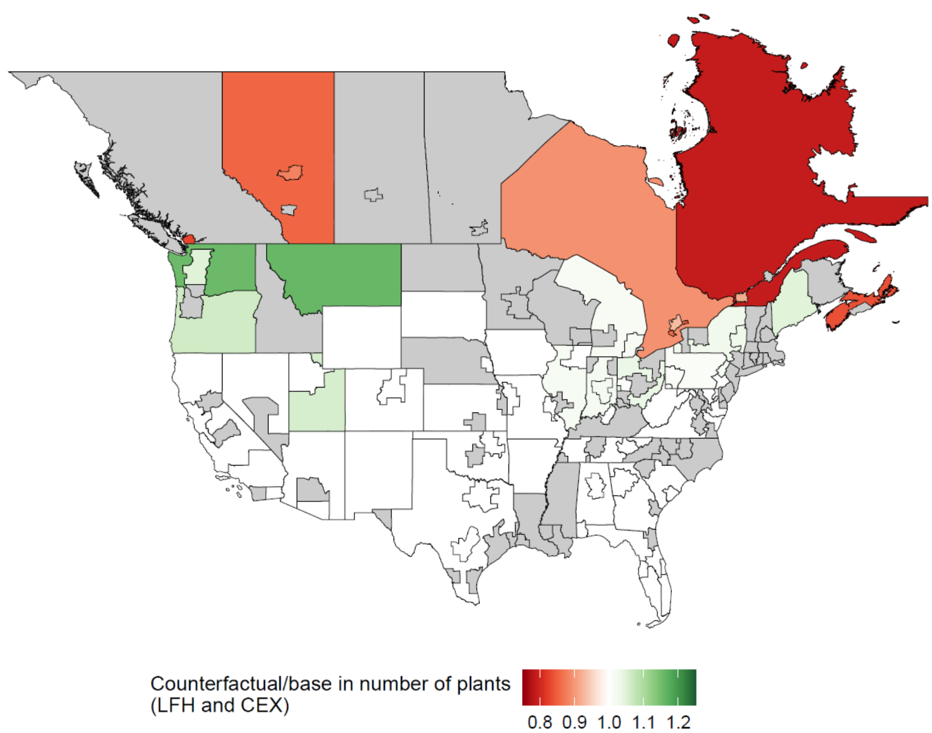


Table 7 presents the effects of carbon policies on the Canadian market. When Canada charges a $50 carbon tax on fossil fuels, the top two cement firms lost around 13 percent of Canadian plants relative to the baseline, and these losses are not fully compensated by building plants in the US. The

Table 7: Aggregate effects of carbon policies in Canada on market outcomes

	Number of plants		Price	Consumption	Production	Trade	
	LFH	CEX				Canada	US
(a) Baseline:							
Canada	6.74	0.71	96.29	8.56	11.43	8.06	3.37
US	15.76	10.31	107.21	88.27	85.40	0.50	84.90
(b) $50 carbon levy on fuel:							
Canada	6.00	0.50	123.11	5.31	3.87	3.69	0.18
US	15.85	10.43	107.95	85.95	87.39	1.62	85.77
(c) $50 carbon levy on fuel and 33% BTA:							
Canada	6.07	0.51	128.53	3.97	3.92	3.74	0.18
US	15.81	10.41	107.96	85.92	85.97	0.23	85.74
(d) OBPS:							
Canada	6.64	0.69	99.44	7.91	9.79	7.35	2.44
US	15.79	10.33	107.41	87.6	85.72	0.56	85.16

There are 10 potential production locations in Canada and 63 in the US. Number of plants is calculated by summing the probability of entry to locations, and thus, can be fractional. Price is denoted in US dollars. Consumption, production and trade volume are denoted in millions of metric tonnes.

impact of the carbon tax is heterogeneous across firms, with LafargeHolcim, the dominant player in the Canadian market, being the most affected. It is worth noting that the model overestimates the presence of Cemex in Canada compared to the actual data, which suggests that Cemex could potentially benefit from the weakening of a competitor following the implementation of the carbon tax.

The average price in Canada for one tonne of cement increases by almost one-third of the baseline price, which is more than the amount of increase in fuel prices due to the rising market concentration. The prediction is in line with Ganapati et al. (2016) and Miller et al. (2017), who found that changes of fuel cost are more than fully passed to cement prices. However, in the US, the impact on prices is modest driving by two opposing forces: the downward pressure from intensified market competition through new plant entries and the upward pressure from the loss of cheap cement imported from Canada, in which case the latter slightly dominates.

Consumption and production are more responsive to the policy changes than the extensive margin adjustment on plants entry and exit. Consumers in both countries substitute cheaper alternatives for more expensive cement. The contraction of production in Canada is substantial, at approximately 66 percent, some of which "leaks" to the US. The difference in changes between production and the number of plants implies that the Canadian plants become underutilized, whereas US plants experience the opposite.[51]

[51] Data shows that the average capacity utilization rate of a US cement plant was 70 percent in 2016, which leaves room for higher utilization.

Table 8: Aggregate effects of carbon policies in Canada on welfare and emissions

	Δ CS	Δ PS	Δ TaxRev	Δ Emissions	Leakage rate
(a) \$50 carbon levy on fuel:					
Canada	-310.50	-68.04	77.40	-6.05	26.32
US	-35.54	10.70	-	1.60	-
(b) \$50 carbon levy on fuel and 33% BTA:					
Canada	-322.76	-66.27	89.09	-6.00	7.60
US	-36.30	10.93	-	0.46	-
(c) OBPS:					
Canada	-46.36	-9.57	19.58	-1.31	19.51
US	-9.57	2.67	-	0.26	-

Change is relative to baseline. Consumer surplus, producer surplus, and government revenue are denoted in millions of US dollars. Emissions are denoted in millions of tonnes. The leakage rate is represent as a percentage.

