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

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Abstract

I develop a quantitative model of multi-plant oligopolists where each firm decides where to locate the set of plants and how to serve each market, taking into account cannibalization across its own plants as well as competition with others. In contrast to canonical trade models with multinational firms where neither spatial interdependency of decisions nor oligopoly is considered, I advance the existing research by allowing for interdependent entry, oligopolistic rivalry and variable markups. Despite having a high-dimensional discrete choice problem, I provide a toolkit to tractably estimate the model in a three-step procedure, leveraging the gravity-type regressions, the analytical expression for market price derived from the model, and the solution algorithm for a combinatorial problem when the location game is submodular. As an application I estimate the model for the cement industry in the US and Canada. Counterfactual experiments quantify firm-level responses to changes in environmental, trade and competition policies and highlight welfare implications of having multi-plant production.

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1 Introduction

Policies affecting the costs of business operations may cause firms to relocate production and re-optimize prices. These indirect effects could undermine the intended purpose of a policy and impose costs on the economy. An example is a carbon tax that induces firms to move to jurisdictions with laxer standards (carbon leakage), leading to employment loss in the host economy and limited changes in total emissions. Consequently, optimal policy design requires understanding the spatial organization of firms and industries.

Understanding how firms, especially multi-plant firms, operate across space in a complex problem. A multi-plant firm confronts decisions on where to locate a set of plants and which plant to supply where, taking into account the competition with rival firms and within itself. Since plants owned by the same firm can cannibalize each other's markets, whether to build a plant in one location cannot be considered separately from building in another. Firms having too many establishments close to consumers incur higher fixed costs and stronger cannibalization. Having too sparse establishments means higher costs for getting products to consumers. The geographic distribution of plants determines not only the profitability of firms, but also the characteristics of locations and consumer welfare. Perhaps due to the difficulty in tackling the combinatorial problem theoretically or empirically, there has not been a framework that solves a high dimensional spatial equilibrium for an oligopolistic industry and is sufficiently general to be used for assessing firms' responses to a variety of policy changes.

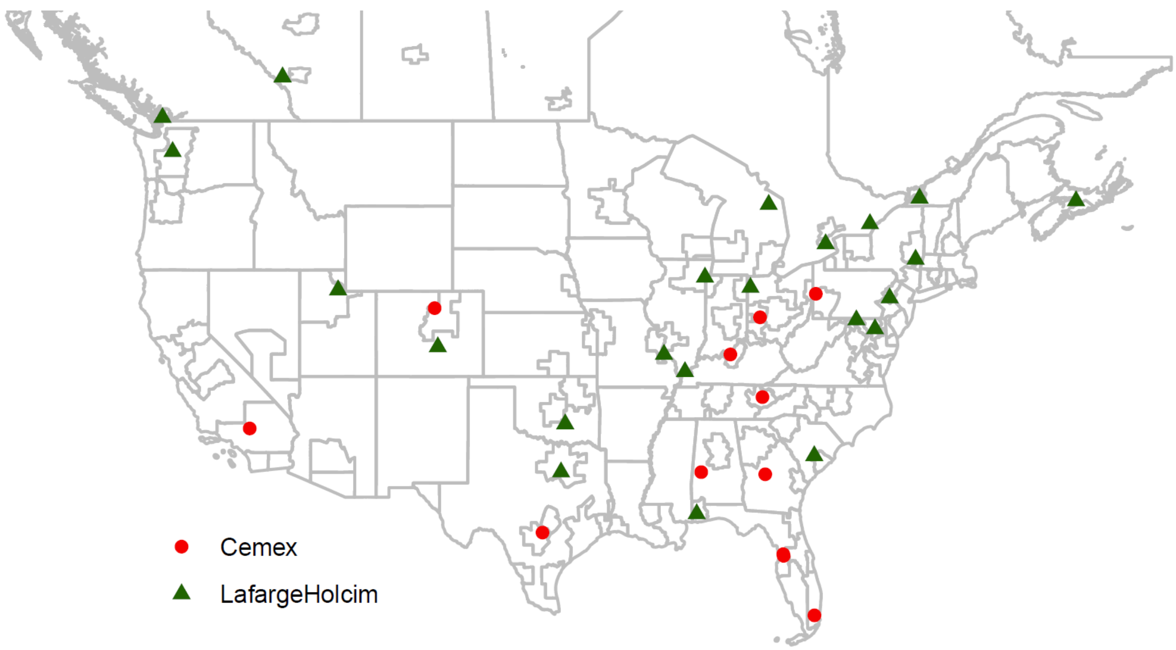
In this paper, I develop a quantitative model of heterogeneous spatial oligopolists with multiple plants to study their decisions on interdependent production locations, output and pricing. The model is firmly grounded in the intersection of trade and industrial organization theory. Advancing existing research, I allow for interdependent entry, oligopolistic rivalry, and variable markups. I estimate the model using a solution algorithm for the combinatorial discrete choice problem and separate identification of three sets of model primitives. My solution method serves as a toolkit that can be adapted to many other spatial organization problems. I use data from the cement industry in North America to demonstrate how to apply the general framework to evaluate environment, trade and competition policies.

It is instructive to consider the case of the largest two cement producers in North America, LafargeHolcim and Cemex, the firms featured in the application of this paper. Figure 1 shows plant locations of LafargeHolcim and Cemex across space. The borders indicate "markets" defined by metropolitan areas or the remaining areas of states and provinces in the US and part of Canada.[1] LafargeHolcim is the largest player owning 22 plants in 2016 in the sample region and

[1]The geographic definition of locations is according to Freight Analysis Framework areas (Commodity Flow Survey areas), which contain two general types: metropolitan areas and remainder of state areas. In some cases, the remainder of a state/province is the entire state if there is no finer type in the state/province, such as Idaho and New

Cemex operates 12 plants. Clearly, the presence of cement plants is not everywhere. Moreover, the two rivals never locate plants in the same market. Additionally, Cemex plants are concentrated in Southeastern US whereas LafargeHolcim plants are concentrated in the Northeast. Lastly, an anecdotal evidence suggests that the discrete choices of whether to build a plant or not are interdependent across locations. Lafarge once operated a plant at Kamloops, a city in the interior of British Columbia, but it was shuttered due to a drastic downturn of demand in Alberta.[2] Apparently, cannibalization between this plant and another Lafarge's plant at Exshaw, Alberta matters and makes the firm to close one but not the other. My model captures the forces that give rise to a spatial pattern of this type and sheds light on events where firm reorganizes plants.

Figure 1: Plants distribution of LafargeHolcim and Cemex



To explain the decisions of spatial firms with multiple plants, three elements feature formally in the model. First, plants are heterogeneous. Second, oligopolistic competition among granular firms is prevalent. Third, firms interdependently enter a set of heterogeneous locations. These building blocks are key to my model and differentiate it from the canonical models of multinational firms.[3] Specifically, a firm selects a set of plants by balancing the costs of production, distribution and entry

Brunswick. In other cases, Combined Statistical Area, when it exits, is used rather than Metropolitan Statistical Area, such as Oklahoma City OK and Houston TX.

[2]Article from Kamloops This Week, October 20, 2016, `https://www.kamloopsthisweek.com/news/lafarge-to-close-kamloops-cement-plant-36-full-time-employees-affected-1.23236513`.

[3]I refer the canonical models to two types. One is the Dixit-Stiglitz type of model with constant elasticity of substitution and a continuum of firms engaging in monopolistic competition. Some multinational firm models in this category are Tintelnot (2017), Antras et al. (2017), and Hu and Shi (2019). Another type of model is studying multi-plant (multinational) firms but does not allow for export platform sales or fixed costs of entry, or assuming locations

across a number of discrete locations, while factoring competition within and across firms. When competing, plants engage in head-to-head oligopolistic competition except that those owned by the same firm coordinate. The model predicts that the more and better located plants a firm owns, the higher its comparative advantage and therefore more profits. However, the marginal benefit of an additional plant decreases with entry and eventually cannot cover fixed costs of building the plant. Optimal entry decisions maximize a firm's expectation on total profits.

Contributing to solve the theoretical model is that the model yields an analytical distribution function of firm-market-specific variable markups. Existing work has long been using constant markup derived from the workhorse model of constant elasticity of substitution (CES) with monopolistic competition. I relax those assumptions and incorporate strategic pricing among oligopolistic rivals, while keeping the markup distribution tractable. The model predicts that the more plants a firm builds, the more productive it is and the higher markup it charges.

The multi-plant firm model conforms to a gravity trade framework with scalable aggregation properties. It highlights the role of spatial distribution of plants in trade besides the usual technological differences and geographic barriers. As the geographic configuration of plants shapes the relative competency of firms, it also reinforces differences in comparative advantage across locations. A numerical comparison between the three forces shows that the effect of this new channel is significant and sizable.

At the aggregated level, due to the spatial interdependency of decisions, changes in policies would induce global shuffling of all plants' locations and affect costs of plants, market prices, trade flows and eventually welfare. Quantifying changes of the entire network and predicting new market outcomes relies on solving the model empirically. A key feature of this framework is its empirical tractability and separability in estimation. Interdependent entry decisions imply a hard permutation problem whose computation was almost infeasible without a solution algorithm. When there are L number of possible production locations, there are 2^L possible choices. A duopoly game further complicates the combinatorial discrete choice problem as it now involves 4^L combinations. The location problem is solved by applying the repetitive fixed point search algorithm designed in Eckert et al. (2017). I exploit the submodularity in the location decisions of firms so that substantial amount of possibilities are eliminated and only a fraction of configurations need to be evaluated. To further save the computational cost, I propose a three-step procedure so that the dimensionality of the problem at each step is reduced. In the first step, gravity regressions at inter-regional and international level are used to estimate the dispersion of plants' productivities, trade costs and relative production costs for each location. In the second step, using the model-consistent price index constructed from the parameters recovered from the last step, I estimate demand with instruments

are predetermined. Examples are Helpman et al. (2004), Ramondo and Rodríguez-Clare (2013), Irarrazabal et al. (2013), Head and Mayer (2019).

through generalized method of moments. In the third step, forming expected firm profits, solving firms' location sets and fitting moments using the plant-level data, I estimate parameters governing the fixed costs distribution. Overall, all types of costs faced by the multi-plant firms and the demand primitives are identified.

The payoff for assembling all this machinery comes from the ability to use the estimated model to explore policies. I apply the framework to the cement industry in North America and study the implications of having multi-plant production and welfare effects of environmental, trade and competition policies. Cement is an emissions-intensive and trade-exposed industry with high risk of carbon leakage listed by the European Commission (Europejska 2009), which places it at the center of many policy debates. I first examine effects of the Greenhouse Gas Pollution Pricing Act (the Act) in Canada. Three carbon schemes are considered, namely carbon tax with and without border tax adjustment, and the output-based pricing system (OBPS). All three carbon pricing policies would induce plant relocation from regulatory area to pollution haven, with the carbon tax being the most aggressive policy such that 13% of the Canadian plants owned by the top two firms will be closed. In terms of social welfare, OBPS outperforms the other two. It improves the welfare in Canada if reducing one tonne of carbon emissions would save 49.2 dollars of social cost to the economy. The result justifies the use of OBPS for the cement industry in the Act and also supports the \$50/tCO_2 carbon price set by the Canadian government. The second counterfactual experiment focuses on a unilateral tariff increase by the US towards imported cement from Canada. Results show that the US would lose seven times more than its trade partner Canada for a 20% increase in tariff. The protectionism strategy is ineffective in expanding the set of US plants since less than 1% of plants would be added including those from relocation or newly built. Lastly, I simulate a hypothetical acquisition of a leading US cement producer by the second largest player in the market. The firm does internalize and close plants with overlapping markets post acquisition. The acquisition generates pro-competitive effects through cost synergies and intensified competition with the largest firm. Both countries gain, which rationalizes the recent wave of consolidation happened in this industry.

The model presented in this paper extends the head-to-head oligopoly trade framework introduced in Bernard et al. (2003) (hereforce BEJK) and developed in Holmes et al. (2011), Holmes et al. (2014) and De Blas and Russ (2015). Bernard et al. (2003) have markup distribution being impervious to any characteristics of market structure. Subsequent papers by Holmes, De Blas and others generalize the model to incorporate the effects of finite number of firms in a market. This group of papers takes different view of the world compared to the way Atkeson and Burstein (2008) modeling oligopoly in trade. In Atkeson and Burstein (2008), each firm produces a distinct good in a specific sector and firms maximize profits given imperfect substitution within a sector and across sectors. In contrast, BEJK model multiple producers producing the same good and there are a continuum of imperfectly substituted goods. However, none of these papers distinguish a plant and a firm. In other words, firms are treated as single-plant owners, which is concerning given mounting evidences that support differences between plants and firms (i.e., Rossi-Hansberg et al. (2018), Hsieh and Rossi-Hansberg (2019), Aghion et al. (2019), and Cao et al. (2017)). My model addresses the omission and allows firms to own multiple plants. The extension is not trivial because one cannot simply treat competition among plants within a firm and across competitors' plants the same. The distributions of firms' costs and markups derived from the multi-plant firm model nest those in BEJK and others for single-plant firms. Therefore, I am able to obtain more generalized insights on the firm-level decisions regardless they are single- or multi-plant owners.

I also build on and contribute to a vibrant area of ongoing research that explores interdependencies in firm-level decisions. Several papers in the industrial organization literature has analyzed how retailers set up distribution networks in space, namely Jia (2008) and Holmes (2011). The repetitive fixed points search algorithm by Eckert et al. (2017) used in this paper is a generalization of what is applied in Jia (2008). Jia (2008) imposes a "supermodular" condition on the return function, meaning that there is only positive spillover but not cannibalization among chain stores. The algorithm by Eckert et al. (2017) is more powerful since it can deal with either "supermodular" or "submodular" problem as long as the return function satisfies single crossing difference. This algorithm is further developed by Hu and Shi (2019) to a continuum of heterogeneous firms over a monotonic type space engaging in monopolistic competition, in contrast to mine which uses oligopolistic head-to-head competition between granular firms in a game setting. The recent paper by Oberfield et al. (2020) handles the combinatorial optimization in an entirely different way. They derive a limit case where the optimal plant density is differentiable in a continuous space. On the other hand, an alternative approach to combinatorial problem is using moment inequality to partially identify parameters without solving the model, such as Holmes (2011). The downside for this method is the difficulty to perform counterfactual policy experiments which is a main focus of my paper.

In the international trade literature that explores extensive margin of multinational firms, my work shares the most similarities with Antras et al. (2017). However, their paper speak to a very different problem of firms' global sourcing decisions, whereas mine is to investigate firms' production location and inter-regional export decisions. Furthermore, they model a monopolistic competitive market and treat firms as infinitesimal with constant markups, whereas I highlight a small group of sizable firms competing oligopolistically and exercising market power to increase markups. The drastic difference in setup makes my model more suitable for analyzing one industry that is dominated by a few large multi-plant (multinational) firms. Tintelnot (2017) is more close to my paper in understanding firms' decisions on export platforms. Nevertheless, his work evaluates all possibilities in a very small location set, besides different assumptions in the competition structure.

These two papers and mine advance the traditional way of studying multinational firms which does not allow for combinatorial decisions either by ignoring the spatial interdependency among affiliates, assuming predetermined locations or no fixed costs (Helpman et al. (2004), Ramondo and Rodríguez-Clare (2013), Irarrazabal et al. (2013)).

Broadly, my model proposes ownership as one form of correlations in Lind and Ramondo (2018). Other than interdependency in location choices, the paper also sheds light on multi-product firms when there is cannibalization among products within the same firm. Specifically, the endogenous markup distributions drawn from this paper and Nocke and Schutz (2018) share the same shape.

Due to the sector of interest, this paper is also related to the extensive research conducted on the cement industry. Some have been focused on the impact of environmental policies as what is done in my counterfactual exercise, such as Ryan (2012) and Fowlie et al. (2016). These works use a dynamic setting and find that environmental policies significantly increase the cost of entry, exacerbate distortions, and result in social welfare losses. Others, such as Miller and Osborne (2014) and Miller et al. (2017), focus their analysis at pricing strategy of cement firms, or horizontal and vertical mergers and acquisitions, like Perez-Saiz (2015) and Hortaçsu and Syverson (2007). However, this is the first paper in the cement industry which exploits the tradable nature of cement and regards production locations as correlated and endogenous decisions for firms. The impacts of policies are then not only about firms' pricing decisions, but also about production relocation. Issue such as carbon leakage which used to be measured as an aggregated increase in imports can now be directly tackled through the degree of plant relocation and subsequent adjustments at the firm level.

The remainder of the paper is structured as follows. Section 2 discusses the model and propositions derived from it. I describe the data set and provide background of the cement industry and stylized facts in section 3. The model is estimated structurally in section 4, and in section 5, I perform counterfactual experiments. Section 6 concludes.