The effects of the carbon tax on trade in cement are enormous. The cement exports from Canada to the US almost vanish. 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 US produced cement into the Canadian market rises from 6 percent to 30.5 percent.

Table 8 reports the welfare changes based on the equations in section 2.4. Facing a \$50 carbon tax on fuel, Canadian consumers lose around \$310 million and producers lose around \$68 million annually.[52] The combined loss amounts to roughly 5 percent of the \$7.4 billion revenue generated by the Canadian cement industry in 2016. Consumers bear about 82 percent of the tax burden, comparable to the 89 percent 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 approximately \$77 million.[53] Producers can be fully compensated with 88 percent of the revenue obtained from the carbon tax. Although one may expect a negative cost shock in Canada to benefit the US, the welfare assessment indicates otherwise. The US also incurs a loss of around \$25 million driven by higher prices faced by consumers. Just as the carbon pollution has a global impact, the effects of a carbon tax in one country also transmit to others through multi-plant production and trade.

Assuming an emission intensity of 0.8 tonne of CO_2 per tonne of cement produced in both the US and Canada, the carbon leakage rate is estimated to be approximately 26 percent. This means that for every 100 tonnes of CO_2 abated in Canada, around 26 tonnes leak, resulting in a net reduction of carbon emissions of 4.45 million tonnes.

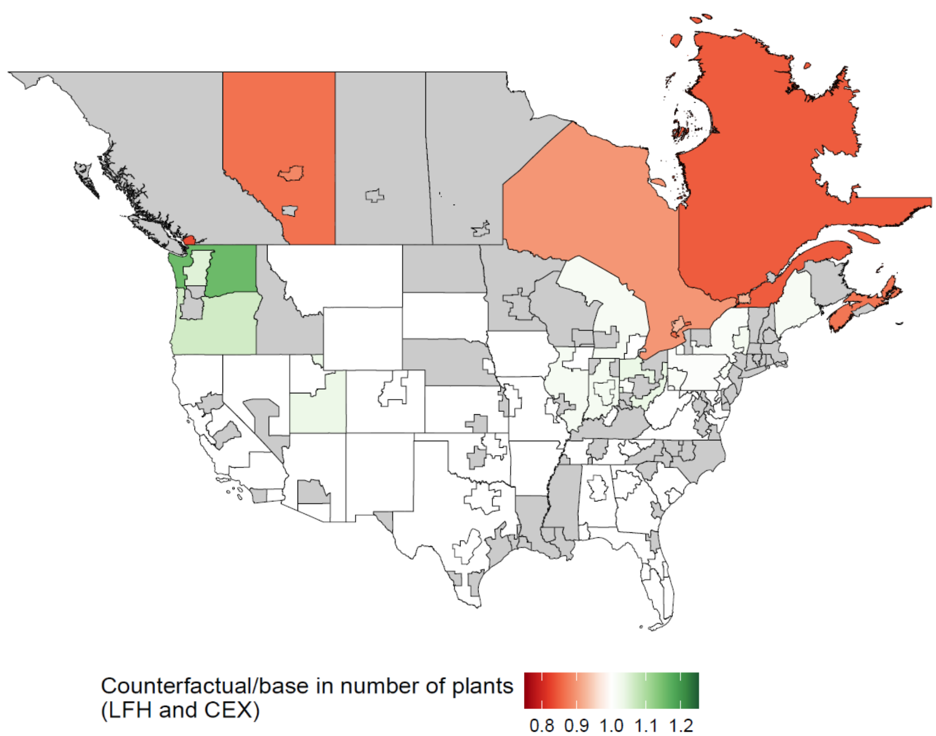
[52] Producer surplus is calculated by combining all firms including the small ones operating in the region. The profit change of LafargeHolcim and Cemex comes from different plant locations and adjustments in prices, whereas changes of small firms' profits are only from prices.

[53] Government revenue is calculated as $50 \times 0.4 \times 3.87 = 77.4$.

5.2 Border tax adjustment

In this section, I examine the effectiveness of a border tax adjustment (BTA) in mitigating carbon leakage and its associated welfare implications. After the imposition of a carbon tax, downstream consumers turn to unregulated imports, which leads to carbon leakage. A BTA that imposes an *ad valorem* border tax on unregulated imports offers a solution to such leakage by equalizing the competition between domestically produced and foreign-made cement. In this case, a $50 carbon tax on fossil fuels is equivalent to raising the border tax by 33 percent.[54]

Figure 9: Change of plant locations with $50 carbon levy on fuel and 33% BTA in Canada



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 9 to Figure 8, there is a reduction in Canadian plants exiting, and fewer locations in the US are seen with significant plant entry. Specifically, the plant exit ratio in Quebec drops from over 20 percent to 15 percent. New plants no long enter Montana, and the number of new plants in other

[54]Note that trade costs τ and input costs w enter the sourcing probability from a location in the same way through a power of $-\theta$. Therefore, assuming the composition of fuel usage and related fuel prices are the same in Canada and the US, a 33 percent border tax is needed to achieve the same level of carbon tax.I calculated that the carbon tax is equivalent to a 33 percent increase in w, so the border tax should be 33 percent to achieve the same level of carbon tax. This also implies that the import penetration of US cement in Canadian consumption will remain at the same level (6 percent) as before the carbon tax was imposed.

US FAF zones also declines. Compared to the scenario with a carbon tax alone, Table 7 presents smaller changes in the number of plants for both firms and higher level of production in Canada.

In addition to the decrease in production leakage, the border tax adjustment is effective in reducing the carbon leakage from 26 percent to 7.6 percent, as shown in Table 8. It cuts down the total emissions by 1.2 million tonnes by restraining the US production through exports. However, BTA cannot override the closure of cement plants or eliminate carbon leakage because Canadian exporters—a significant share of Canadian cement producers—would still relocate their production to the US.

5.3 Output-based pricing system

In the previous section, I demonstrated that a sufficient level of BTA in addition to a carbon tax is likely to improve welfare. However, if the majority of Canadian plants are exporters that compete in foreign markets, the gain from this strategy is minimal. 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, defined as emissions per unit of output. For the cement industry, the Canadian Greenhouse Gas Pollution Pricing Act sets the output-based standard at 95 percent of the sectoral average carbon intensity, resulting in an emission limit of 0.76 tonne CO_2 per tonne of cement.[55] Under OBPS, if a plant emits more than 76 percent of its cement output, it faces a marginal rate of \$50/tCO_2 and is taxed for the excess portion.[56]

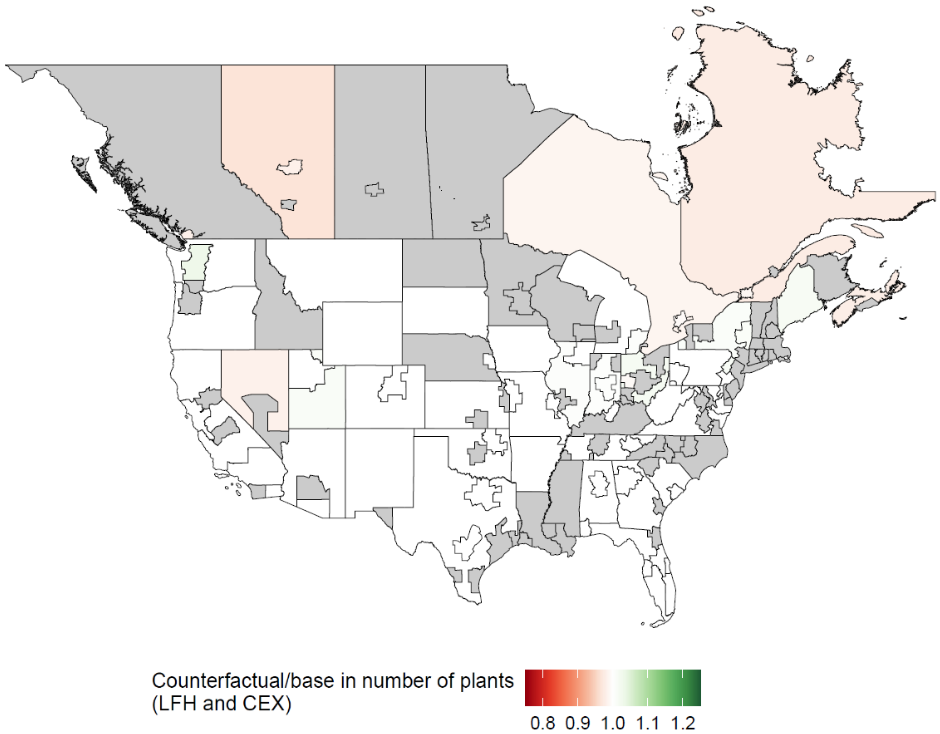
The objectives of OBPS are twofold: firstly, to provide relief from fuel charges to emission-intensive and trade-exposed industries so that domestic firms retain some level of competitiveness compared to foreign rivals, and secondly, to incentivize firms financially to reduce their emissions intensity and transition to cleaner technologies. However, this carbon pricing scheme comes with a notable side effect—smaller carbon reductions in targeted industries—as I will show in Table 8.

I model the OBPS as an output-based "rebate" following Canada Gazette (2019). Given that 95 percent of the sectoral emission intensity is tax-free for the cement industry, I assume 95 percent of the proceeds from OBPS will be returned to the sector. However, due to data limitations, the sample used for this analysis does not contain information on firm- or plant-level carbon emissions intensity, and the static model is unable to accommodate endogenous technological improvement. I take a simple heuristic approach and assume that all cement plants operate at the industry average,

[55] In the Act, the calculation for OBPS covers both combustion and non-combustion emissions, unlike only combustion in the case of carbon tax on fuels. The sectoral average carbon intensity including combustion and non-combustion is 0.8tCO_2/tonne of cement, and thus, the emission limit is $0.8 \times 95\% = 0.76$.

[56] Firms that emit less than their limit will obtain surplus credits that can be sold to firms that need credits for compliance. For the purposes of this analysis, the carbon trading aspect of OBPS is ignored due to limited firm-level data.

Figure 10: Change of plant locations with OBPS in Canada



$0.8tCO_2$/tonne of cement. The assumption is not as unreasonable considering the industry has standardized production practices for almost all plants as mentioned in section 3.2. Therefore, in this counterfactual exercise, the OBPS is effectively a lower carbon tax at the average rate of $2 per tonne of cement, or *ad valorem* 2.76 percent increase in the production cost of Canadian plants.[57] One caveat is that predictions here are an upper bound of the effect of OBPS on plant locations and a lower bound on carbon reduction, as firms are treated as passive taxpayers without actively seeking cleaner production technology.

Figure 10 illustrates that OBPS triggers the least amount of change in plant sites among the three carbon pricing schemes. Very few locations in the US are observed with entry, and some locations, such as Nevada, even experience plants exiting due to expansion in the nearby area (Seattle). The changes in market outcomes are not qualitatively different from those facing a $50 carbon tax, albeit with smaller magnitudes. The number of plants, the amount of production, and the exports to the US all return to the levels close to the baseline. The mitigation of production leakage is accompanied by a reduction in carbon leakage rate from 26 percent to 19.5 percent. However, the net carbon emissions abatement is only 1 million tonne, which is the lowest of the

[57]The effective rate of OBPS is calculated as $50 \times 0.8 \times (1 - 95\%) = 2$ per tonne of cement based on the amount exceeding the 95 percent cap. The estimated average Canadian plant production cost is $72.56, calculated from equation (4). Therefore, $2/72.56 = 2.76\%$.

three policies and around a quarter of the emissions reduction achieved with $50 carbon tax on fuels.