2 A Model of Multi-plant Firms

I develop a model that explains multi-plant firms' decisions on where to set up production facilities, from which plant to serve each market, and how much to charge. The model considers plants and firms as distinct, albeit related, economic entities. Firms' trade-off depends on the interaction among costs they are facing and competition forces among plants with the same firm and across different firms. In particular, a firm would build fewer plants to economize on fixed costs and reduce cannibalization between its own plants. On the other hand, it also has incentive to build more plants because trade costs are reduced if plants are in close proximity to consumers, productivity is augmented through specialization in certain goods, and competitors' plants are crowded out.

The decision on the number of plants is extended to a portfolio of plant locations when geography heterogeneity is taken into account. Locations differ in endowments of government quality and inputs. While the marginal cost of production for a plant is in part determined by exogenous local efficiency and input costs, there is also an idiosyncratic productivity shock such that plants within the same location are different. However, a firm can only produce in a location and learn its plant's productivity after paying a fixed cost of setting up production in that location. The fixed cost is also plant (firm-location) specific. In sum, I allow a flexible description of firms to be heterogeneous in productivity, fixed cost, the number and locations of plants, while maintaining the model's empirical tractability. The key is that the model delivers a smooth and intuitive expression of the probability with which a location exports to a market, aggregated from the firm-level decisions. The model entails a gravity trade model and thus makes it possible to recover some parameters using aggregated trade data.

Deviating from the workhorse model of constant elasticity of substitution (CES) demand and monopolistic competitive firms, I adopt oligopolistic competition with granular firms in the model. In essence, I add one more layer of firms owning multiple plants in the structured pioneered by Bernard et al. (2003) and developed by Holmes et al. (2011). This involves thinking two firms simultaneously select the set of locations to build plants, taking the competitor's choices as given. Plants engage in Bertrand competition. The lowest-cost plant sets price to undercut the competing firm's lowest-cost plant by matching its marginal cost but not other "sister" plants.[4] The pricing strategy reflects the multi-plant firm's interest in coordinating its plants' pricing decisions, while preserving the competition among "sister" plants for the least-cost supplier to consumers. The formulation of competition structure simplifies the problem because only the lowest-cost plant within the best two firms matter. With the handy property of extreme value distribution for plants' productivity, a firm moves up the ladder when it establishes more plants. Therefore, the advantage in specialization as mentioned before. The model still delivers variable markup following a truncated Pareto distribution. The expressions in BEJK and other work along the line serve as special cases of the profit function for the multi-plant firms in my model.

I start with the description of demand and then turn to the problem of the firm.

2.1 Demand

The demand is characterized for a single product consumed by a continuum of projects (consumers) j on the unit interval in market m. Overall, the market consumes Q_m units of the good. I

[4]Sister plants are referred to plants owned by the same firm.

assume an isoelastic demand curve at market level, given by

$$\ln Q_m = \alpha_m + \eta \ln P_m, \tag{1}$$

where η is the elasticity of demand, the market price index of the good P_m, and the exogenous demand shifter α_m.[5] I assume $\eta < -1$ to be consistent with profit maximization of monopolists. I formulate the market demand instead of the project demand because projects within a market are not systematically different from one another from the point view of suppliers. The expected markup a supplier charges different projects in market m is the same, although the realizations can vary. Suppliers make multinational production decisions based on their expectation on the market profit and the fraction of projects they can serve in that market. All firms' production decisions subsequently determine the market-level price index whose expression will be provided later with the firms' pricing equations and the market's sourcing probabilities. One can easily add more structure to the demand side as what I've shown in Appendix B.1. However, the additional demand parameters add no benefit in solving the firm's problem but bear more complication in the estimation.

2.2 The multi-plant firm's problem

We consider the problem of a multi-plant firm deciding where to establish production operations and how to serve projects located in each market. A finite number of oligopolists appoint their plants to produce the same product facing the aforementioned demand function. The timing of game is that at $t = 1$, firms simultaneously decide the set of locations to build plants in order to maximize expected profits, and pay realized fixed costs. At $t = 2$, firms learn about the exact efficiency of plants and decides to which project plants supply. Plants engage in Bertrand competition and choose the optimal prices for projects served. For simplicity, I assume there are no fixed costs of exporting and every plant can be potential supplier of each consumer in every market.[6] I solve the model by backward induction.

[5] The CES type preference is a special case of isoelastic demand.

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

2.2.1 Export and pricing decisions given plant locations

A plant is indexed by a firm f and a location ℓ.[7] Denote the finite set of locations a firm chooses to build plants by a vector of dummies $\{\mathbb{I}_{f\ell}, \forall \ell \in \mathcal{L}\}$. In those locations where the firm has set up a plant, the firm converts one bundle of inputs into a quantity $Z_{f\ell}(j)$ of the good delivered to project j in a market at constant return to scale. The term $Z_{f\ell}(j)$ can vary by projects in a market for the same plant. This reflects some degree of vertical differentiation required across the nature of projects. It also captures the internal distribution efficiency of the good from the port of the market to which projects are exactly located, and any other idiosyncratic shock at plant-project level. Rather than dealing with each $Z_{f\ell}(j)$ separately, I assume that they are realizations of random draws from a Fréchet distribution. The cumulative distribution function of the productivity that a plant in location ℓ serves a project is

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

The positive scaling parameter T_{ℓ} represents the location-level efficiency, reflecting factors such as government quality and contract enforcement. Dispersion of productivity is represented by θ. The bigger θ is, the more similar are the productivity draws. I assume that $\theta + \eta + 1 > 0$ to maintain the submodularity property of firm profit function which will be explained further in section 4.4. Otherwise, heterogeneity in productivity is so large relative to curvature of preferences that expressions involving firm sales become undefined. The process of drawing productivity is independently and identically distributed across all firms at the same location for all projects.

The use of Fréchet distribution instead of the Pareto, as Melitz and Ottaviano and other papers have done, is attributed to its grounding in extreme value theory.[8] In cases where the variable of interest is the minimum of a large collection of random factors, limiting distributions such as Fréchet is a likely candidate model. Unlike mine which is leveraged on the lowest cost plant within a firm, the property is irrelevant in the other papers that are models of monopolistic competition. While technical advantages dictate my choice, empirical distributions of productivity are typically bell-shaped found by the literature, which is in favor of the Fréchet.[9]

[7] I assume a firm cannot have more than one plant at a location. The existence of production facility at one location is regarded as having a plant there. Technically, one can define the location finer enough in accord with the setup. The cement data used in the empirical section of the paper shows only four out of 149 locations have two plants belonged to the same firm. In those cases, I combine plants to one.

[8] Other papers include Helpman, Melitz and Yeaple (2004), Chaney (2008), and Eaton, Kortum and Kramarz (2008).

[9] The Fréchet and the Pareto distribution both have fat right tails, but very different on the left side. The former density is bell-shaped whereas the latter density is downward-sloping throughout. Plotting the capacity of cement plants in my sample, I demonstrate the shape displays the best-fitting log normal curves instead of Pareto, despite the fact that it would be hard to distinguish log normal with Fréchet. Another candidate will be truncated distributions. However, properties are more obscured and hard to applied to my model with no strong support of empirical evidences.

Inputs to produce the good are mobile within locations but not between them. The cost of an input bundle at location ℓ is denoted by w_ℓ. The trade cost of transporting the good from a representative point (centriod or port) in location ℓ to a representative point (centriod of port) in market m follows the iceberg assumption, and is denoted by $\tau_{\ell m}$. Combining with $Z_{f\ell}(j)$ which includes the internal transportation cost within the location and the market, I have captured the total transportation cost of shipping the good from the plant (f, ℓ) to project (j, m).

Combining productivity, input and delivery costs, the marginal cost of a firm f at location ℓ supplying cement to a project j in market m is therefore

$$C_{f\ell m}(j) = \frac{w_\ell \tau_{\ell m}}{Z_{f\ell}(j)}. \tag{2}$$

A caveat here is that plants at the same location are ex-ante identical but ex-post different in productivity, even if owned by different firms. The setup is analogous to Antras et al. (2017) where as long as the productivity draws are from a location-specific distribution, any firm specific term is absorbed. One may argue to include a firm's core productivity parameter to shift its plants' productivity as in Tintelnot (2017) such that more productive firm will generate more efficient plants on average. As I demonstrate in Appendix B.2, it is simple to generalize the benchmark model and allow the firm to bear a core productivity term. The qualitative results of the extension remain the same, but incorporating the feature would require additional firm-level data to identify the parameters.[10] Although firms do not endow with core productivity, its selection on plant number and locations actually imply how productive a firm is in general. It will be clear when I characterize a firm's lowest-cost plant. A preview of the intuition is that more plants established in technology advanced locations increase the firm's likelihood in serving a larger fraction of markets. Driven by systematic difference in fixed costs, firms' plant location sets typically vary.

Firms compete in price to supply the good to projects in each market.[11] Each project in a market is served by its lowest-cost supplier. If firms are single-located, the winning firm is constrained not to charge more than the second-lowest cost firm's marginal cost. In the case of multi-located firms, suppose plants are managed by their respective local manager. All managers working for the same firm are headed up by the firm headquarter to coordinate in competition. The winning

A thorough examination and comparison of distributions can be found in Head (2011) and Kotz and Nadarajah (2000).

[10] To estimate the set of firm core productivity parameters, I would need each firm's market share in every market which is not available in the cement data used for my empirical exercise. I welcome researchers who have the relevant data to use the extensive version of the model in the Appendix. Moreover, the cement industry practice suggests that the majority of cement plants are using the state-of-art dry process technology. The share of outdated wet process kilns in global production capacity is merely 5.6% (Cochez and Nijs (2010)). Therefore, it is not necessarily that certain group cement plants are better than the other in terms of production technology.

[11] The competition structure closely depicts the cement industry practice where plants price to the market (Miller and Osborne (2014)). Considering cement being a rather homogeneous product, competing for price instead of quality or other dimensions is rationalized.

plant will not undercut its "sister" plants owned by the same firm, until the next lowest-cost plant is owned by a competing firm. Hence, the price charged is constrained by the marginal cost of the lowest-cost plant owned by the second-lowest cost firm. The competition structure mimics a nested second-price auction, which also makes it easier to solve the model. Instead of fully characterize cost ranking across all plants, what really matter are the lowest-cost plant within a firm and the two lowest-cost firms. By identifying the distribution for each, firms' decisions can be solved in equilibrium.

The Distribution of Lowest-cost Plant within a Firm. The first group of plants matter to the competition is the lowest-cost plant in each firm. It determines which plant ultimately serves the project in a market. I begin by deriving the distribution of a firm's lowest-cost plant for a market.

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

$$\tilde{Z}_{f\ell m}(j) = \frac{Z_{f\ell}(j)}{w_\ell \tau_{\ell m}}.$$

With the Fréchet distributed $Z_{f\ell}(j)$, the c.d.f. of $\tilde{Z}_{f\ell m}(j)$ is thus

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

where $\phi_{\ell m} = T_\ell (w_\ell \tau_{\ell m})^{-\theta}$ indicates the capability of location ℓ serving the market m. Plants' cost-adjusted productivity draws are from the distribution which depends on the origin and destination.

I define the kth highest cost-adjusted productivity (lowest-cost) plant owned by firm f for supplying the good to project j in market m as $\tilde{Z}_{k_{(\ell)} fm}(j)$. For simplification, I suppress subscript ℓ in the ranking and use $\tilde{Z}_{k,fm}(j)$ for later analysis. Given a firm's equilibrium plant location set $\{\mathbb{I}_{f\ell}\}$, its most productive plant for the market m is drawn from

$$\tilde{F}_{1,fm}(z) = \exp(-\Phi_{fm} z^{-\theta}), \tag{3}$$

where $\Phi_{fm} = \sum_\ell \mathbb{I}_{f\ell} \phi_{\ell m}$ refers to the capability of a firm f serving market m. The firm's capability depends on where and how many plants a firm owns. In light of equation (3), the addition of a new location where the firm builds plant increases firm's capability of supplying the good and necessarily lowers its effective marginal cost.[12] Intuitively, an extra production location grants the firm an additional cost draw, and greater competition among plants. Although plants within

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

the same firm coordinate their pricing strategy by not undercutting one another, they still compete for being the lowest-cost supplier to each project. Greater competition among plants reduces the expected minimum marginal cost of the firm. The property of the minimum cost distribution of a multi-plant firm allows me to establish the following result (the proof is straightforward and omitted in the main text).

Proposition 1: An additional location with non-degenerate ($\phi_{\ell m} > 0$) cost efficiency to the firm's active location set shifts the distribution of firm's lowest-cost draw being first-order stochastic dominated, i.e. the value of c.d.f. increases.

Sourcing Probability. After characterizing the lowest-cost plant for each firm, I now derive the probability of a firm or a location successfully supplying the product to projects in markets. With firms' cost distributions in equation (3), the probability that firm f^* supplies to a project in market m is then

$$\mathbb{P}_{f^*m} = \int_0^\infty \prod_{f \neq f^*} \tilde{F}_{1,fm}(z) d\tilde{F}_{1,f^*m}(z) = \frac{\Phi_{f^*m}}{\Phi_m}, \tag{4}$$

where $\Phi_m = \sum_\ell N_\ell \phi_{\ell m} = \sum_f \Phi_{fm}$ denotes the sourcing capability of projects in market m, and N_ℓ is the number of firms producing in location ℓ. For simplicity, I assume there is no fixed cost in exporting, and consequently, every plant can be potential supplier to every project in every market. Hence, the probability that a firm wins the project in a market depends on its relative capability of supplying the good compared to all other competitors. In fact, since all projects in a market are infinitesimal and uniformly distributed on an unit interval, the probability of winning one project ex-ante is the same as the expected proportion of projects in a market to which firm f^* supplies.

Similarly, the probability that location ℓ^* exports to a project in market m is

$$\mathbb{P}_{\ell^*m} = \int_0^\infty \prod_{\ell \neq \ell^*} \tilde{F}_{1,\ell m}(z) d\tilde{F}_{1,\ell^*m}(z) = \frac{N_{\ell^*}\phi_{\ell^*m}}{\Phi_m}, \tag{5}$$

where $\tilde{F}_{1,\ell m}(z) = \exp\left(-N_\ell \phi_{\ell m} z^{-\theta}\right)$ characterizes the distribution of the lowest-cost plant at location ℓ across all firms entered.[13] The probability represents the location ℓ's comparative advantage. The more plants, higher local efficiency, lower input costs and lower trade cost in a location, the higher its capability in supplying the good. Since plants at the same location are ex-ante identical, the probability can also be regarded as a composition of two parts. One is the number of plants located at ℓ^*, and the other is the probability of each plant exporting to market m, ϕ_{ℓ^*m}/Φ_m. Similar to the interpretation of firm-market probability, the probability of one project sourcing from location ℓ^* is the same as the expected proportion of projects in a market sourcing from the loca-

[13] The full notation should be $\tilde{F}_{1_{(f)}\ell m}(z)$, but I suppress the subscript f in ranking.

tion. Different from BEJK which does not have granularity in firms, this paper shows more firms producing in a location increases the probability of it capturing the market.

The sourcing probabilities derived here establish a direct link between theoretical model and empirical trade data. It significantly simplifies the estimation and reduces the computational cost. I defer the empirical transformation to section 4.1.

Conditional Joint Distribution of the Two Lowest Cost Firms. Recall the relevant productivity characterization at firm level is equation (3). Let $\tilde{Z}_{1m}(j)$ and $\tilde{Z}_{2m}(j)$ be the cost-adjusted productivity of the lowest-cost firm and the second-lowest one across all locations for project j in market m. Conditional on the winning plant being (f^*, ℓ^*), $\tilde{Z}_{1m}(j) \equiv \tilde{Z}_{1,f^*m}(j) = \tilde{Z}_{f^*\ell^*m}(j)$ and $\tilde{Z}_{2m}(j) \equiv \max_{f \neq f^*}\{\tilde{Z}_{1,fm}(j)\}$. I show in Appendix A.1 that the conditional joint density is

$$f_{12,m}(z_1, z_2; \ell^*, f^*) = \Phi_m(\Phi_m - \Phi_{f^*m})\theta^2 z_1^{-\theta-1} z_2^{-\theta-1} e^{-(\Phi_m - \Phi_{f^*m})z_2^{-\theta}} e^{-\Phi_{f^*m} z_1^{-\theta}}, \tag{6}$$

given $z_1 > z_2$.

Notice that the conditional joint distribution is independent of ℓ^*. Hence, when firm f^* is the supplier to projects in market m, the distribution follows equation (6) regardless of which plant the good originates. The density can be generalized to $f_{12,m}(z_1, z_2; f^*)$, as conditioning on the supplying firm f^* only. The rationale is that the cost ranking among plants within a firm does not matter to the game except for determining the firm-level minimum cost.