Figure 11: Welfare comparison of carbon policies

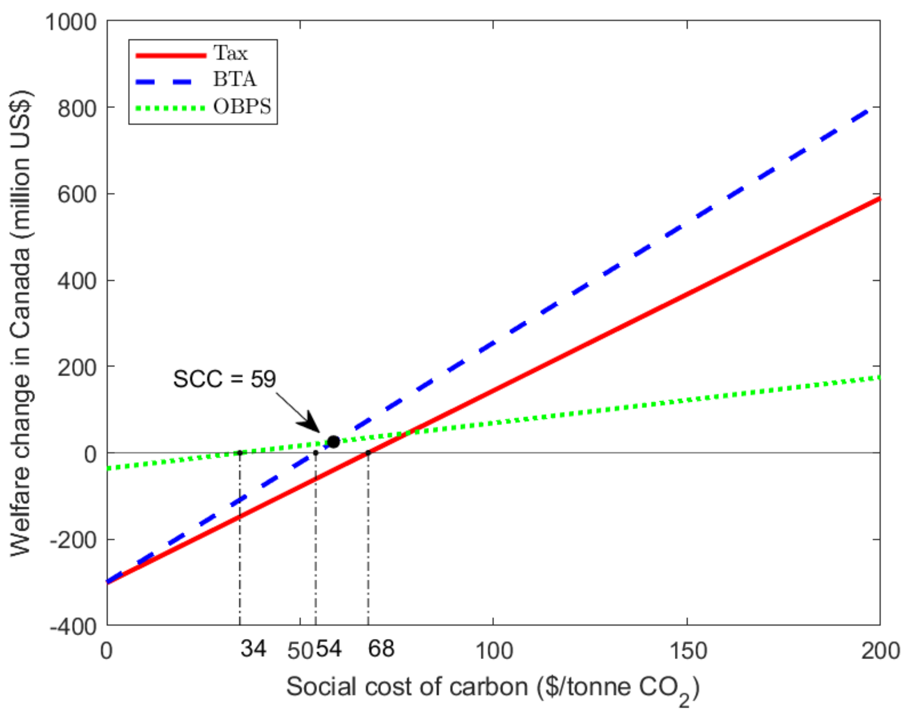


Figure 11 presents a comparison of the welfare effects of three carbon pricing schemes in Canada, at various levels of social costs of carbon, as derived from equation (16).[58] When the social cost of carbon (SCC) is below $34 per tonne of CO_2, none of the carbon policies is welfare improving. The losses experienced by consumers and producers due to high production costs and prices are not offset by the reduction of a less damaging pollutant. As carbon emissions become more harmful, the output-based pricing system emerges as the first policy to generate a positive welfare change for Canada. By granting free allowances to cement producers, OBPS incurs the least losses for consumers and producers per tonne of emissions abatement, which can be easily outweighed by the benefits from reducing carbon emissions.

A carbon tax with border tax adjustment achieves the same amount of welfare gain as an output-based pricing system when the social costs of carbon are equal to $59. Above this threshold, the BTA dominates the other two schemes by achieving the greatest reduction in carbon emissions through the imposition of a tax on foreign-produced goods.

[58]Based on EPA Social Cost of Carbon Fact Sheet (2016), the social cost of CO_2 could range from $14 to $138 in 2025.

The carbon tax on fossil fuels alone is never a preferred strategy in this analysis. There are two reasons why the carbon tax is suboptimal. First, implementing a carbon tax alone is incomplete and creates carbon leakage, whose damages are global. Second, the market distortion is exacerbated in the presence of oligopolists, which is demonstrated by the more than complete pass-through of fuel costs. Using a simple carbon tax results in significant welfare losses from these two channels relative to the environmental gains. In contrast, a BTA directly addresses the first concern by internalizing the leakage. An OBPS tackles the second concern by reducing costs and alleviating the downward pressure on production which is already below the efficient level in the concentrated cement industry.

6 Single-plant Approximation

Although I present in this paper a model characterized by 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 of incorporating interdependent entry when studying multi-plant firms. In this section, I address such doubt when applying this model: Does interdependent entry matter?

In reality, a multi-plant firm could operate with 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 a 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 a combinatorial optimization problem. Instead of arguing which premise is correct, I present comparisons between the two.

Holding the multi-plant firm model the same, I approximate the fixed cost assuming that each plant makes separate location decision instead of estimating them jointly. A plant enters if and only if its own expected variable profit is not less than its fixed cost. The expected variable profit of a plant at ℓ is proportional to its parent firm's profit depending on the share of consumers it supplied due to the identical price distribution (6) across plants owned by the same firm. With the Fréchet distributed productivities, the share of consumers sourcing from plant ℓ over all its firm's consumers in m is

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

Multiplying the probability with firm's profit equation (11) and subtracting the associated fixed costs, I obtain the expected profit of a plant at ℓ owned by firm f,

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

where $E\left[\pi_{f\ell}\right] = s_{f\ell m} E\left[\pi_f\right]$. The expected variable profit is constructed using the same first two-step estimates from Sections 4.1 and 4.2 to disentangle the effects solely stemming from assuming separate entry of plants.