The conditional joint density nests equation (14) in Holmes et al. (2011) which is the single-plant version of the model. Unlike BEJK which assume infinite number of firms, subtracting one firm's capability Φ_{f^*m} from all firms' Φ_m does make a difference to the joint distribution. Therefore, we could expect that the number of firms and firm identities determine the markup distribution and expected profits in my model, as in Holmes et al. (2011) and De Blas and Russ (2015), but not in BEJK.

The Price and Markup Distribution. As described in the competition structure, the lowest-cost supplier is constrained not to charge more than the lowest cost of the second-lowest firm supplying the market. With the isoelastic demand, profit maximization of a monopoly also implies the lowest-cost supplier would not want to charge a markup higher than $\bar{\mu} = \eta/(\eta + 1)$. Hence the price of project j in market m is

$$P_m(j) = \min\{\frac{1}{\tilde{Z}_{2m}(j)}, \frac{\bar{\mu}}{\tilde{Z}_{1m}(j)}\}. \tag{7}$$

The corresponding price distribution varies by firm and is

$$F_m^p(p; f^*) = 1 - \frac{\Phi_m}{\Phi_{f^*m}} e^{-(\Phi_m - \Phi_{f^*m})p^\theta} + \frac{\Phi_m - \Phi_{f^*m}}{\Phi_{f^*m}} e^{-\Phi_m p^\theta} + \frac{\Phi_m}{\Phi_{f^*m}} - \frac{\Phi_m}{\Phi_{f^*m}} e^{-\Phi_{f^*m}\bar{\mu}^{-\theta} p^\theta} \quad (8)$$

conditional on firm f^* supplies to market m with derivation shown in Appendix A.2. The price distribution implies that a firm more capable of producing and transporting the good lowers the average price charged. Since expanding the set of production locations will decrease the firm's marginal cost as shown in proposition 1, the pass through will be one considering only the constant monopoly markup and less than one if the second-lowest cost is binding and remains the same. A closer look at equation (8) reveals that the first three terms are attributed to the cost ladder, while the last two terms are derived from the probability to charge monopoly price. Disregard either part of the constraint will lead to a higher price on average.

A further observation is that the price distribution for each plant is identical within a firm. Hence, the sourcing probability (quantity share) is the same as expenditure share at firm-market level as in Eaton and Kortum (2002). The property is handy empirically when firm sales are observed in every market and a standard firm-level gravity trade regression can be applied. However, at market level across all firms, because prices charged by each firm are distributed differently, the distribution of price paid for projects in market m depends on the realized supplier.

The markup equals $\mu_m(j) = \min\{\bar{\mu}, \tilde{Z}_{1m}(j)/\tilde{Z}_{2m}(j)\}$. Conditional on firm f^* serves market m, the markup is the realization of a random draw from a Pareto distribution truncated at the monopoly markup,

$$F_m^\mu(\mu; f^*) = \begin{cases} 1 - \frac{1}{(1-\mathbb{P}_{f^*m})\mu^\theta + \mathbb{P}_{f^*m}} & 1 \leq \mu < \bar{\mu} \\ 1 & \mu \geq \bar{\mu} \end{cases}. \quad (9)$$

See Appendix A.3 for derivation. Recall in equation (4), $\mathbb{P}_{f^*m}$ is market m's sourcing probability from firm f^*. Essentially, what solely matters in deciding a firm's markup is the fraction of market a firm is expected to capture, the extensive margin. Specifically, for $1 \leq \mu < \bar{\mu}$, a firm owning more plants in locations with production advantage charges higher markup. For $\mu \geq \bar{\mu}$, I compute the probability of firm f^* charging monopoly markup given the second-lowest cost,

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

Therefore, knowing that the otherwise price charged will be z_2, the firm has a higher chance to exploit the maximum markup if it is more capable of supplying the product through plant allocation. This is intuitive since the marginal costs of these firms are lower and the difference in cost with the next competitor is too big to be optimal in pricing. A related result is that wider dispersion in plant productivity also increases the likelihood of charging the monopoly price.

The markup distribution again generalizes what is in the single-plant firm model, equation (15) in Holmes et al. (2011). In the case of infinite number of firms competing head-to-head, the markup distribution converges to that in BEJK, $1-\mu^{-\theta}$. To summarize results in the following proposition,

Proposition 2: (i) An additional location with nondegenerate ($\phi_{\ell m} > 0$) cost efficiency to the firm's active location set shifts the firm's price distribution being first-order stochastic dominated, i.e. the value of c.d.f. increases; (ii) An additional location with nondegenerate ($\phi_{\ell m} > 0$) cost efficiency to the firm's active location set shifts the firm's markup distribution in a first-order stochastic dominance sense, i.e. the value of c.d.f. decreases; (iii) cost pass-through is incomplete.

2.2.2 The expected profit and choice of plant locations

The firm chooses the set of plant locations to maximize its expected total profit. To complete the expected total profit function, I first derive the expected variable profit from all of the firm's plants to all markets, with details presented in Appendix A.4 and A.5.

Combining the market demand, the firm's pricing strategy, and its probability in supplying to a market, I have the expected sales to market m for such a firm as

$$\mathbb{E}\big[R_{fm}\big] = A_m \kappa \hat{R}_{fm},$$

where the market demand scaler $A_m = \exp(\alpha_m)$, constant $\kappa = \Gamma\left(\frac{\theta+\eta+1}{\theta}\right)$, and

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

Analogously, the expected marginal costs for a firm in selling the good to market m is

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

where

$$\hat{C}_{fm} = \Phi_{fm} \times \Bigg[(\theta+\eta+1)(\Phi_m - \Phi_{fm}) \int_1^{\bar{\mu}} \mu^{-\theta-2}\left(\Phi_m - (1-\mu^{-\theta})\Phi_{fm}\right)^{\frac{-\eta-2\theta-1}{\theta}} d\mu \\ + \bar{\mu}^{-\theta-1}\left(\Phi_m - (1-\bar{\mu}^{-\theta})\Phi_{fm}\right)^{\frac{-\eta-\theta-1}{\theta}}\Bigg]. \tag{10}$$

Consequently, the firm's expected variable profit is

$$\mathbb{E}[\pi_f] = \sum_m A_m \kappa \left(\hat{R}_{fm} - \hat{C}_{fm} \right).$$

The expectation is taken over random productivity draws for all plants and projects. Clearly, the variable profit depends on the capability of supplying the good for all of the firm's plants and its competitor's, and more importantly, each plant is not separately additive. Plants' cannibalization defines the plant location problem to be combinatorial optimization. In an example of L potential locations and F number of oligopolists, there are 2^{FL} feasible combinations of allocations.

A multi-plant firm incurs fixed costs for setting up plants, $\{FC_{f\ell}, \forall \ell\}$.[14] I allow the fixed costs to vary by plant to partially compensate the omission of firm-level marginal cost shifters. For different firms, expecting plants to be identical at the same location, what drives one firm to have more plants than the other is having lower fixed costs on average. The exact location choices of plants, however, is a complex decision considering local demand and surrounding markets, location efficiency and input costs, trade costs between every dyads, and competition from other firms, summarized by the expected total profit. Firms then decide on a set of plant locations $\{\mathbb{I}_{f\ell}, \forall \ell\}$ such that the expected total profit,

$$\mathbb{E}[\Pi_f] = \mathbb{E}[\pi_f] - \sum_\ell \mathbb{I}_{f\ell} FC_{f\ell} \tag{11}$$

is maximized.

In general, combinatorial discrete choice problem could have multiple sets of choices to be optimal for the firm. In this model, because the profit function satisfies single crossing differences condition, Eckert et al. (2017) proves that it guarantees a unique location set for the firm. For a multi-player game, the profit function forms a best-response potential game, and therefore reaches a pure strategy Nash equilibrium. Further details in section 4.4 and the appendix.

Lastly, I close the model with the market-level price index, which is a composite of prices that

[14]There is a strand of literature concerning greenfield entry versus merger and acquisition. The one that is particularly related to the cement industry is Perez-Saiz (2015). However, the case of M&A need not to be fundamentally different from my benchmark model. Acquisition price can be seen as the fixed cost, except the case that the acquisition price depends on the sellers residual value that is past dependent. If then, fixed costs are also endogenous and need to be solved using a dynamic model.

all potential firms charge to projects in market m.

$$\begin{aligned} P_m &= \sum_f \mathbb{E}[P_{m|f}] \times \mathbb{P}_{fm} \\ &= \Gamma\left(\frac{\theta+1}{\theta}\right)\Phi_m^{-1/\theta} \times \left[(1-N_f) + \sum_f \left(1-(1-\bar{\mu}^{-\theta})\mathbb{P}_{fm}\right)^{-1/\theta}\right], \end{aligned} \tag{12}$$

where N_f is the number of potential supplier to market m.

3 Data and Industry Background

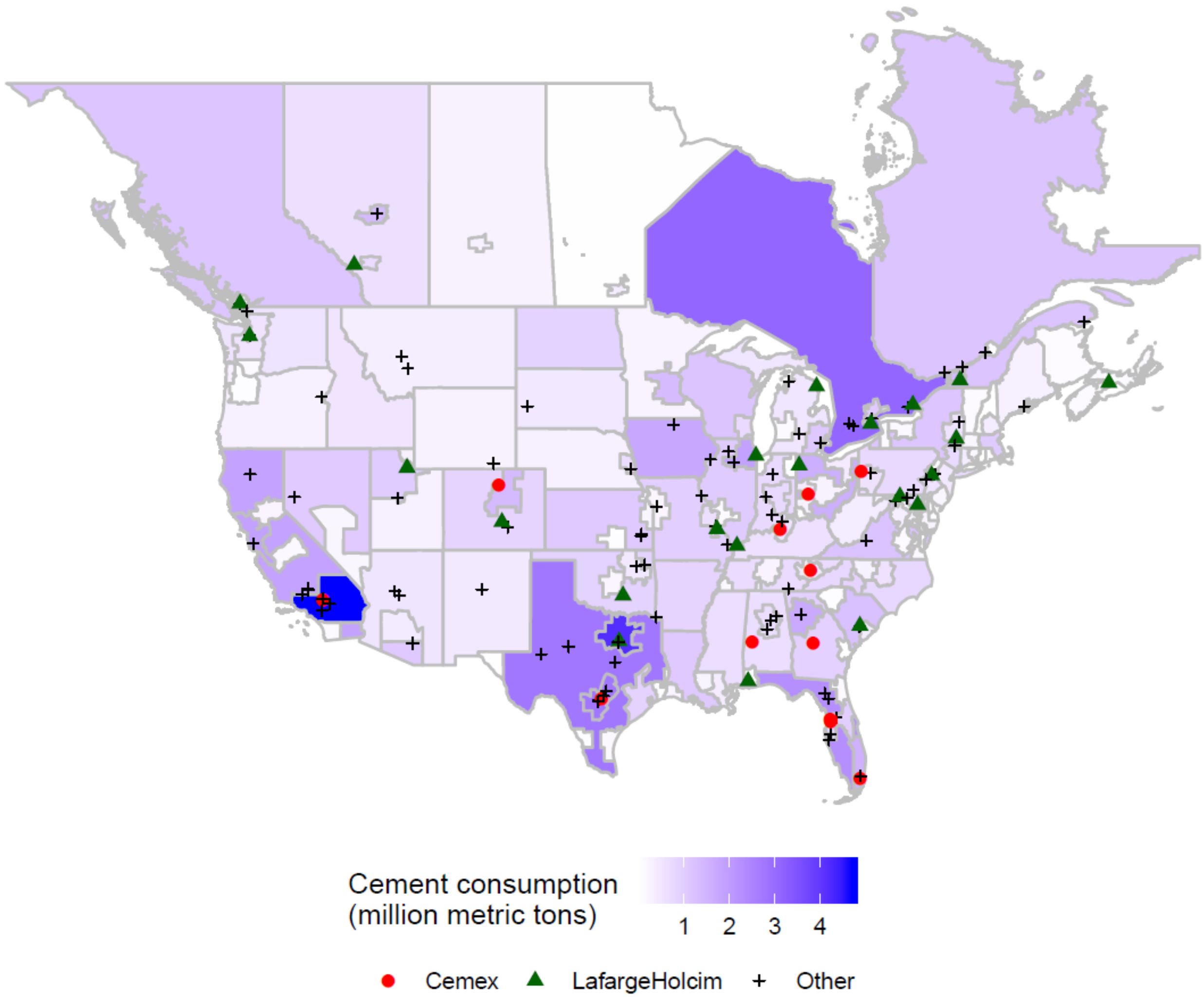
3.1 Data Description

I apply the model to the cement industry. Rather than analyzing cement trade and plant location choices on an international scale, I focus on examining the portland cement industry across contiguous US states and the part of Canada that border the US which have more active commodity flow. Locations and markets are zones defined in Freight Analysis Framework (FAF), in which they include census agglomeration, census metropolitan area, rest of province/state, province/state across Canada and the US. There are four main sets of data. The data on cement plant locations come from Global Cement Report published by International Cement Review. The directory covers 2108 operating cement plants in 2016 across 161 countries. For each plant, the directory lists its name, ownership, location, and capacity. Unfortunately, without information on plant opening year nor closed plants, I take the snap shot of plant location configurations in 2016 as the equilibrium. The data is post merger of Lafarge and Holcim in 2015. There has been strategic divestment of plants following the merger of Lafarge and Holcim to eliminate unoptimized locations after the ownership changed, and those exited plants no longer appear in my plant-level data. Other M&A activities, such as the acquisition of Italcementi by Heidelberg is announced by the end of 2016 and the plants have yet been reshuffled until later years. Furthermore, the past decades in the U.S. and Canada feature a period of time when few cement plant enter but more exits due to outdated technology. By 2016, more than 90 percent of the cement plants are upgraded with the new technology. Hence, although the plant-level data is cross sectional, the year of 2016 captures a time when major changes in the cement industry have been completed to reach a relatively stable equilibrium. With the plant ownership data, I can identify all the multi- or single-plant firms in these markets. The two main players are LafargeHolcim and Cemex, competing with a set of local firms and small multinationals.[15] Figure 2 shows the location distribution of cement plants across

[15]Heidelberg is also a main player in the US and Canada. However, as it is prior to a major acquisition shock and not as large as LafargeHolcim and Cemex pre-merger, it is less suitable for the equilibrium analysis.

the 149 FAF zones in the sample, together with the cement consumption indicating market size. Among 121 cement plants, 104 of them are in the US and the rest in Canada. LafargeHolcim and Cemex control 34 plants out of the total, which shows that there are still a large number of fringe plants belonging to the other 24 firms. Los Angeles and Dallas are two most cement-consumed markets.

Figure 2: Cement plant location distribution and market consumption



Cement shipping flow for each FAF zone dyads is computed from Freight Analysis Framework by U.S. Department of Transportation, Canadian Freight Analysis Framework by Statistics Canada, and US Geological Survey database (USGS). Due to limited data on trade across FAF zones, assumptions are made in order to disaggregate trade from state/province level to FAF zone level. Details of computing the implied trade flow is provided in Appendix D.1. The estimation also uses bilateral cement trade at country level which is obtained from UN Commodity Trade Statistics Database.

Gravity variables, such as distance, tariff, whether two FAF zones are adjacent, belong to the same state/province or the same country, whether two countries share the same language, belong to the same Free Trade Agreement, are collected from various sources. At FAF zone level, distance is measured as great-circle distance between the zone center. Within a zone, internal distance is measured as great-circle distance between the northeastern boundary and the southwestern boundary. At country level, I uses CERDI-seadistance database and shipping days measured in Feyrer (2018). The former computes sea distance as the shortest sea route between two highest traffic ports in respective country, and landlocked countries are associated with the nearest foreign port. The later calculates round-tripe shipping days between primary ports for each bilateral pair assuming an average speed of 20 knots with adjustments. Tariff data is from World Integrated Trade Solution by World Bank. Other gravity variables are sourced from CEPII research center.

To estimate demand, I collect input costs from various sources (US Energy Information Administration, US Quarterly Census of Employment and Wages, Statistics Canada, Natural Resources Canada, USGS Quebec Hydro) to construct instrument variables, including durable goods manufacturing wage, limestone prices, natural gas and electricity prices. Demand shifters including population and units of building permit issued are also collected from US Census and Statistics Canada.

3.2 Industry Background

Portland cement is used to manufacture concrete. It is a fine mineral dust that acts as the glue after mixed with water to bind the aggregates together. Concrete, in turn, is the most-used manufactured input to many construction and transportation infrastructure due to its affordability, strength, resilience to fire, floods, pests, and flexibility to produce complex and massive structures. Cement comprises 10 to 15 percent of the concrete mix, by volume.