I keep the same parametric assumption of fixed costs and take logs of the plant entry condition $E\left[\pi_{f\ell}\right] \geq FC_{f\ell}$ to obtain the empirical form of entry probability under single-plant approximation,

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

Parameters that govern the fixed cost distribution are estimated via binary Probit.[59]

Table 9: Estimation of fixed costs: MP estimation vs. SP approximation

	(1) Multi-plant estimation	(2) Single-plant aproximation
β^F_{cons}	-6.631	-0.219
	(1.616)	(2.668)
$\beta^F_{\text{CEX-USA}}$	-0.406	-0.294
	(0.373)	(0.495)
$\beta^F_{\text{LFH-CAN}}$	-3.734	-1.570
	(1.867)	(1.016)
β^F_{dist}	1.795	0.734
	(0.220)	(0.401)
σ^F	2.790	1.777
	(0.481)	(0.551)

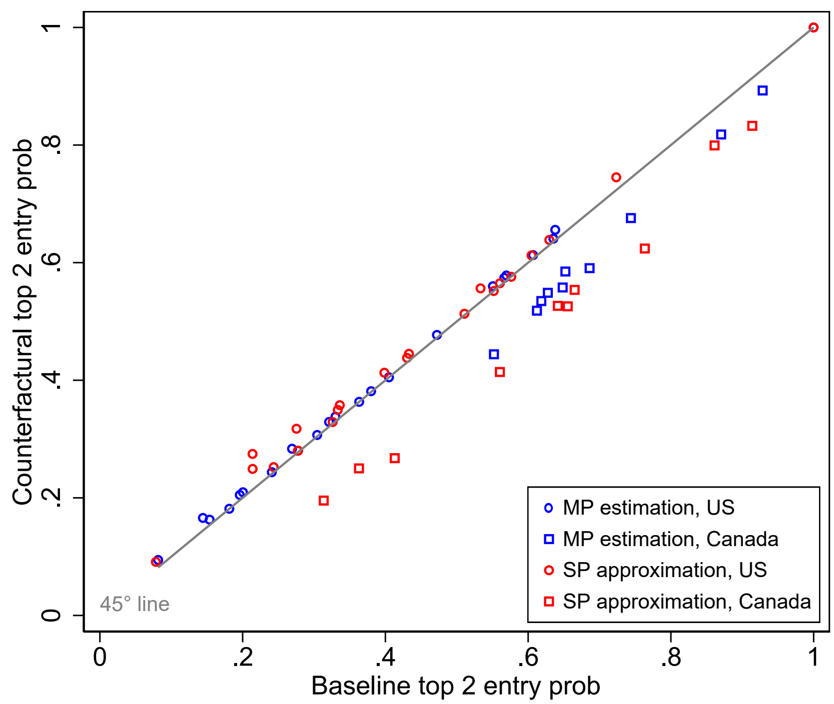
Column (1) is taken from Table 4 column (1) as the baseline estimates of fixed cost distribution estimated with interdependent location choices. Column (2) shows the estimates approximated by separate plant entry. Standard errors in column (2) are computed using Delta method.

Table 9 compares the estimates under the SP separate entry assumption and MP interdependent entry assumption. Interpreting the estimates in column (2) in monetary terms, the average fixed

[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.17.

costs of building a LafargeHolcim plant is \$63.4 million, about one-third of the amount estimated with multi-plant approach. Those of a Cemex plant is \$61.9 million, almost one-fifth of what is estimated before.[60] The fixed costs approximated by assuming separate plant location choices are significantly downward biased due to the omitted interdepedencies. The intuition is that in the multi-plant firm model, firms benefit from having more plants to compete against rivals. Hence, entry to a location can be profitable at the firm level but not at the plant level. The SP approximated fixed costs need to be lower to match the observed number of plants. Moreover, the magnitude of bias is smaller for LafargeHolcim which has the most number of plants. This is because the marginal benefit from building a plant diminishes, counteracting the omitted variable bias from the first channel. It is important to note that one should not generalize the comparison between LafargeHolcim and Cemex to larger firms having smaller bias because the MP estimated and SP approximated fixed costs are equivalent when a firm has only one plant. This implies that the bias exhibits a hump shape.[61]

Figure 12: Change of plant locations for \$50 carbon levy on fuel: MP vs. SP



The differences in fixed costs estimates cause departure of counterfactual policy evaluations. Figure 12 compares the change of plant locations using the estimated fixed costs from the SP

[60] I also use 140.575 as the scalar to match actual prices and discount rate 6% to be consistent when comparing to the multi-plant estimates.

[61] I leave more investigation of the firm size that would suffer the largest estimation bias assuming separate entry to the future.

approximation and the MP estimation with a $50 carbon tax in Canada. Each dot represents the probability of either of the top two firms entering a FAF zone. The graph shows that the case of separate plant entry exhibits a larger dispersion from the 45-degree line, indicating stronger relocation from Canada to the US, which is consistent with smaller approximated fixed costs. The difference in plant entry and exit is also demonstrated in Panel A of Table 10. Specifically, compared to using the multi-plant estimates, the SP approximation predicts a 10 percentage point decrease in the number of Canadian plants relative to the baseline, implying an over-prediction of 75 percent more closures of the top two cement firms' plants due to biased fixed cost estimates.

Table 10: Aggregate effects of $50 carbon levy on fuel: MP vs. SP

Panel A: Impacts on market outcomes

	%ΔNumber of plants			%ΔPrice	%ΔConsum	%ΔProd	%ΔTrade	
	LFH	CEX	Combined				Canada	US
(a) MP:								
Canada	-10.98	-29.58	-12.75	27.85	-37.97	-66.14	-54.25	-94.67
US	0.57	1.16	0.81	0.69	-2.63	2.33	224.83	1.02
(b) SP:								
Canada	-19.16	-34.69	-22.35	28.68	-37.95	-66.84	-55.39	-94.91
US	1.06	1.55	1.28	0.56	-2.38	2.52	234.88	1.14

Panel B: Impacts on welfare and emissions

	Δ CS	Δ PS	Δ TaxRev	Δ Emissions	Leakage rate
(a) MP:					
Canada	-310.50	-68.04	77.40	-6.05	26.32
US	-35.54	10.70	-	1.60	-
(b) SP:					
Canada	-324.59	-64.87	77.25	-6.22	28.95
US	-30.02	9.54	-	1.80	-

Columns in Panel A are denoted as percentage change relative to baseline using MP or SP fixed cost parameters. Columns in Panel B are changes in levels relative to baseline. Consumer surplus, producer surplus, and government revenue are denoted in million US dollars. Emissions are denoted in million of tonnes. The leakage rate is represented as a percentage.

Panel B of Table 10 finds that an over-prediction of plant relocation leads to an increase in the carbon leakage rate from 26 percent to almost 29 percent. The large difference in the prediction of plant relocation is partially offset by intensive margin adjustment among remaining plants, resulting in moderate but still nontrivial difference in carbon leakage rate. In terms of welfare, the biased estimates lead to a further reduction of 11 million for Canada. Policymakers who use the naive separate-entry approach to estimate multi-plant firms' interdependent location decisions would exaggerate the amount of production and carbon leakage. These findings highlight the positive and negative spillovers from multi-plant production, which are absent in a world with only single-plant firms.

7 Conclusions

In this paper, I develop a multi-plant oligopoly model with endogenous and interdependent location decisions. At the intensive margin, the model derives multi-plant firms' pricing and markup rules in closed forms that generalize findings from 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. A greater number of plants increases the production advantage of a firm, improves its capability to compete against rivals, and enhances the firm's market power to charge higher markups. At the same time, the increasing cannibalization and fixed costs hinder the expansion of the plant set. These positive and negative spillovers among plants within the same firm differentiate multi-plant from single-plant firms, highlighting the importance of spatial interdependency when studying multi-plant production decisions.

A key contribution of this paper is to address the empirical challenge of solving combinatorial discrete choice problem for a multi-player game with strategic substitutes. Submodularity and aggregative property of the location game underpin the method to solve for combinatorial optimization by eliminating many location configurations. I extend the algorithm in Arkolakis and Eckert (2017) to a game-theoretic framework and show that one can always find a pure strategy Nash equilibrium.

The framework does well 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 locations 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 if plants are primarily exporters. An output-based pricing system lessens domestic market distortion caused by a carbon tax but performs poorly in cutting down carbon emissions if firms are not incentivized to adopt greener technologies. The welfare comparison across three carbon pricing regimes suggests that for an emission-intensive, trade-exposed and concentrated industry like cement, policymakers should use OBPS if emissions' damages are mild and BTA if damages are severe.

The paper goes on to demonstrate that neglecting spatial interdependencies in estimation leads to a downward bias in fixed costs and predicts stronger carbon leakage. The size of the bias is hump-shaped with respect to the number of plants owned by firms.

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

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Appendices

A Model details

For simplicity of derivation, I invert the marginal cost and derive the following equation 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 two lowest cost firms

Since the conditional joint distribution of the lowest two costs is the same as that of the 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 based on the definition of $\tilde{Z}_{2m}(i)$. The numerator can be further simplified as

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

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

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

By summing equations (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^* serving the consumer in the market, the complement of the price c.d.f. is

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

By deriving 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 T1 and T2 and subtracting from one, I get the price distribution exactly equals 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^* serving the consumer i in market m, for the range below the monopoly markup, the distribution is

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

I 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 is 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 wherea firm builds plants. Moreover, I 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 a 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 the first-order derivative with respect to Φ_{f^*m}, the probability of the firm earning a monopoly markup strictly increases with its producing capability Φ_{f^*m}. Since Φ_{f^*m} increases with the firm's number of plants, this implies that the more plants a firm builds, the more likely it will be able to charge a 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 $p_m(i) = \min\left\{\frac{1}{\tilde{Z}_{2m}(i)}, \frac{\bar{\mu}}{\tilde{Z}_{1m}(i)}\right\}$, I 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,

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

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 find that conditional expected revenue is equal to

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

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

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

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

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

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 in deriving the second term in the expected revenue function, the second term here can be simplified to

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

Combining the two terms, I find that the conditional expected cost is equal to

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

where

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

The unconditional expected cost is therefore

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

A.6 Best-response potential game

A best-response potential game is where potential functions infer the differences in the payoff due to the unilateral deviation of each player to the best response. It was 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 decision, if players simultaneously deviate 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.12 shows examples of 6 to 12 locations and two firms. Each is solved 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 quickly.

Table A.12: 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 follows in completing the multi-plant firm model all remains the same. Specifically, the probability that a location exports goods to a market becomes

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

By transforming the sourcing probabilities into the gravity-type regression, I obtain the same form as in equation (20), but with the location fixed effects being $\mathrm{FE}_\ell = \ln\left(T_\ell w_\ell^{-\theta} \sum_f \mathbb{I}_{f\ell} Z_f^\theta\right)$. Therefore, I 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 the 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

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

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 to perform 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 cost distribution using the Method of Simulated Moments 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 spaced further apart. Another modification with spatial dependence regards the asymptotic normality of the MSM estimators, specifically the variance covariance matrix. According to Conley (1999) and Conley and Ligon (2002), the asymptotic covariance matrix of moment function 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 belonging to the same region as location ℓ.[62]

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 simulations of the fixed cost draws. In practice, I take 600 simulation draws from a van der Corput sequence for 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.13 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

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

[62] 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 the 2-step estimators in Table C.13, columns (3), (6) and (9), where the first step is performed using identity weight on moments, followed by computing 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.13: 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)

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

C.2 Additional tables

Table C.14 provides alternative specifications for the first-step gravity-type regression using the country-level sample. Table C.15 presents the first-stage results of the demand estimation using the price survey data. Table C.16 provides details of computing fuel costs for the carbon tax in the fossil fuel counterfactual exercise. Table C.17 reports the binary Probit regression results in the single-plant approximation, and Table **??** reports the binary Probit regression results in the third step estimating a single-plant firm model.

Table C.14: 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 the correlation of fitted and true dependent variables. Robust standard errors are in parentheses. Significance levels: ^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01.

Table C.15: 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 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 includes year fixed effects from 2012 to 2016. Variables other than the number of building permits and population are excluded instruments. Robust standard errors are in parentheses. Significance levels: ^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01.