Different raw materials, such as limestone, sand and clay, are mixed and ground into a powder, from which clinker is produced in kilns that can reach peak temperatures of 1400-1450° Celsius (Miller and Osborne 2014). The final output, cement, is produced by grinding clinker with gypsum or small amounts of other components to control its properties. There are two types of technology involved in clinker production, "wet" or "dry", depending on the moisture content of raw materials. The wet process is more energy intensive as the moisture needs to evaporate, and thus gradually phased out during the past decades. Currently, around 93 percent of the cement produced in the United States is manufactured through the dry process according to the survey by Portland Cement Association.

Although being a rather homogeneous product, cement is still vertically differentiated. Each type of cement has its properties, uses, and advantages based on composition materials used during its manufacture. For example, Portland pozzolana cement is prepared by adding pozzolana to the 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 the early days and used in road works. Sulfate resisting cement is used in construction exposed to severe sulfate action by water and soil in places like canals, culverts, retaining walls, etc.

This paper draws on several key industry features.

3.2.1 Cost and pricing of the industry

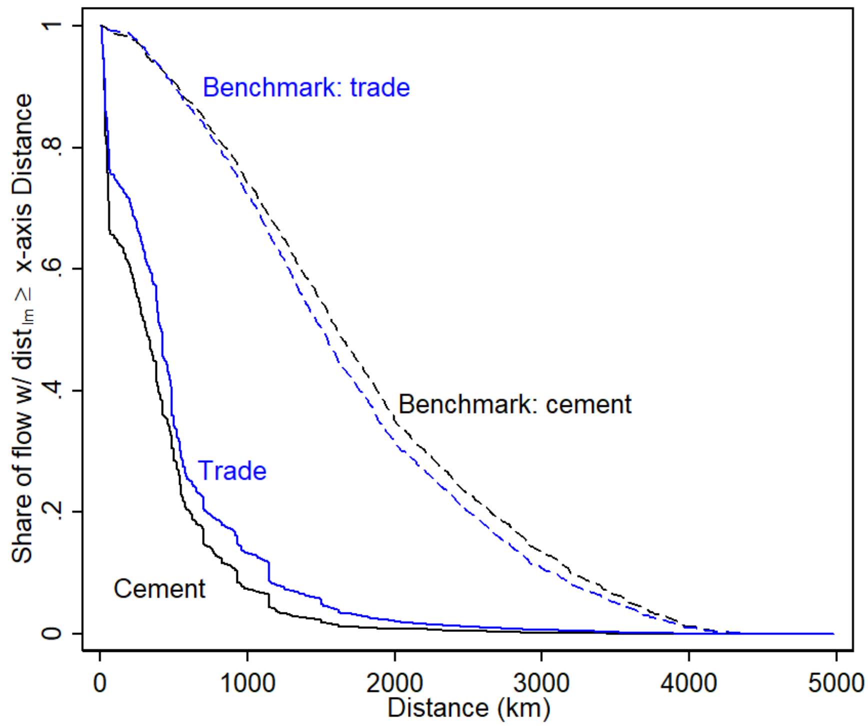
The main costs occurred for a cement plant are variable cost for materials, fuel, labor, maintenance, fixed cost of building the plant, and trade cost for delivery. According to a company report by LafargeHolcim, raw materials, energy, and labor each accounts for a third of the total variable costs. Ryan (2012) has developed a workhorse dynamic model to estimate maintenance cost in the form of shadow cost when cement production approaching capacity limit of 87 percent utilization rate. However, the USGS database shows that none of the survey region in the U.S. exceeds a plant utilization rate of 80 percent and the average is merely around 65 percent in 2016. I hereby focus on other costs in this paper.

The bulk (around 85 percent) of the intermediate inputs for cement manufacturing is limestone (Van Oss and Padovani 2003). Since the transportation cost of limestone from quarries to cement plants is high, cement firms mostly use limestone extracted from quarries nearby and transport the limestone using a belt conveyor, truck or marine. It is natural for one to mistakenly assume that cement plant location is entirely determined by locations of limestone quarries. I show in Appendix D.3 that limestone is available throughout the country so that the upstream constraint in cement plant location is not binding in general. At the upstream, there are around 3000 limestone quarries and at the downstream, there are more than 5000 ready-mix concrete plants (US Geological Survey, US Census). Cement plants try to position closer to some limestone quarries while taking the market demand and competition into account. I model the upstream consideration into costs of materials embedded in a composite measurement, local cement production capability.

The second set of cost is fuel cost, either coal, gas, or oil. Since cement production requires extremely heated kilns (approximately 3 to 6 million Btu per ton of clinker), substantial amount of coal, gas, or oil is burnt to provide such energy (Van Oss and Padovani 2003). The extensive energy usage in this industry is also accompanied with environmental concern and policy intervention. In response, there has been attempts by firms to optimize fuel usage by improving technology and shifting fossil fuels to more environmentally friendly substitutes but the process is slow and gradual. In this paper, I am examining the effects of environmental policy on firms' location, production and pricing strategies through manipulating fuel costs while holding the fuel type and combustion efficiency the same.

Other than variable cost of production, building cement plant requires great amount of fixed cost investment. Therefore, cement plants are scarce and suitable for modeling as discrete location choices, unlike the case of limestone quarries or ready-mix concrete plants. Past literature as well as firm accounting records has reported that the fixed cost for building a one million tonne cement plant is around $200 million (Ryan 2012; Fowlie et al. 2016; Salvo 2010). Firms, therefore, face the trade-off between paying fixed costs if build plants and bearing trade costs if export.

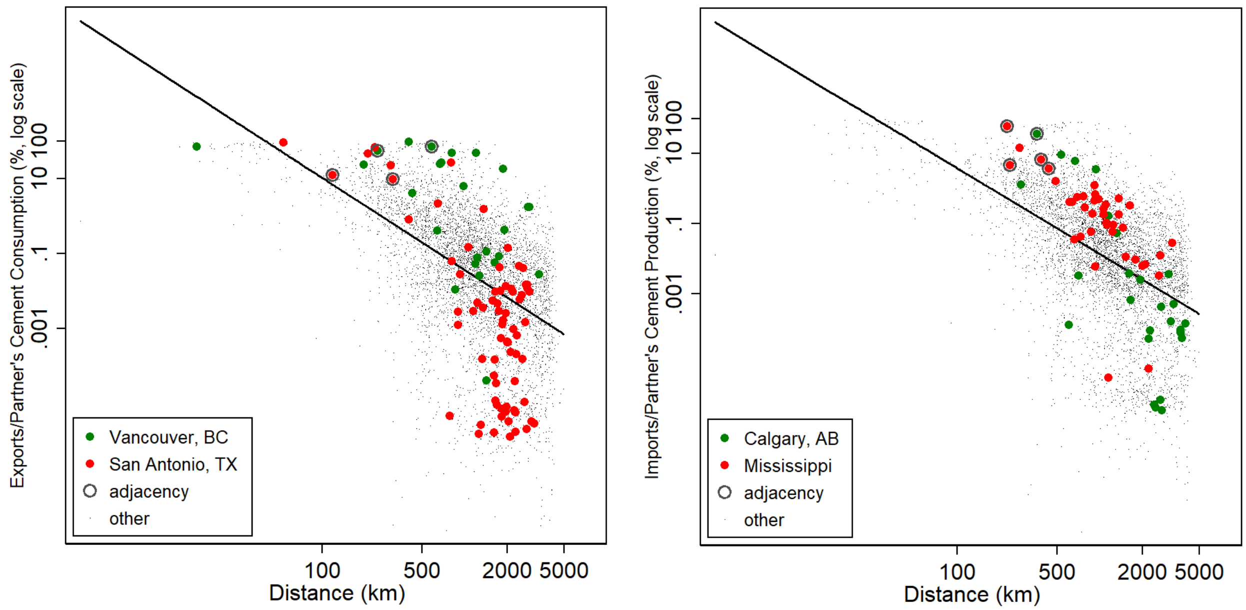
Figure 3: Distribution of distances for cement and trade in goods



Trade cost is relatively high considering cement as a low value-to-weight product. They are typically shipped by truck across the US and Canada. Figure 3 shows how trade decreases with distances in our sample, and compare with the benchmark frictionless trade case where each origin is equally likely to export to a destination regardless of distance. Compared to the total manufacturing trade, cement trade is more elastic to the increasing distances. Half of inter-FAF cement trade is transacted within 300 kilometers, whereas the distance is extended to 420 kilometers for manufacturing goods in general. Furthermore, there is still about 10 percent cement trade occurred beyond 900 kilometers, indicating cement can trade in long distance despite being viewed as a localized product in literature. Decrease in cement trade with distance is also shown by the negative correlation in Figure 4. Contiguous partners trade more with each other.

Given the aforementioned costs in production and delivery of cement, firms price to the market. Customers select the supplier with best price available.

Figure 4: Inversely proportional cement trade to distances



(a) Exports (b) Imports

3.2.2 Highly concentrated market with multi-plant oligopolists

The Portland cement industry is highly concentrated with few multi-plant oligopolists, both at the international and US-Canada regional markets. Prior to 2015, the global cement production is dominated by five largest multinational corporations, namely Lafarge, HeidelbergCement, Holcim, Cemex and Italcementi. Since 2015, there has been major consolidation in this industry led by the merger between Lafarge and Holcim and subsequent acquisition of Italcementi by HeidelbergCement. The active mergers and acquisitions provide us with the great opportunity to access their effects on the industry, which I will address as one of my quantitative applications in section 5.3.

In 2016, top four companies in each of the 161 countries on average collectively control 90 percent of cement capacity, with 146 out of 161 countries having a four-firm concentration ratio over 60 percent. Specifically, in the U.S. and Canada, the four-firm concentration ratio in terms of cement capacity at national level is 51 and 86 percent, respectively. There are at most four cement plants in a single FAF zone. LafargeHolcim and Cemex, the two players I studied in the empirical section, in total accounts for 32 percent of the US and 30 percent of the Canadian cement market measured in capacity.

In the international market, the past literature by Bernard and others has well documented findings about multinational firms participating along multiple margins of international activities. At the regional level, the patterns remain the same for multi-plant firms. Largest cement firms not only produce in more locations, own more plants, but also have greater production capacity within

Table 1: Distribution by plant and FAF zone

Panel A: Percentage of firms

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

Panel B: Percentage of capacity

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

Panel C: Percentage of plants

Number of plants	Number of FAF zones				
	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**

each location. In Table 1, I report joint distributions for 26 cement firms by the number of plants owned and the number of production locations entered in the sample covering the US and Canada. Panel A reports the distribution of cement firms; panel B reports the distribution of market share measured in capacity; and panel C reports the distribution of market share measured in number of plants owned. Comparing results across three panels, around 35 percent of cement firms is highly localized with a single plant at one FAF zone. The single-plant firms account for only 6.5 percent of production capacity and around 7 percent of cement plants. On the contrary, 3 firms that own 11 or more plants across 11 or more FAF zones control around 41 percent of production capacity and similar share of plants overall. The positive correlation across different margins of multi-plant firms' operation ensures that the market is dominated by few firms. Along the intensive margin, Table 2 shows the average market share within locations where firms enter measured in capacity. FAF zones with only one firm is excluded to separate the impacts from extensive margin. The last row demonstrates that firms having plants in more locations generally obtain larger market share within each location through building larger plant. Similar interpretation for firms owning more plants can be drawn from the last column in the table.

Table 2: Average market share by plant and FAF zone

Number of plants	Number of FAF zones				
	1	2-4	5-10	11+	**Mean**
1	29.7	0	0	0	**29.7**
2-4	0	39.2	0	0	**39.2**
5-10	0	37	38.3	0	**38.1**
11+	0	0	0	47.1	**47.1**
Mean	**29.7**	**38.9**	**38.3**	**47.1**	**36.6**

Market share is measured by production capacity. Only FAF zones with more than one firm located are included in this table.

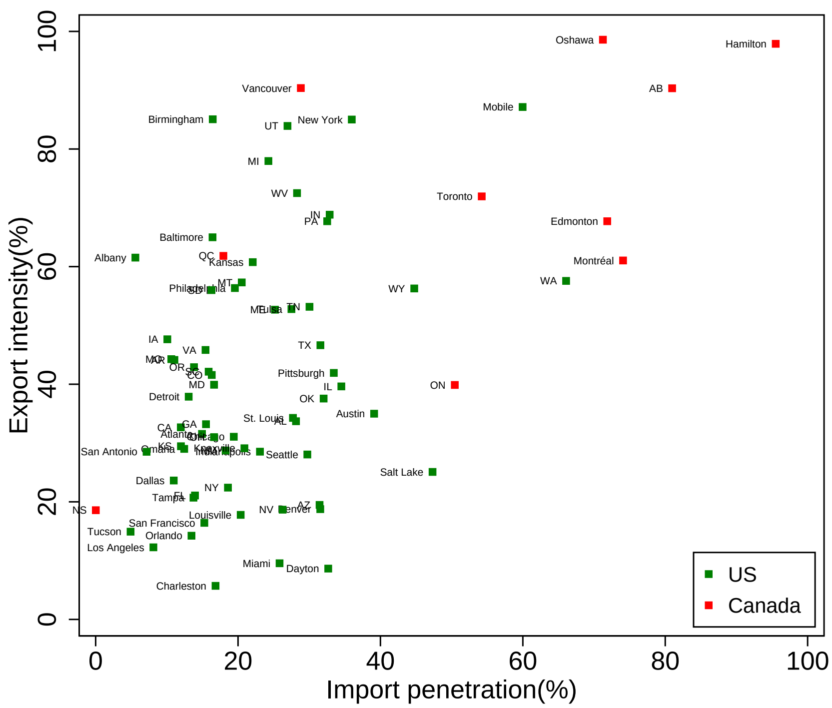
Although the top three multi-plant firms play a significant role across the US and Canada, the group of local and smaller cement firms is too big to ignore. These fringe firms collectively control 60 percent of the cement market and an average of 35 percent within each location. A large multi-plant firm faces potential competition from the fringe firms when deciding whether to build a plant or not.

3.2.3 Active shipping flow

Cement trading represents a vital part of the industry. As fixed cost of setting up cement production facilities is high, it is rather difficult to adjust the capacity once it has been the built. The kiln is typically running at its peak capacity once operated for technological reasons. Output is adjusted based on the operation duration instead. In terms of cement storage, it requires maintaining certain atmospheric moisture content and other precautions due to the nature of cement. Therefore, the stickiness in production and difficulty in preservation create friction in cement supply. Cement demand, on the other hand, can be cyclical depending on the infrastructure need and economic condition. The interaction of these factors leads to surpluses and shortages across markets, which requires cement trade to iron out.

Before the US housing bubble, the cement trade share out of world production can reach as high as nearly 8 percent. Although cement trade has suffered sluggish recently and the international trade share drops to 4 percent, regional trade in cement remains to be active. Across Canada and the US, not every FAF zone has positive cement production. In fact, out of the 149 FAF zones in my sample, only 73 of them have at least one cement plant, whereas the rest are entirely supplied through imports. Multiple factors interact resulting in the vacant area without any cement plant, such as limited limestone resource, low local demand of cement. I include and examine these factors in the model section of the paper. Figure 5 shows the export intensity and import penetration distributed across the 73 FAF zones with cement production. On average, a zone exports around 44% of its local production and imports around 27% of its cement consumption.[16] The positive correlation between export intensity and import penetration ratio suggests intra-industry trade in cement across locations. I exploit plants heterogeneity and plant-location idiosyncratic shock to explain intra-industry trade pattern.

Figure 5: Cement trade intensity, 2016



Multi-plant firms take the possibility of cement trade into consideration when deciding the set of locations to built plants. Since a plant does not only serve the local market, but also acts as export platform, the entire set of potential locations and markets form a network where whatever happens to one location has influence on the others. Therefore, the plant locations of a multi-plant firm are interdependent on one another, making the problem combinatorial discrete choice.

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

3.2.4 Carbon dioxide emissions and environmental concern

Cement production is one of the largest manufacturing sources of carbon dioxide emissions. For every tonne of cement produced, around 0.8 tonne of carbon is released into the atmosphere, which is almost equally contributed by combustion of fuels and chemical reactions when converting limestone to calcium oxide (Van Oss and Padovani 2003, Kapur et al. 2009). With significant CO_2 emissions, the cement industry has been at the center of the debate about environmental regulations. Carbon policies could lead to major changes to the industry's cost structure, and subsequently affect firms' operating decisions worldwide. To reduce carbon emission, governments impose regional climate change policies. However, they tend to be classic examples of incomplete regulation when only a subset of sources that contribute to the environmental problem are controlled and cause market distortion as well as emissions leakage. Specifically, carbon leakage is referred to shifts in production of CO_2-intensive goods to other non-regulated regions but emissions damages are independent of the origin (Copeland and Taylor 2005, Fowlie et al. 2016). Several papers have found that emissions leakage indeed exists and will offset domestic emissions reductions and result in social welfare losses, such as Fowlie (2009), Aichele and Felbermayr (2015) and Fowlie et al. (2016). In particular, Fowlie et al. (2016) which also focuses on cement industry found that certain carbon tax can create significant welfare losses as much as \$18 billion. To access the effect of environmental policy, I will perform a counterfactual analysis in section 5.1.

4 Estimation

A firm's decision is to choose the set of production locations from a potential set of 149 FAF zones across the US and part of Canada, and then decide which market to supply from where. Firms' objective is to maximize total expected profit shown in equation (11). The firm's profit depends on endogenous demand Q across all markets, efficiency T and input costs w across all locations, trade costs τ for each location-market combination, the dispersion parameter θ which governs plant productivity, and the fixed costs of setting up plants FC. The expected payoff varies across firms due to their location choices $\mathbb{I}$ and differentiated fixed costs. I use the firm-level data in conjunction with aggregated market and location data to recover the key parameters of the model.

The estimation is performed in a three-step procedure to reduce the dimensionality of solving the problem. First, I use a gravity-type regression to estimate each location's production capability, trade costs and plants' productivity dispersion parameter. The sourcing probability derived from the model provides a natural link between theoretical implication and the bilateral trade data. With the estimates and observed plant locations, market price index is then formed conditional on the unknown price elasticity. Next, I project the observed market demand on the predicted price index and other demand shifters to estimate the price elasticity using nonlinear least squares with instruments. In the final step, I combine the expected variable profit with the simulated fixed cost draws to obtain the total expected payoff as a function of plant location choices and fixed costs parameters. What has been obtained in the first two steps are critical for constructing the expected variable profit conditional on a location configuration. Maximizing the firm's total expected profit while matching the estimated optimal location set to the actual ones, uniquely identifies fixed costs parameters via the method of simulated moments. To solve the combinatorial discrete choice problem, I adopt the algorithm developed by Eckert et al. (2017) in a L-location, two-agent game setting. Essentially, generating a gravity trade equation enables a decomposition of the seemingly complex estimation to tractable steps.

Besides the separability in estimation, the framework also allows me to identify parameters using rather aggregated data. The only firm-level data I use here are plant location and ownership, which are widely available across industries and countries. Other firm-level data for which the access is more limited, such as market share or shipping flow, is not necessary in estimation. Therefore, the theoretical model and estimation method proposed here broaden the toolkit of studying many other questions associated with multi-plant firm as well.

4.1 Step 1: Estimation of location production capability, trade cost, and plant productivity dispersion

I specify trade costs as a function of observable determinants, denoted $\mathbf{X}_{\ell m}$.

$$\tau_{\ell m} = \exp\left(\mathbf{X}_{\ell m}^{\prime} \beta^{\tau}\right), \tag{13}$$

where β^{τ} is a vector of the primitive trade cost parameters. The vector $\mathbf{X}_{\boldsymbol{\ell}\mathbf{m}}$ includes the standard explanatory variables used in gravity equations: distance, contiguity, whether the dyads are located at the same state, province, or country.[17] These variables have been shown to matter for trade flows in the past literature.

The first step is to estimate each location's production capability summarized by the term $T_{\ell} w_{\ell}^{-\theta}$, trade cost parameters β^{τ} and the plants' productivity dispersion θ. To do so, I take the plant location as given and exploit differences in trade originated from other attributes vary by locations, such as technological efficiency, input costs, and trade costs. Recall that equation (5) provides the probability of market m sourcing cement from location ℓ, which is the location's comparative advantage to all the market's potential suppliers. Empirically, the model-predicted sourcing prob-

[17]Between different FAF zones, distance is measured by the great-circle distance between the center of each FAF zone. Within a FAF zone, internal distance is measured by the great-circle distance between its Northeast and Southwest corner. Both types of distances are included in the regression.

ability can be mapped to the quantity share of export from ℓ to m in total consumption of market m, i.e. $\mathbb{P}_{\ell m} = \frac{Q_{\ell m}}{Q_m}$. Transform equation (5) to its estimable version,

$$\frac{Q_{\ell m}}{Q_m} = \exp\left[\mathrm{FE}_\ell + \mathrm{FE}_m - \theta \mathbf{X}'_{\ell m}\beta^\tau + \epsilon_{\ell m}\right], \tag{14}$$

where the location fixed effect $\mathrm{FE}_\ell = \ln\left(N_\ell T_\ell w_\ell^{-\theta}\right)$, and the market fixed effect $\mathrm{FE}_m = -\ln \Phi_m$. The equation is estimated using Poisson Pseudo Maximum Likelihood (PPML) due to the consistency it delivers under very general conditions and its capability of incorporating zeros as clearly explained in Silva and Tenreyro (2006) and Head and Mayer (2014).

The sourcing probability here is directly associated with trade share in volume. To build the connection between sourcing probability and trade value which is most widely available, price distribution needs to be considered. As seen in equation (8), the price distributions are the same for cement supplied from firm f to market m regardless of the firm's plant locations, but they are different at market level across all firms. Therefore, the sourcing probability is also expenditure share at firm-market level. The property becomes very handy with firm-market shipping data. However, without firm-level data but only trade across FAF zones in this paper, I am not able to use cement shipping value for gravity estimation.

Three issue occur when estimating equation (14). One is that θ cannot be separately identified from β^τ. To deal with the first issue, I apply the gravity regression to country-level data and include tariff, whether the two countries share the common language, belongs to the same regional trade agreement (RTA) as additional observable. Distance at the country level is replaced with proxies to sea distance as explained in section 3.1 to reflect the fact in sea-borne trade. 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 $-\theta$.[18] The trade cost parameters β^τ can be recovered through dividing the estimated elasticities with the FAF-zone sample by the effect of tariff. Estimating the trade elasticity at different level of data is justified because the model provides nice aggregation properties such that trade elasticity remains to be θ even at country level.

The second and more important issue is that N_ℓ embedded in the estimated location fixed effects reflects the equilibrium plant location configuration that have yet been solved. The endogeneity of plant locations jeopardizes the separability in estimation which could otherwise significantly increase the computational cost. If I were to calibrate firm entry and all other costs simultaneously

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

to data on bilateral trade flows and observed plant locations, I would also need to make parametric assumptions on the local efficiency and input costs which could potentially suffer from misspecification. To address the problem, I substitute N_ℓ with the data on the number of firms producing in the FAF zone ℓ and then use it to divide the estimated fixed effect. The composite of the location's efficiency and input costs, $T_\ell w_\ell^{-\theta}$, is then inferred from the observed equilibrium number of plants built there and its overall capability in producing cement. The validity of this approach relies on local characteristics such as institutional quality, raw material, labor or fuel costs being the economic conditions exogenously given and not determined by the plants spatial allocation. Consequently, using the observed plant configuration instead of model-predicted ones is enough to back out the underlying location characteristics. The assumption is consistent with my model being partial equilibrium without general outcomes on income or factor markets.

The last issue is that there are only 73 out of the 149 FAF zones having positive cement production. Hence, running the trade regression can only recover the location fixed effect for 73 FAF zones. Firms' objective is then built upon the expected profitability of the 73-zone subset selling cement to all the markets. So are the firm's potential production locations. The assumption is isomorphic to imposing infinite production cost of cement at other FAF zones.

After the first step, I obtain estimates of the efficiency and input costs of each location, trade costs and dispersion parameter of the plant productivities. The effect of these components on firm profits depends on the price elasticity, η. I now turn to estimating the demand.

4.2 Step 2: Estimation of demand

To estimate demand featured in equation (1), I combine it with the market price index derived from the model. Recall in equation (12), the market price can be constructed using what has been estimated in the first step (i.e. location fixed effects, trade cost and plant productivity dispersion parameter), the number of firms and their plant locations, and the unknown price elasticity η that shapes a firm's markup. Since η enters the demand function non-linearly, I apply Generalized Method of Moments (GMM) with instruments for price. The model provides a channel explaining the endogeneity of price which comes from firms' entry decisions in response to consumer demand. I use the average of input costs domestically and in nearby locations as price instruments, weighted by the trade costs inverse. The input costs include durable goods manufacturing earning, limestone prices, natural gas and electricity prices. Other demand controls are population in each FAF zone and the number of building permit on new privately-owned residential construction units.[19]

In implementation, the demand is estimated using a panel data across the 149 FAF zones from 2012 to 2016. Although the data on cement consumption, demand and cost shifters are available

[19]The cement is also widely used for non-residential, commercial construction projects. Unfortunately, data on the volume of non-residential construction activities is unavailable for my sample.

for this period, cement plant location data is limited to year 2016, which makes the estimation prone to measurement error. Using instruments mitigates such problem.

The baseline estimate is consistent with the multi-plant firm model. To corroborate the finding, I also estimate the demand using a more "reduced-form" approach with data to approximate cement market price instead of deriving it from the economic primitives. The market-level cement price data is provided by the USGS based on survey area. The classification of price survey area is wider than FAF zones, consisting 28 states/provinces and clusters of them. Again, I leverage on the instruments to address the issue of measurement error and price endogeneity.

4.3 Step 3: Estimation of fixed costs

Having estimated the input costs and efficiency in each location, trade costs and parameters that govern the plant productivity distribution and market demand, the last step is to solve for firms' optimal location sets and estimate the fixed costs of establishing plants. Recall that the model features plants that are symmetric in the same location ex-ante. It implies firms' expected variable profits are identical prior to deciding where to build plants. Therefore, given the estimates from the last two steps, the expected variable profits can be calculated for each location configuration of all firms.[20] In contrast, firms differ by firm-location-specific fixed costs of entry.[21] Instead of estimating each firm-location combination which is impossible to be identified given the level of observation is at plant level, I specify the fixed costs are realizations from a log-normal distribution with dispersion parameter σ^F and scale parameter $\mathbf{X}'_{f\ell}\beta^F$. The distributions of fixed costs are shifted by the distance between FAF zone and the firm's North American headquarter, as well as an interaction dummy of firm and country where the FAF zone locates. Distance is a proxy for the management and communication friction for multi-plant firms, while the firm-country dummy captures idiosyncratic shock such as M&A activities or the legacy from historical policies.[22]

[20] The expected variable profit function (11) 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 10 intervals from 1 to $\bar{\mu} = -\eta/(-\eta - 1)$, [1, 1.1, 1.2, 1.3, 1.4, 1.45, 1.5, 1.54, 1.57, 1.59, $\bar{\mu}$]. 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 $\int_1^{\bar{\mu}} f(\mu) \approx \sum_{s=1}^{S} w_s f(\mu_s)$.

[21] In the recent media release by LafargeHolcim in March 2020, the company has announced a target to trim fixed costs by CHF 300 million in response to a decrease in construction due to the Coronavirus pandemic. This suggests possible variation of fixed costs across firms.

[22] Lafarge started off its North American market in western Canada in 1956. It faced unprecedented growth after the merger with Canada's largest cement producer, Canada Cement Company, in 1970. Cemex, on the other hand, invested in the US market after the anti-dumping duty order on imports of gray Portland cement from Mexico went into effect on August, 1990. The company then shifted its strategy from export to FDI. In particular, Cemex acquired Southdown in 2000 and RMC in 2005, which both owned assets throughout the US. The data shows Cemex as of now does not have any cement plants in Canada, which makes it impossible to identify Cemex-Canada dummy. I therefore drop the Cemex-Canada and LafargeHolcim-US dummies and preserve a constant, Cemex-US and LafargeHolcim-Canada dummies.

The model does not yield a closed form solution to firms' production location choices. Hence, simulation is necessary to numerically solve the problem. Given a set of log-normal distributions with a common shape and mean varying by firm-location, I draw a FL-dimensional vector of fixed costs for a large number of times.[23] For each fixed costs vector, the firms maximize total expected profit by choosing where to build plants. I then calculate the empirical approximation of entry probability for every firm in each location by taking the share of entry among all simulations. I construct 25 moments to estimate five parameters governing the fixed costs distribution using the simulated entry probabilities. Moments are to match the model-predicted and the observed values of (a) number of LafargeHolcim plants and Cemex plants, in the sample, in Canada, in the US, and in every region.[24] (b) average distance between LafargeHolcim's or Cemex's headquarter and plants,[25] (c) number of locations where neither LafargeHolcim nor Cemex enters. The moments are informative about the overall magnitude of the fixed costs of entry, as well as how they vary by distance and the identity of firm and the country of interest. Roughly, the mean of fixed costs is identified by the entry decision of firms in locations, and the dispersion parameter of the fixed cost distribution comes from the correlation between firms entry decision and locations profitability. When the variance is large, the relationship is weaker, which means the realized fixed cost plays a dominant role in determining entry decisions.

I denote the parameters of interest in the last step to be $\delta_0 = \{\beta^F, \sigma^F\} \subset \mathbf{R}^P$. The vector of moment functions, $m(\cdot) \in \mathbf{R}^K$ where $K \geq P$, 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 δ_0,

$$\mathbb{E}\big[m(\delta_0; \mathbf{X}_\ell, \hat{\eta}, \hat{\theta}, \hat{\beta^\tau})\big] = 0 \tag{15}$$

where $\mathbf{X}_\ell = \{\widehat{T_\ell w_\ell^{-\theta}}, \{\hat{\alpha}_m, \mathbf{X}_{\ell m}, \forall m\}, \{\mathbf{X}_{f\ell}, \forall f\}\}$.

The method of simulated moments (MSM) finds an estimate of δ_0 such that

$$\hat{\delta} = \arg\min_{\delta} \frac{1}{L}\left[\sum_{\ell=1}^{L} \hat{m}(\delta)\right]' W \left[\sum_{\ell=1}^{L} \hat{m}(\delta)\right], \tag{16}$$

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

[24]For the one FAF zone in Florida where there are two Cemex plants, I suppress the number of plant in that location to one. By the definition of "plant" in this paper, it refers to the existence of production capability. Matching the number of plants in each country and every region is relevant for the counterfactual exercises below where policies are imposed to one country and trigger significant effects on cross-border regions. Regions include 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, South Atlantic.

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

where $\hat{m}(\cdot)$ is a simulated estimate of the true moment function and W is a weighting matrix.[26] I use the identity matrix and weight the moments equally.[27]

The complexity when having spatial correlation is that the moment functions $m(\cdot)$ are no longer independent across production locations. Any two entry decisions are correlated due to the existence of export platform sales and competition effect. In order for the method of moments estimators using dependent cross section data to be consistent, Conley (1999) proves the sufficient condition is that the dependence among observations should die away quickly as the distance increases. In the current model setup, the spatial correlation becomes weaker when locations are further apart. Trade cost to a market increases for a distant cement supplier, and then decreases its probability of winning the market and weakens its role as a competitor to other locations. The negative effect of distance on location cannibalization shown in equation (5) satisfies the consistency condition. To ensure the speed of dependence decay, I segregate the 149 FAF zones to eight regions and assume that competition is negligible across regions. The regions are categorized by USGS as relatively separated markets. FAF zones on average export more than 88% of the cement production and import more than 82% of the consumption within the same region. Details of each region are shown in the Appendix D.2.[28]

4.4 Solution algorithm for the multi-agent location problem

So far, I have yet discussed in detail how the interdependent location choices is solved in equilibrium. This section will adapt the solution algorithm for combinatorial discrete choice in Eckert et al. (2017) to a two-player, L-location setting. Following the active trade of cement across FAF zones in the U.S. and Canada and the existence of export platform, a firm faces an enormous discrete choice problem when solving for its optimal location strategy for plants. With L potential production locations, a firm selects among 2^L possible configurations. When there are two firms competing with each other and no closed form best response function, the number of configurations to be examined are 4^L. Clearly, a brute force method of calculating the profits for each of these strategies is infeasible. To reduce the dimensionality of the firm's problem, I rely on the

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

[27]As pointed out by Mátyás and Sevestre (1996), in the case of fairly small samples, suboptimal matrices often perform better because the performance of the efficient GMM estimator deteriorates quickly if the number of instruments approaches the number of cross-sectional units. Although the estimate will not be asymptotically efficient, the loss in efficiency may be small. Here, I have 73 locations and also further divide them into eight regions, so the problem suffers from limitations of small sample.

[28]An alternative way is to assume the spillover effect only happens for the set of locations whose centroid is within certain miles of the location, as in Jia (2008). However, such assumption will not work for my case because the existence of overlapping across each location's competition area causes the firm's profit function to violate the single-crossing difference condition which is essential for finding the optimal location set.

Arkolakis-Eckert-Repetitive (AE-Repetitive) algorithm developed by Eckert et al. (2017).