Table C.16: 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 remaining 11% energy is provided by electricity and 7% by other sources, which are not included in computing cost of fuels, and not 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.17: Estimation of entry without interdependency

	Probit
constant	0.123
	(1.489)
log distance to HQ$_{f\ell}$	-0.413^b
	(0.202)
log variable profits$_{f\ell}$	0.563^a
	(0.174)
LFH-CAN	0.884^c
	(0.482)
CEX-USA	0.166
	(0.281)
Observations	146
R^2	0.161

Robust standard errors are in parentheses. Significance levels: ^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01.

D Data appendix

D.1 Implied trade across FAF zones

There are three groups of trade flows 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 is directly provided by the Canadian FAF survey. The drawback of using Canadian Freight Analysis Framework is that it is a logistics file built on 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 are classified at the 2-digit level of Standard Classification of Transported Goods (SCTG). Cement is a subcategory of nonmetallic mineral products. 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, not by FAF zone, I further assume that the consumption ratio of cement over nonmetallic minerals is the same for every FAF zone within the same state.

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. This leaves the question of 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 apportioning the associated state-province trade by the 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 are implied from trade in nonmetallic minerals, I validate that the trade coefficients are not significantly different between these two groups using country-level data, as shown in Table D.18. 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 for trading.

D.2 Districts

The map in Figure D.13 and Table D.19 show the division of the sample to 8 districts and an overview of the cement market. The areas shaded in gray 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 areas outside. Explicitly, Figure D.14 shows the distribution of FAF zones trading within the same district. Out of the 73 producing zones, all of them exported at least 50% to other FAF zones within the same district and more than three-fourths exported more than 80% within the same district. As for the importing cement markets, the distribution is slightly dispersed. But still, three-quarters of the 149 markets imported 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. These trade flow statistics validate my assumption of districts being relatively separated from one another. The competition among plants across districts is negligible.

Figure D.13: Districts map

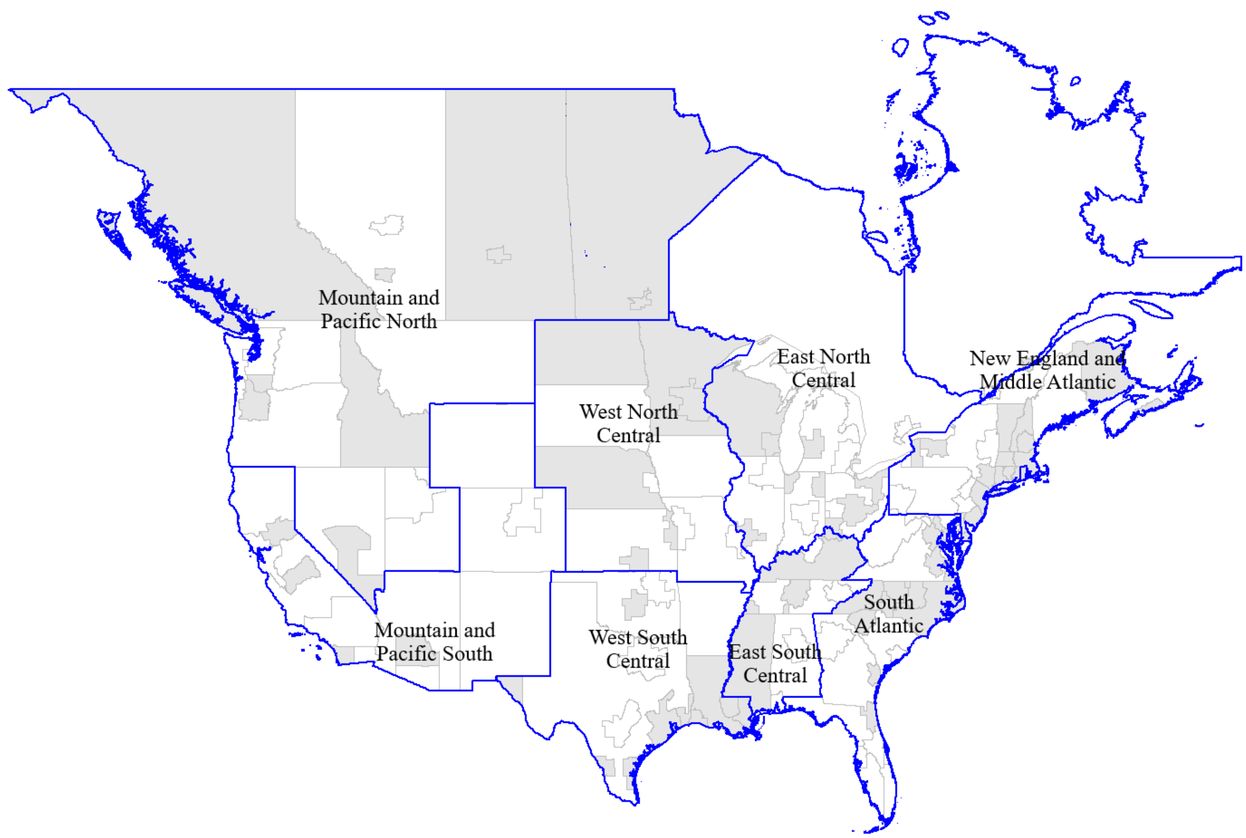
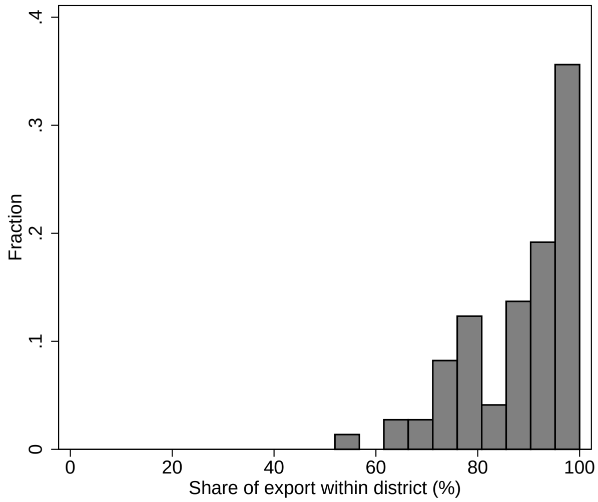
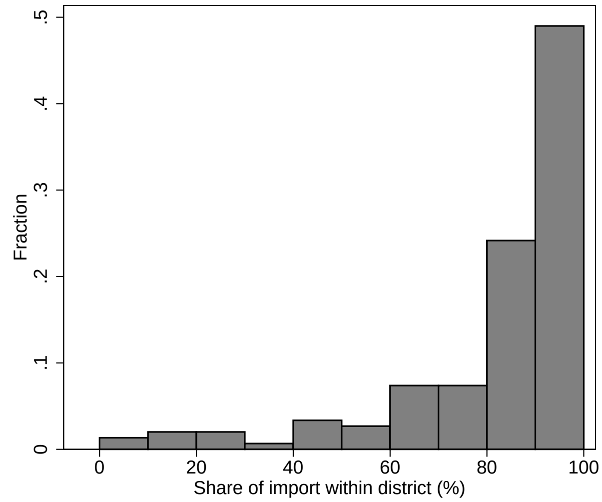