Define the marginal value of including location ℓ in a guess of location strategy $\mathbf{I}$ as

$$D_\ell(\Pi(\mathbf{I})) = \Pi(\mathbf{I}^{\ell\to 1}) - \Pi(\mathbf{I}^{\ell\to 0}),$$

where $\mathbf{I}^{\ell\to 1}$ is the Boolean vector $\mathbf{I}$ with the ℓth coordinate set to 1, and $\mathbf{I}^{\ell\to 0}$ is the otherwise. The AE-Repetitive algorithm works as follows. Starting from the vector $\bar{\mathbf{I}}$ which contains all locations, search for the locations in which the marginal value increases when removing them from $\bar{\mathbf{I}}$ and set those coordinates to zero. Similarly, starting from the vector $\underline{\mathbf{I}}$ which contains no entries, search for the locations in which the marginal value increases when adding them from $\underline{\mathbf{I}}$ and set those coordinates to one. The first round of mapping results in possible vectors for which some of the coordinates are confirmed. Iterating the process helps to maximize the objective function $\Pi(\cdot)$. A complete equilibrium location set is reached when no more refinement can be made with respect to any coordinate after a number of rounds. In some instances, however, there are still indefinite coordinates which lead to more than one possible vectors after iteration. To further identify the optimum, I split the non-singleton set to any two subsets and repeatedly operate the mapping on each of them separately, thus the AE-Repetitive algorithm. If the resulted set from each of the iteration is the same and contains a single location configuration, then the unique equilibrium is obtained. Otherwise, repeat the slicing the AE mapping until a unique optimal location vector emerges.

Eckert et al. (2017) proved that the AE-Repetitive algorithm converges to a unique equilibrium if the objective function exhibits single crossing differences (SCD). Intuitively, the fact that we can decide upon entering a location based on its marginal effect of total profit by adding or subtracting it one-by-one from the interdependent location vector suggests that profitable locations remain profitable or unprofitable locations remain unprofitable when more are added to the set. The former features supermodularity (complementaries) among locations, whereas the latter features submodularities (substitutes) among locations. In a continuous domain, the condition corresponds to the second-order derivative and cross derivative of the profit functions being positive (complementaries) or negative (substitutes).

In Appendix C.2, I prove that the total expected profit function in my model satisfies the SCD condition if $\theta+\eta+1>0$, and thus, qualifies for using the algorithm to solve for the interdependent plant locations. In particular, the marginal gain diminishes when the firm itself builds more plants, and the marginal loss exacerbates when its competing firm add more plants. The profit function exhibits submodularity due to the negative competition effect. The condition on θ and η implies that plants are rather homogeneous relative to curvature of demand. Therefore, within a firm, when the existing active set is large and the firm is less likely to have another efficient draw, both the increase in markup and the raise in amount of supply through entry would not be as much. Across different firms, when competing firms dominate with a large set of plants, the firm's effort in catching larger market share through building more plants also becomes more difficult.

The next question is what happens when there are multiple agents in the game. Theorem 3 in Eckert et al. (2017) shows that iteratively applying AE-Repetitive for all players eventually terminates in a pure strategy Nash equilibrium if the profit function forms a best-response potential game. In Appendix C.3, I show that there always exists a potential function corresponding to the profit function in equation (11).[29] To implement a two-player setting with LafargeHolcim and Cemex, I start from either player solving for its best response by taking the current strategies of the other player as given. Then do the same to find the best response of the other player, iterate until both best responses converge. To obtain the equilibrium most profitable for LafargeHolcim, I start with the smallest vector in Cemex's strategy space: $\mathbf{I}_{\text{cex}}^{(0)} = \underline{\mathbf{I}} = \{0, ..., 0\}$. Derive LafargeHolcim's best response $\mathbf{I}_{\text{lfh}}^{*(1)} = \arg\max \mathbb{E}\big[\Pi(\mathbf{I}_{\text{lfh}}; \mathbf{I}_{\text{cex}}^{(0)})\big]$ given $\mathbf{I}_{\text{cex}}^{(0)}$, using the algorithm. Similarly, find Cemex's best response $\mathbf{I}_{\text{cex}}^{*(1)} = \arg\max \mathbb{E}\big[\Pi(\mathbf{I}_{\text{cex}}; \mathbf{I}_{\text{lfh}}^{*(1)})\big]$ given $\mathbf{I}_{\text{lfh}}^{*(1)}$, using the algorithm again. The first round finishes with $\{\mathbf{I}_{\text{lfh}}^{*(1)}, \mathbf{I}_{\text{cex}}^{*(1)})\}$. Repeat the above procedure until $\mathbf{I}_{\text{lfh}}^{*(k)} = \mathbf{I}_{\text{lfh}}^{*(k+1)}$ and $\mathbf{I}_{\text{cex}}^{*(k)} = \mathbf{I}_{\text{cex}}^{*(k+1)}$. Then, the convergent vectors $\{\mathbf{I}_{\text{lfh}}^{*(k)}, \mathbf{I}_{\text{cex}}^{*(k)})\}$ constitute a pure strategy Nash equilibrium. Similarly, the most profitable equilibrium for Cemex starts from the smallest vector in LafargeHolcim's strategy space of all entry dummies being zero for every location. Besides these two starting vectors as the extreme cases, I also find equilibria within these bounds by starting from a vector in which one firm has advantage entering some locations but not others. The speed of convergence in a best-response potential game is exponential proved by Swenson and Kar (2017). Running 1000 simulation, I show in Table C.2 that the average time of convergence is 0.0934 to 0.1275 seconds with 10 locations and two firms. It takes a maximum of three rounds of iteration to find the best response for two firms.

4.5 Discussion

In this section, I discuss two assumptions in estimation: the game's information structure and issues of multiple equilibria, and what role do small firms play in the competition with oligopolists.

4.5.1 Information structure and 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,

[29] Jia (2008) provides a counter example in her appendix B.2 showing game with submodular profit function does not necessarily have pure strategy Nash equilibrium. However, the example she provides is not a best-response potential game.

raises the well-known coherency problem in econometric inference (Heckman 1978, Tamer 2003). In the absence of interdependency across locations, for a $2 \times 2 \times 1$ (two players choosing enter one location or not) game, either firm can profitably enter but not both. With interdependency across 149 FAF zones, the game would accommodate a lot more equilibria.

Surveying the literature, there are four main approaches to deal with the multiplicity of equilibria.[30] The first is to model the probabilities of aggregated outcomes that are robust to multiplicity. For example, in the simplest $2 \times 2 \times 1$ game, the number of entrants is unique although the firm identity is undetermined (Bresnahan and Reiss 1990, Bresnahan and Reiss 1991, Berry 1992). However, the solution does not come without its cost: information on firm heterogeneity is lost. Parameters that guarantee individual firm's behavior cannot be identified. Should I use it in this paper, I would not be able to estimate the fixed costs distributions which are firm-location specific. Moreover, uniqueness in the number of entrants can also be threatened with sufficient amount of firm heterogeneity.

Second, one can embrace the multiplicity and take a bounds approach (Manski 1999, Ciliberto and Tamer 2009). The method generally sets identify parameters which in some cases earn a tight enough bound that can reject interesting hypotheses. However, in other situations, the set may be too large to be informative and difficult for performing counterfactual and welfare analysis. Estimating a bound also causes inference to be computationally intensive, such as placing confidence region on the set.

The third and the approach adopted in this paper is to change the timing of the game such that firms move sequentially rather than simultaneously. When firms make their entry decisions in a predetermined order, the early mover has advantage to preempt subsequent entrants. Hence, what order to take is essential to the outcome. Without making strong assumptions, I solve the equilibrium with several ordering specifications. In the baseline case, I estimate the model using the equilibrium that is most profitable for LafargeHolcim due to historical reasons. Lafarge (prior to the merged entity LafargeHolcim), a leading French cement producer, built its first cement plant at Richmond in western Canada as early as 1956. By the end of 1960s, Lafarge is the third largest cement producer in Canada. Lafarge's market in the US expanded after its acquisition of General Portland in 1983. The internalization of Cemex which headquartered in Mexico went an entirely different path. In 1990, the US Department of Commerce imposed an anti-dumping duty order on imports of gray Portland cement and clinker from Mexico, primarily to limit Cemex's export to the US. Responding to the trade sanctions, Cemex acquired a one million ton cement plant in Texas and shifted the focus to foreign direct investment instead of pure trade. As a robustness check, I also estimate the equilibrium that is most profitable for Cemex due to the shorter distance between

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

Cemex's headquarter to the US, especially the southern states, and another one that gives each firm regional advantage in moving first.[31]

The recent development of the literature is around specifying a more general equilibrium selection rule that is a function of covariates and observables (Bjorn and Vuong 1985, Tamer 2003, Bajari et al. 2010). All in the context of complete information games. The solution requires the computation of all equilibria and an equilibrium selection parameter as part of the primitives to be estimated together with the model. Clearly, although this approach is more general than imposing certain sequence of entry, the computational burden to calculate all equilibria in an interdependent entry game is too high.

4.5.2 The role of small firms

In the structural estimation, I assume that small firms compete with the two oligopolists in price, but do not respond by entry or exit. Small firms can be either local or foreign firms which produce in the US and Canada, but they typically own fewer establishments compared to the large multinationals. An average small firm in the sample has 3 plants, compared to LafargeHolcim and Cemex who owns 22 plants and 11 plants respectively. Considering small firms, the timing of events is that small firms enter without anticipating LafargeHolcim and Cemex in the later period; the distribution of small firms then become covariates which LafargeHolcim and Cemex take as given in making location choices. Once the entry decisions are made, all plants compete in price and profits are realized.[32] Any ex-post regret by the small firms is then ruled out by the one-shot static game. One could be motivated to change the timing of the model to sequential moves and allow for dynamic structure of the game. However, estimating dynamic discrete games while incorporating

[31] Although the I intend to "solve" the coherency problem and obtain consistent estimates of the model, multiplicity of equilibria continue to raise difficulties at the counterfactual stage. For example, the moving sequence I used in estimation to characterize the data may no longer be valid under the counterfactual. Reguant (2016) proposes a new methodology to determine conservative bounds to counterfactual outcomes by minimizing and maximizing an equilibrium outcome of interest subject to equilibrium constraints. For her method to work, one need to be able to define necessary and sufficient conditions to a game in the form of a vector of equilibrium constraints, and then reform them to a relaxed mixed-integer linear program. However, the method relies heavily on approximation techniques that can affect precision of the bounds, easily resulting in a bound that is too wide to be informative. Additionally, the equilibrium conditions in this network model can be hard to fully characterize without a loose relaxation that again compromise the informativeness of the counterfactual bounds. Computational burden would also increase substantially. Therefore, I leave the treatment of multiple equilibria in counterfactual exercise to future research.

[32] Papers that study Stackelberg competition with endogenous entry typically make the assumption that big firms enter first and choose their prices anticipating the reactions of small firms. Next, small firms enter or exit the market and choose their prices treating big firms' choices parametrically (Etro 2006, Etro 2008, Anderson et al. 2020, Kokovin et al. 2017). Having the opposite sequence of entry as assumed in this model, those papers provide a way to endogeneize the entry and exit of fringe firms. However, the staging is inconsistent with the fact that the US and Canadian cement market was dominated by small local firms before large multinationals entered. The "unique" market development of the cement industry is closely tied to the historical localization of the product and improvement of the transportation and production technology.

interdependency across locations and time greatly complicates the problem and increases the computational burden. Firms would adjust to an ever-evolving flow of new information, which is no longer limited to the entry decisions of competing firms, but also changes in demand, adjustment to production capacity and many other factors. Estimation of a dynamic model needs also be substantiated by a richer set of data. Therefore, I control the dimensionality of the problem by restraining the model to a static game as an approximation to long-run equilibrium. Implications from a static game may very well be meaningful to policy makers without the loss of generalization.

An alternative structure could be to model every firm simultaneously entry, including the large and small ones. Instead of a two-agent game, I would estimate a 26-player, L-location game. With the negative competition effects, the profit function for all players will exhibit submodularity such that applying the AE-Repetitive algorithm will still reach a pure strategy Nash equilibrium. However, the estimation will be computationally intensive since the number of iterations to solve all firms' best responses increases dramatically. In addition, treating large oligopolists and small firms equally does not fit the empirical fact that local cement firms flourished in the US and Canada before 1970s when the large multinationals eventually stepped in.

4.6 Parameter estimates

The first step of estimation is to recover trade costs, the dispersion parameter of plant productivities, and the production capability for each location through a gravity-type trade regression. The baseline estimates are obtained by running equation (14) via PPML, but I also applied alternative specifications to valid the results. Table 3 summarizes the estimates of trade costs and the Fréchet parameter θ. Column (1) to (3) report the results for our targeted sample - the US and Canada FAF zones, whereas column (4) and (5) regress on an auxiliary sample of 144 countries. As expected, OLS overestimates the effect of distance compared to PPML in the presence of heteroskedastic gravity errors. The estimates obtained from running PPML on trade flows and trade shares are very close although the latter imposes less weight to large flows. At FAF zone level, the effects of distance from other FAF zones and its internal distance between boundary points are separately estimated. The elasticity of distance to other zones is estimated to be around -1.2, which is consistent with what has been found in the past literature (around -1). The effect of internal distance is smaller around -0.4, suggesting that cement is more than proportionally consumed at home location, a result accords by the positive and significant home coefficient in the country-level regression. The distance elasticity estimated using the country sample is also around the same magnitude despite that distance is measured differently. All columns show more trade if markets are adjacent. State/province and country border matter at the FAF zone level. Sharing common trade agreements boosts trade between countries, but not common language. The key parameter of interest in the country-level gravity regression is the elasticity of trade with respect to trade costs. It has the fundamental interpretation in the multi-plant model of being the negative of plant productivity dispersion parameter, i.e. $-\theta$. I exploit the tariff variation across country dyads and estimate coefficient on the log of one plus the ad valorem bilateral tariff rate. Column (4) and (5) obtain similar estimate of the trade elasticity with an average of -11. Therefore, productivities of cement plants are less dispersed with the shape parameter being 11. The estimate is at the higher end of what is typically found in the literature (around -6.7), but justifiable by the homogeneous nature of cement. For the following steps of estimation, I take $\theta = 11$ and the estimated trade costs computed from Table 3, column (3) as my benchmark since Head and Mayer (2014) claim that PPML on trade shares perform better in simulations than that on flows.

Running the gravity trade regression also reveals each location's relative input costs and production efficiency through the location fixed effects adjusted for the number of plants. Figure 6 plots the estimated cement production capability against the actual production volume for each location. The left panel uses the implied production capability after teasing out the number of firms entered, whereas the right panel directly uses the estimated location fixed effects from the gravity regression. The positive correlation between estimates and cement production in both figures suggests a credible ranking of estimated production capability across locations. Comparing the two panels, the number of firms is different across locations and contributes in explaining cement production suggested by the improvement of R-square.[33] Specifically, locations above the fitted line of panel (a) produce more cement than what are predicted by the input costs and its production efficiency. The difference is attributed to more firms located in these zones which clearly shifts the points at top left and top right corner towards the right in panel (b). As comparison, locations whose predicted cement production is higher than the actual amount are not shifted as much. In other words, higher input costs and local production efficiency do not necessarily lead to more plants, suggesting that fixed costs of establishing plants matter and are likely to vary.[34]

In the second step, I feed the estimates from step one combined with actual data on cement plant locations into the market price index up to the parameter η which is the price elasticity of demand. Given the demand model is nonlinear in the parameter of interest and also the explanatory variable price is endogenous, the GMM estimation will be consistent. Table 4 presents the results. As expected, the price elasticity corrected for endogeneity is larger in absolute value compared to the estimate without instruments. As for column (3) in which the cement consumption is log-

[33] The fit displayed in Figure 6 is the R-square by regressing log of production on log of location production capability and the control for average trade costs weighted by destination market size. One can derive from equation (5) that $\ln \sum_m Q_{\ell m} = \ln N_\ell T_\ell (w_\ell)^{-\theta} + \ln \sum_m \left(\frac{\tau_{\ell m}^{-\theta} Q_m}{\Phi_m} \right)$, where the second term is the average trade costs controlled for in plotting.

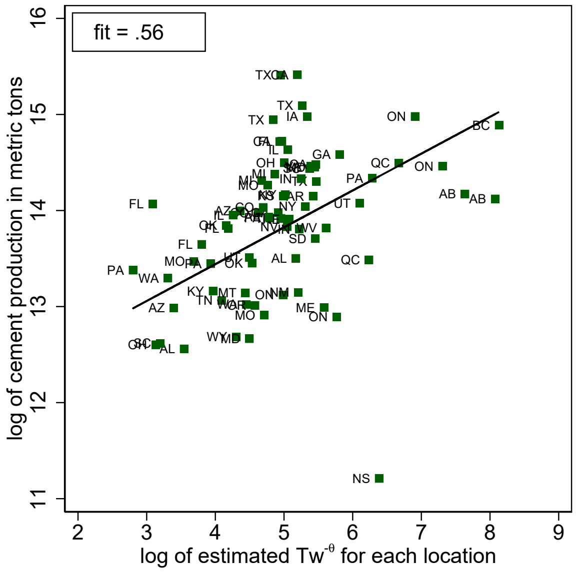
[34] Of course, more plants in less capable locations could also be due to the fact that these locations have very low trade costs to large market which compensate their local inefficiency and still expect to earn high variable profits.

Table 3: Estimation of trade costs

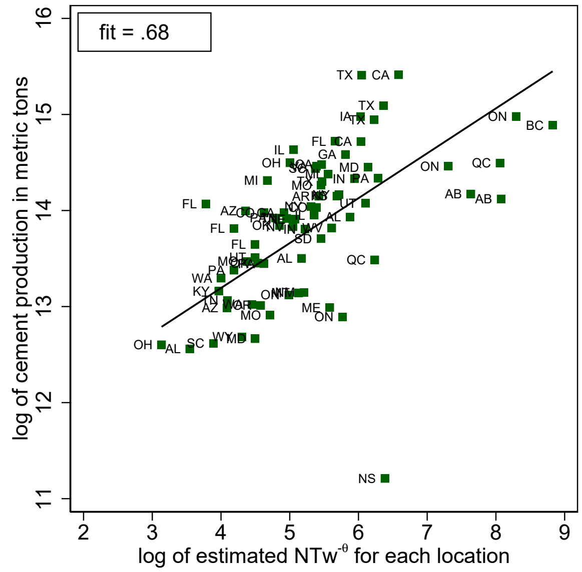
	FAF zone sample			Country sample	
	(1)	(2)	(3)	(4)	(5)
	OLS, $\log Q_{\ell m}$	PPML, $Q_{\ell m}$	PPML, $Q_{\ell m}/Q_m$	PPML, $Q_{\ell m}/Q_m$	PPML, $Q_{\ell m}/Q_m$
log $\text{dist}_{\ell m, m\neq\ell}$	-2.297^a	-1.174^a	-1.198^a		
	(0.032)	(0.034)	(0.032)		
log $\text{dist}_{\ell\ell}$	-1.499^a	-0.462^a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

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

Figure 6: Cement production and estimated capability by location



(a) Exclude number of firms



(b) Include number of firms

linearly regressed on the instrumented price survey data, the price elasticity still falls in the range of -2 to -3, and therefore validates the model.[35] The effects of two demand shifters, population and building permits allocated, are both estimated to be positive and significant. The magnitudes are similar to what has been found by Ryan (2012), both being smaller than one.

The literature studying the cement industry has yet reach a consensus about its demand elasticity. Jans and Rosenbaum (1997) estimate the US domestic demand elasticity of -0.81. Sato, Neuhoff, and Neumann (2008) estimate a demand elasticity of -1.2 using the European data. Miller and Osborne (2014) estimate an aggregate demand elasticity of -0.02, using the data from south-western United States. Ryan (2012) estimates a range between -1.99 and -3.21, and later on -0.89 to -2.03 in another study with Fowlie and Reguant in 2016. My estimate falls along the interval where the literature has found, although being at the upper range. An estimate of price elasticity -2.68 and productivity dispersion parameter 11 also confirms $\theta + \eta + 1 > 0$, which is the sufficient condition for the multi-plant firms problem to be submodular.

To verify the validity of the instruments, I present the first-stage results in Table C.4. The coefficients on the input costs with respect to the cement market price are positive and statistically significant in general, with an exception being local natural gas price. The F-statistic of the ex-

[35] For the first two columns where I use the constructed price index, the instruments are the weighted sum of input costs from every potential location, weighted by the estimated $\tau^{-\theta}$ to be consistent with the model. For the last column where a pure empirical specification is used, I include the input costs for the market itself and a distance-inverse weighted sum of input costs from all other potential locations as the price instruments. The input costs data for Washington DC is unavailable, therefore five observations are dropped in column (3).

cluded instruments on the endogenous regressor is 21.64, and the Stock-Wright S statistic is 95.59, which are all well above the rule-of-thumb threshold of 10. Hence, the tests reject the weak IV concern and indicate that the instruments are most likely to be valid.

Table 4: Estimation of demand

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

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

From the last two steps, I've estimated two types of costs that are essential to construct the firm's expected payoff, namely the trade cost based on the bilateral gravity terms, and the marginal cost of production formulated from the plant productivity distribution and the recovered location covariates. The price elasticity of demand is also estimated, which together with the firms' plant location decisions, governs the distribution of markup heterogeneous across firms and markets. In the last step, vectors of the plant-level fixed costs are simulated from a log-normal distribution that I'm going to estimate using MSM. Combining all these key components, a firm's objective in choosing the optimal production location set to maximize the expected payoff is set up as a function of fixed costs parameters.

The structurally estimated parameters for three different equilibria are displayed in Table 5, corresponding to the scenario that is most profitable for LafargeHolcim (LFH), Cemex (CEX), or allowing LFH to have local advantage in Canada and CEX in Texas and Florida. Estimates across equilibria are not significantly different, which ease the generality concern of the counterfactual results. To understand why the equilibrium selection rule does not have "bite" here, we need to look into the data and the particular power structure between the two firms. In particular, LafargeHolcim is quite a dominant player, owning twice the amount of plants than the second largest player, Cemex. The asymmetry between oligopolists mitigates the effect of sequential move assumption in selecting equilibrium. Assuming Cemex is most profitable and moves first, the model must rationalize the fact that Cemex enters half the number of locations as LafargeHolcim. It does so by making Cemex to acquiesce LafargeHolcim's entry and choose to forgo some locations expecting LafargeHolcim would enter. The intercepts and covariates are estimated such that Cemex has disadvantages in those locations. Vice versa, assuming LafargeHolcim moves first, the estimated model continues to imply that LafargeHolcim is the more profitable player to generate the patterns in the data.

I find a location that is 10% more distant from the firm's headquarter, the average fixed costs of establishing plants will be nearly 20% higher holding everything else constant. The effect seems to be large considering communication and management cost alone, but should be interpreted with caution. First, setting up a cement plant is time and capital intensive which involves several layers of regulatory approval, such as environment clearances for mines, for handling effluents, and land procurement. As states/provinces are not uniform in regulatory procedures, the administrative cost due to information friction at locations further away could be tremendously high. Second, the literature on multinational production has well documented the costs of producing far from headquarters, i.e. MP cost. The baseline model does not feature the loss of productivity with transferring headquarter services to production locations, but instead the friction could be absorbed by fixed costs. With the limited plant-level data in this paper, I could not separately identify the variable costs from the fixed costs as in Tintelnot (2017). However, one can easily extend the model by incorporating a $h(f)\ell$-level term in the marginal cost of production. I present this variation in the appendix. Third, compared the magnitude to the literature, Tintelnot (2017) estimates the distance elasticity of variable MP cost is 0.004 and that of fixed cost is almost zero. But the elasticity of a country being adjacent to the headquarter is about 1 or 1.5 with respect to the variable or fixed costs respectively. Head and Mayer (2019) estimate the friction between a car brand's home country and its country of assembly and find that the effect of distance is insignificant but assembly at the home country is 9.5 more likely to happen than choosing other assembly locations. The distance elasticity to fixed costs I estimated could potentially be upward biased due to the omitted contiguity and home variable.

The average fixed cost is lower and weakly significant when LafargeHolcim builds a plant in Canada because the firm has accumulated local knowledge through its long presence in Canada since 1956 followed by a wave of M&A activities with Canadian cement firms. On the other hand, Cemex does not share the advantage in fixed costs shown by the insignificant coefficient. The variance of the fixed cost distribution is not small, which means that the correlation between firms entry decision and locations profitability is rather weak and the realized fixed cost is dominant in entry decisions. It makes sense given that the sunk cost of building a cement plant and the maintenance costs could easily be hundreds of millions of dollars.[36]

Table 5: 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)

Table reports coefficients and standard errors from estimating the model via method of simulated moments. Standard errors are based on 100 bootstrap samples drawn with replacement. Regional vectors are re-sampled to preserve the dependence among locations. I also calculated the asymptotic standard deviation addressing the dependent concern of moments in Appendix C.1.

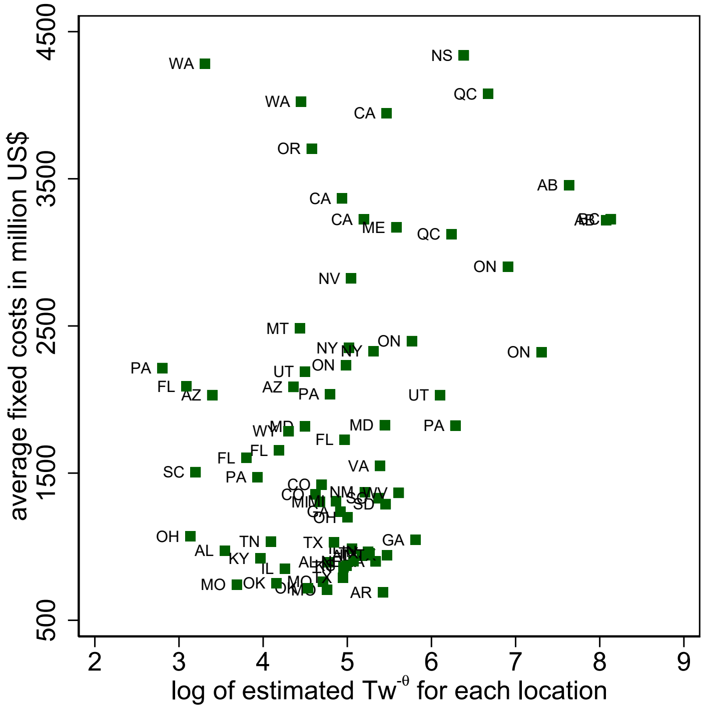
As the production capability of each location is estimated up to a scale, I need to back out the scale parameter in order to compare the level of estimated costs to the industry norm in monetary value. The scaling is computed by comparing the predicted market price with the actual price since it passes through Φ_m in equation (12).[37] Since plant productivities are distributed Fréchet, the marginal costs of production excluding trade costs follows a Weibull distribution with mean $\left(T_\ell w_\ell^{-\theta}\right)^{-1/\theta}\Gamma\left(1+1/\theta\right)$. The average production costs is estimated to be \$85.57 per tonne of cement, reasonably higher compared to the engineering costs of \$60.22 in 2016 reported by the US Environmental Protection Agency. [38] The estimated production costs of cement in Canada is

[36] An alternative interpretation of the large fixed cost dispersion would be that the benchmark model of variable profit for each plant fails to capture all factors. One remedy could be to include the firm-level productivity shifters in determining plants' marginal costs, but as aforementioned it requires more data to identify all the parameters.

[37] I run the actual cement market price on the predicted price constructed from equation (12), the slope is 140.575 suggesting that the normalization has shrunken the model-predicted price by a factor of 140.575. The predicted cement consumption is not affected since the normalization parameter is already absorbed by the year fixed effects when estimating demand. Therefore, when computing the firm profit and the relevant costs in nominal term, I need to multiply them by 140.575 to scale up the price.

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

Figure 7: Estimated fixed costs and production capability by location



around \$72.56 per tonne of cement, which is lower than \$87.64 in the US. The back-of-envelope calculation implies that the average fixed costs across the cement plants owned by LafargeHolcim is around \$181 million and that across the Cemex plants is around \$280 million.[39] The estimated fixed costs for building the cement plants are comparable to the benchmark of \$200∼\$300 million, although the assumption of a log-normal distribution means that the costs can be substantially larger for some realizations. The fixed cost advantage of LafargeHolcim justifies the firm being the leader in the US and Canada and the fact that her plants double those of Cemex in terms of number.

Figure 7 shows the estimated average fixed costs and production capability across FAF zones and it should be interpreted together with panel (a) in Figure 6. It is clear that Nova Scotia, a province having moderate production capability, produces exceptionally small amount of cement. The inconsistency is reconciled by the highest fixed costs there. On the contrary, FAF zones in Texas are as capable in producing cement as Nova Scotia but among the lowest fixed costs locations. Therefore, Texas is the largest cement producer in the sample. Similar findings can be seen by comparing Alberta to Ontario or Quebec. These differences in production capability and fixed costs of entry help explain the variation across FAF zones in the number of plants located and

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

subsequently the amount of production. Figure 7, complemented by the cross-firm analysis above, highlights the importance of heterogeneous fixed costs across firm and location in matching the model to the data.

4.7 Fit of the model

I examine the estimation results by describing the model's fit of the data. Table 6 displays the predictions of the baseline model for the moments it was targeted to match in the estimation. As expected, the model fits the data well in the number of plants, total or regionally, for each firm and the average distance between plants and firm headquarters. Since the plants location directly determine the attractiveness of each location and subsequently affect its comparative advantage in supplying cement to every market, I check the fit of model prediction with trade data in Table 7. The predicted bilateral share of import manages to explain 64.4% of the data variation. What's left can be mostly explained by the gravity error in the first step and trade with FAF zones outside each region which I assume away in estimation. To check to what extent the prediction is affected by the gravity error, 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-regional trade further increases the fit by another 6.7%. If comparing the import share is still insufficient in demonstrating the model's fit because it is indirectly targeted through the first-step gravity regression, I further compares the trade volume as shown in the last column of Table 7. The degree of fit does not fall.

Table 6: Model fit of plants number and distance to headquarter

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

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

Other than comparing trade flow, Figure 8 plots the share of trade by distance and compare the model's prediction with the data.[40] 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

[40]The actual trade data is used for only the dyads within the same region to be comparable with the estimation under such assumption. Same goes for the consumption and production data in Figure 9.

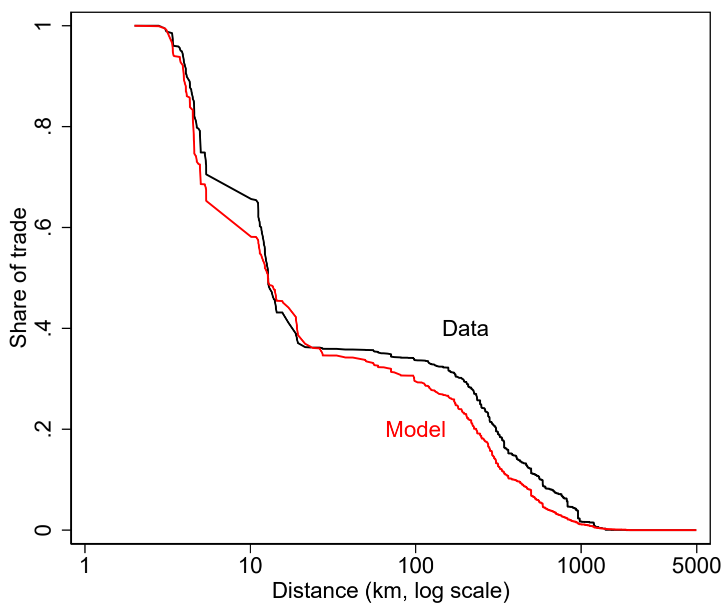
Table 7: Model fit of trade flows

	Bilateral share of import	Gravity-predicted share of import	Gravity-predicted share of import within region	Bilateral import volume
Model predicted	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.

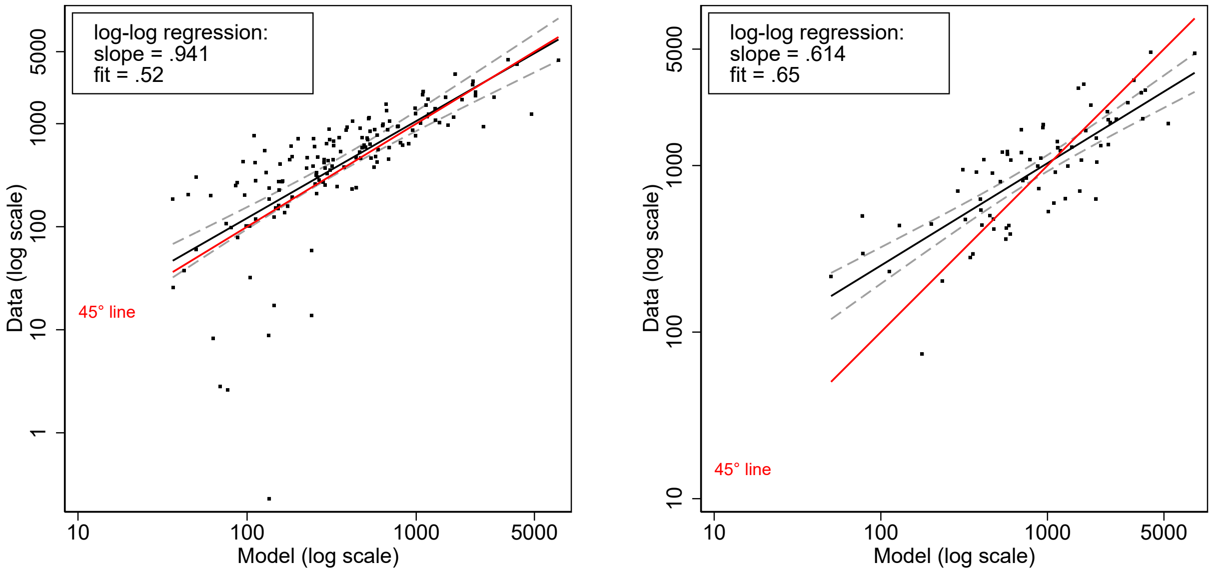
estimation of fixed costs and solution for endogenous plant locations are consistent and do not introduce additional bias.