Figure D.14: Trade within the same district



(a) Exports



(b) Imports

D.3 Locations of limestone deposits and cement plants

Figure D.15 maps the distribution of cement plants versus limestone resources. The information is obtained from the 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 there are no limestone quarries or cement plants. The locations where access to limestone is limited are outside the potential set of locations to establish 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, and 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 only a few kilometers away from the limestone quarries, the location choice of cement plants studied here can be regarded as a decision for an integrated set of facilities, including mining activities and further processing.

Figure D.15: Cement and limestone resource location distribution

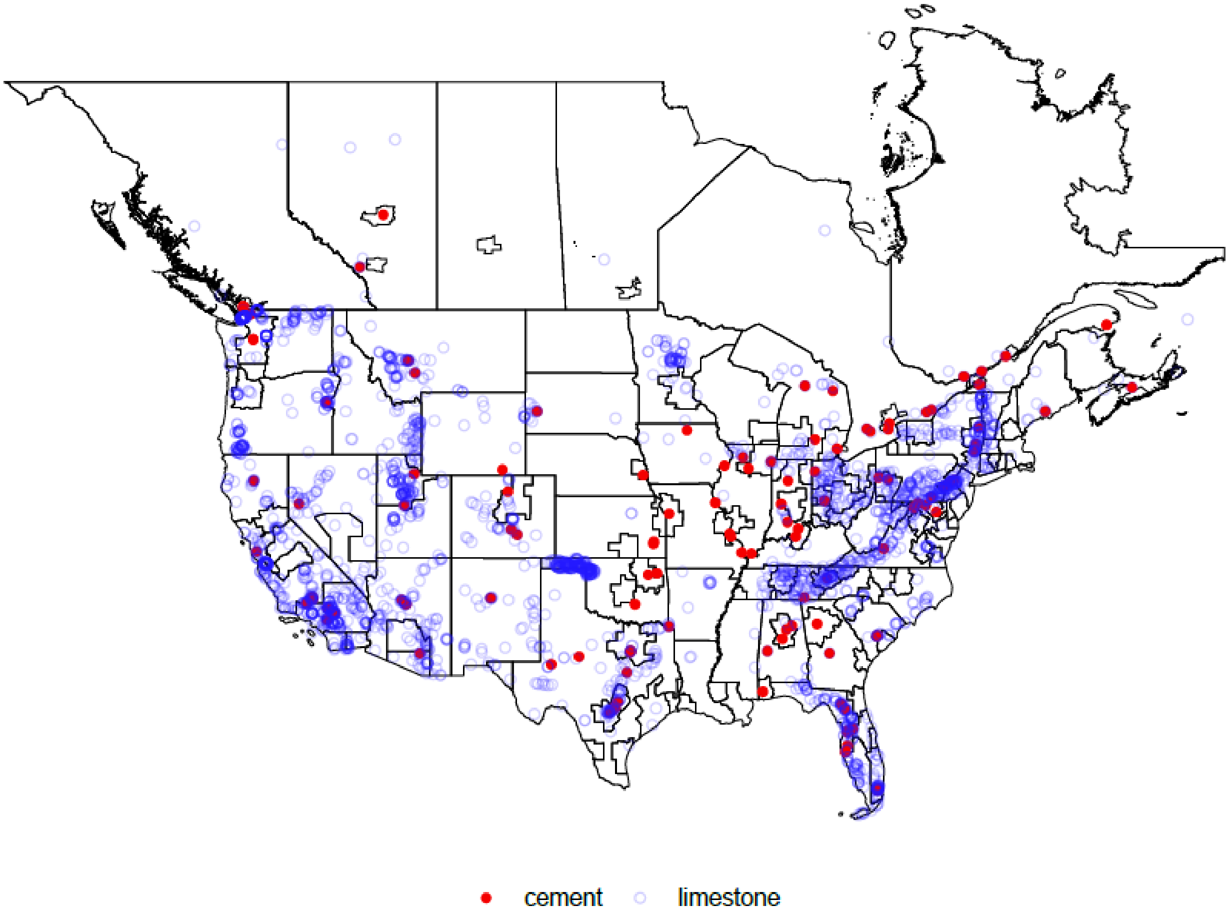


Table D.18: Trade estimates for cement and nonmetallic minerals

	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 2016 and 144 countries. Trade with own is dropped from the sample since the data are unavailable for the nonmetallic mineral products. Different columns use different measurements of distance. R^2 is the correlation of fitted and true dependent variables. Robust standard errors are in parentheses. Significance levels: ^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01.

Table D.19: 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