Figure 8: Model fit of trade flow over distance



Having checked the model validity through plants number and trade, lastly I compare the model predicted cement consumption and production against the data. Figure 9 shows that the model fits the data reasonably well in both dimensions. The actual and predicted cement consumption across markets distribute tightly along the 45-degree line. The prediction on production, although deviates from the diagonal relationship, captures 65% of the data variation. The multiple test results establish confidence in the following counterfactual exercises.

Figure 9: Model fit of cement consumption and production



(a) Consumption (thousand tonnes) (b) Production (thousand tonnes)

4.8 Decomposing the forces of trade

As a variant in the Ricardian world, the model captures the comparative advantage based on technological differences while incorporating the role for geography. The geographic features not only refer to barriers as in Eaton and Kortum (2002) but also the plants distribution in space. Trade is a mixed result of the three forces as presented in equation (5): the variation in marginal production costs represents differences in efficiency across locations; trade costs reflect geographical barriers and fixed costs govern plant locations. Although the literature has provided evidence for the presence of three types of costs, little is known about their quantitative importance. With the help of the estimated parameters, I am able to let firms re-optimize their plants location set and predict changes in aggregated outcome, under different costs scenario.

Table 8 tabulates the results. The model effectively fits the average import penetration and export intensity. While markets on average import 27% of their cement consumption, in the estimated model the average share is 24%. Locations on average export 45% of their cement production, and the model predicts the average share is 44%. The underestimation is expected given the estimated trade is restricted to within region only. If there were no fixed costs for setting up foreign plants, then every firm would have a plant in each location, and trade would decrease such that markets only import 17% of their consumption and exports 40% of their production. Trade would not vanish because plants are heterogeneous. If, on the contrary, the fixed costs were extremely high such that firms would only have one plant in their headquarter but anywhere else, the import and export share would rise to 31% and 47% respectively. Comparing the changes on plant locations to unifying technology across locations, I find that the effect on trade of the latter is not as large as that of the former. If the unit input costs were equalized everywhere to the mean value, markets would lose incentive to trade and the import from foreign is less by 4%, a level of change smaller than 7% in the cases of extreme fixed costs. Exports would reshuffle based on trade costs ranking instead, and the share in production does not necessarily decline. The third factor is geographic barriers. If trade costs were eliminated for each dyads, markets freely trade with each other choosing the lowest input costs and the largest set of suppliers, both import and export share would rocket to around 90%. Overall, I find that all three factors significantly contribute to the level of trade, with geographic barriers being the most important, followed by plants spatial setting, and location differences in technology the least. While the traditional Ricardian model of trade emphasizes on technological differences, geography plays a slightly more important role.

The last two rows of Table 8 present the total consumption of cement across all markets and the associated average price in different scenario. The model underpredicts the total cement consumption by 3 million tonnes in the US and the majority of Canada which is reasonable considering the model is estimated based on intra-regional trade only. When firms re-optimize plant locations, the competition structure changes. So does the equilibrium price. Should every location have plants of each firm, competition becomes tighter, price drops, and demand increases. Vice versa, price rises and demand decreases when firms are single-plant. Quantitatively, I find that the market price on average fluctuates by around $10 than the baseline when having the maximum or the least number of plants. The predicted change is conservative given a large set of fringe plants owned by small firms competing in price, and therefore suppresses the aggregate effect on price imposed by large firms. When all locations have the same input costs, profitability of each location changes dominated by the trade costs to nearby markets, plants relocate. The total number of plants may increase slightly because plants spread out instead of agglomerating around the efficient locations, which leads to a 5 dollar drop in price. The largest price change is seen in the case of free trade. Trade liberalization induces the price to decrease by 36 dollar due to the reduction in cost of supply as well as the facilitation of plant entry. Cement consumption is more than doubled. Understanding the mechanism of price and demand changes in this table guides our interpretation of the counterfactual results.

5 Quantitative Applications

The benefit of estimating a structural model is the ability to simulate counterfactual experiments once the underlying primitives are known. I therefore apply the model to few quantitative exercises and investigate firm dynamics when market conditions change. Since the cement industry is

Table 8: Decomposing sources of trade

	Data	Baseline model	Zero fixed costs	Infinity fixed costs	Same location input costs	$\tau = 1$ everywhere
Import penetration (%)	27	24	17	31	20	89
Export intensity (%)	45	44	40	47	44	93
Total consumption	100	97	121	77	108	235
Price (US$/tonne)	110	106	96	115	101	70

The unit of cement consumption is million tonnes. The model-predicted prices are scaled up by a normalization factor of 140.575. In the case of infinity fixed costs, I assume the firm always has a plant at its headquarter or the nearest location to its headquarter if the headquarter is out of sample. In all columns, locations of fringe plants not owned by the largest two firms are hold constant.

associated with important environmental concern, trade debate and major phase of consolidation, I hereby access the welfare implications for each of the three aspects. Although the counterfactual results shed light on the effects of three different sets of policies, the mechanisms that lead to various results are interconnected through multi-plant firms' operations. Hence, the framework in this paper can be used to answer a wide variety of policy questions.

5.1 The Greenhouse Gas Pollution Pricing Act

According to the World Bank's 2019 State and Trends of Carbon Pricing Report, 74 jurisdictions, representing about half of the global economy, are putting a price on carbon. These regulations would directly affect the energy price and increase the cost of production, especially for the heavy carbon-polluting industries. Responsible for about 8% of the global CO_2 emissions, the production of cement is accessed to be in a high competitive and leakage risk category facing the carbon levy. Therefore, governments aim to design policies such that firms can afford, industries can maintain the competitiveness, while retaining the incentives to reduce emissions.

In 2018, Canada passed the Greenhouse Gas Pollution Pricing Act (the Act) which is a backstop system at the federal level that would raise the carbon price to $50 per tonne by 2022. The Framework is composed of two carbon pricing initiatives: a carbon tax on fossil fuels and an output-based pricing system (OBPS) for industrial facilities.[41] Prior to the pan-Canadian approach, provinces

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

such as British Columbia, Alberta, or Québec have already implemented certain pricing regime on carbon. British Columbia, for example, applies carbon tax to emissions from the combustion of fossil fuel, but not to process emissions during production. My primary interest is to evaluate the welfare costs of these environmental regulations for both consumers and producers through plants relocation and change of market restructure.

5.1.1 Carbon tax on fossil fuels

I first take the policy implemented in British Columbia as a benchmark case and increase the price of fossil fuels used in the cement manufacturing to reflect the \$50 per tonne of CO_2. The average cost of fuel to produce a tonne of cement before and after the carbon levy is \$13.21 and \$30.13 respectively, calculated based on the amount of energy needed in production, breakdown of fuel type used, fuel prices and energy content tabulated in Table C.5.[42] [43] I further assume that the input cost w_ℓ is a Cobb-Douglas composite of worker wage, intermediate material cost, and fuel cost, where each contribute to a third of the total input cost. Hence, the carbon tax on fuel is equivalent to a 32% increase in the input cost of cement and 95% decrease in the production capability of all Canadian FAF zones. The effect of input cost rise on production capability is exacerbated by the relatively large θ. When plants are not widely differentiated, a little change on one's competitiveness could have huge impact on the probability it is selected as a supplier.

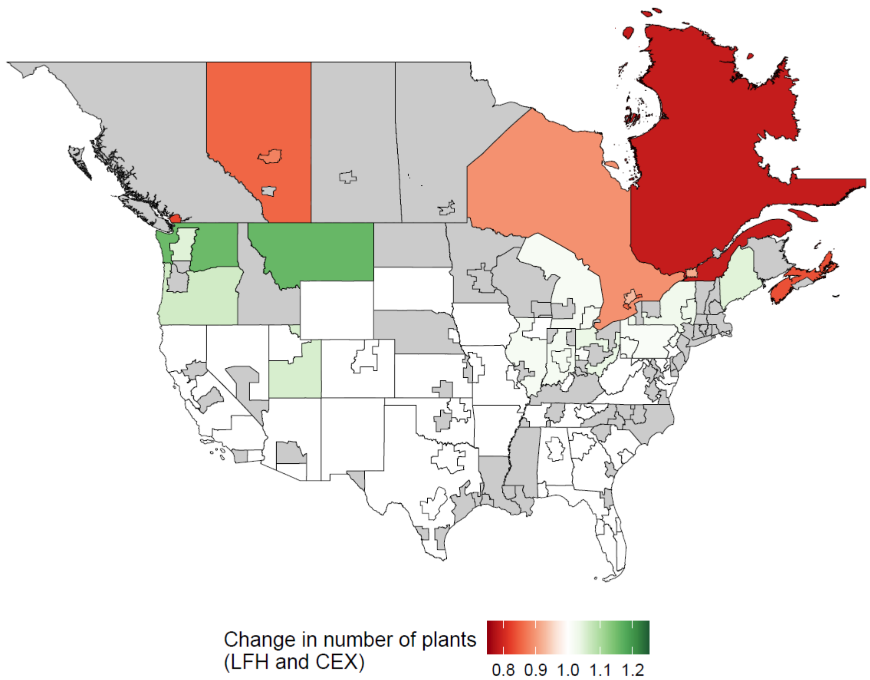
The fuel charge raises the production cost of cement in Canada and threaten firms to relocate plants to "pollution haven". Figure 10 displays the degree of plant relocation from Canada to the US visually. The top two firms would close Canadian plants across all FAF zones nationally, with the most striking exit ratio in Québec where more than 20% of the plants there will be shut down, followed by British Columbia (Great Vancouver metro area), Nova Scotia, Alberta and Ontario. These plants are shifted to locations in the US where close to the pre-existing Canadian plants such that markets that are previously served by these Canadian plants would source from US plants that are not too distant now. On the west side, Montana faces a 16% increase in the top two firm's plants and Washington 15.6% except for Seattle metro area, whereas places in Oregon and Utah face a moderate expansion, and no relocation to Nevada at all. Despite similar distance to Canada, firms enter locations in Utah but not Nevada because Utah is more efficient and cheaper to produce cement. On the east side, the relocation is much weaker because there has already been a dense production network by LafargeHolcim and Cemex such that the firms would not worsen cannibalization within itself. The estimation assumption that trade happens only within region

[42] The pre-tax implied unit cost of fuel is very similar to what is documented in Miller et al. (2017), \$13.82 in 2010.

[43] When calculate the post-tax fuel cost, I implicitly assume that there is no substitution of fuel to other carbon-saving energy sources such that the breakdown of fuel uses stays the same. The assumption is not unrealistic considering the cost of replacing equipment for the new type of energy is very high for a plant.

leads to no relocation towards middle and south of the US, nor the gray area where is outside of the potential set of plant locations.

Figure 10: Plant relocation with $50 carbon levy on fuel in Canada



The first two columns in Table 9 provide quantification to the degree of plant relocation. The model predicts entry probability of each firm at each location through simulation, and thus I describe production relocation using the change in average entry probability. The multi-plant firm model predicts that overall the top two firms in the region will decrease the probability of building a plant in Canada by around 10%, which means closure of one plant counting 10 potential locations to built plants in Canada (12.83% of the two firms' baseline number of plants). On the other hand, the two firms increase the probability of building a plant in the US by merely 0.32%, which is less than one plant given a pool of 63 potential locations in the US. Plant relocation is hence not one-to-one rationalized by the high fixed cost of building cement plants. The 1.38% rise of cement production with insignificant plant entry in the US implies that the US cement plants achieve a higher utilization rate.[44] On the contrary, Canadian cement plants become under-utilized. Across firms, the effect is heterogeneous. LafargeHolcim, which is the dominant player in the Canadian market, is hit harder by the cost shock. The firm faces higher loss of plants in Canada and lower newly builds in the US than Cemex. One thing should be noted is that, the model overpredicts

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

the presence of Cemex in Canada. Therefore, the predicted change in the entry of Cemex suffers downward bias, and Cemex could likely benefit from the carbon tax in Canada.

Table 9: Counterfactual changes with \$50 carbon levy on fuel in Canada

	Entry Probability Δ		Price Δ	Consumption $\Delta\%$	Production $\Delta\%$	Trade $\Delta\%$		CS Δ	PS Δ
	LFH	CEX				Canada	US		
Canada	-7.43	-2.13	26.82	-52.37	-57.63	-54.25	-94.67	-310.50	-68.04
US	0.13	0.19	0.73	-1.04	1.38	224.83	1.02	-35.54	10.70

The columns on entry probability, price, consumer surplus and producer surplus refer to change in level in their respective unit. The unit of entry probability is in percentage. Price is US dollar per tonne. Consumer surplus and producer surplus are in millions of US dollars. The consumption, production and trade columns refer to percentage change in volume. As baseline, Canada consumes 8 million tonne of cement and the US consumes 88.83 million tonne. Canada produces 11.43 million tonne and the US 85.4 million tonne of cement. For trade, rows are origins and columns are destinations.

Although the high fixed cost of entry prohibits firms from adjusting production locations flexibly, the effect of carbon tax on consumption and production of cement is much more prominent. Table 9 shows that consumption and production of cement in Canada is dropped by about 52% and 58% in volume respectively, which is 4.2 million tonne reduction in consumption and 6.6 million tonne decrease in production. Associated the demand and supply change of the cement is the increased average price by \$26.82 that is nearly a third of its baseline level, out of which 16.92 is directly passed on from the increase in fuel price and the rest from the increase in market concentration. This is in line with Ganapati et al. (2016) and Miller et al. (2017) who find that fuel cost changes are more than fully transmitted to cement prices. On the contrary, with the shift of production to the US, 1.2 million more of cement is manufactured in the US. The average price of cement in the US increases by 73 cents which is resulted from two opposing forces: downward pressure from the intensified market competition through more plants entering and the upward pressure from the loss of cheap cement imported from Canada. A carbon levy as high as \$50 per ton of CO_2 makes the latter slightly dominates, and thus consumers in the US also substitute cheaper alternatives for the cement. Overall, the US and Canada produce 5.4 million tonne less of cement and equivalently 4.32 million tonne less of CO_2.[45] Depending on the social discount rate, this can be translated to \$52$\sim$\$531 million savings on the social cost of carbon in 2020 (EPA Social Cost of Carbon Fact Sheet, 2016).

The trade impact of a carbon tax on fuel is enormous. The cement export from Canada to the US almost vanishes. Instead, Canada is flooded with cement from the US, more than tripled the amount before. A simple calculation based on the changes in trade volume and consumption

[45] I use the ratio of 0.8 tonne of CO_2 per tonne of cement to convert.

reveals that import from the US will rocket from 6% of the total Canadian cement consumption to 41% post tax.

Channeled through the industry dynamics and market structure changes described above, the welfare impact of the \$50 carbon levy on fuel in Canada is measured by the consumer loss of \$310.5 million and producer loss of \$68.04 million annually.[46] This can be compared to the Canadian cement industry revenues of roughly \$7.4 billion in 2016. Consumers bear about 82% of the burden of regulation, comparable to the 89% found by Miller et al. (2017) in their study of the US markets alone.[47] Using the 0.4 tonne of carbon emitted from the fuel combustion of producing one tonne of cement, the government revenue is roughly 96.9 million dollars. Producers could be fully compensated by 70% of the revenues obtained from such tax. Provided a social cost of carbon at \$65.2 per tonne or more would make the policy welfare enhancing for Canada.

As one would expect a negative cost shock to Canada may benefit the US, the welfare evaluation shows otherwise. The US also loses \$24.84 million driven by higher price faced by consumers despite that producers gain. Just as the pollution of carbon is globally, the effect of cost increase in one country also transmits to another through trade and production shift.

5.1.2 Border tax adjustment

As demonstrated by the change in trade, downstream consumers turn to unregulated imports after the imposition of carbon tax. The first-best solution to such leakage is a border tax adjustment (BTA) that raises the effective price of unregulated imports. I hereby evaluate to what extent a BTA is effective and its welfare implications as my second counterfactual exercise. The objective is to keep the import penetration from the US to Canada in the cement industry the same level as before imposing the carbon tax on fuels, 6%. Solving the objective function results in a border tax of 33%.

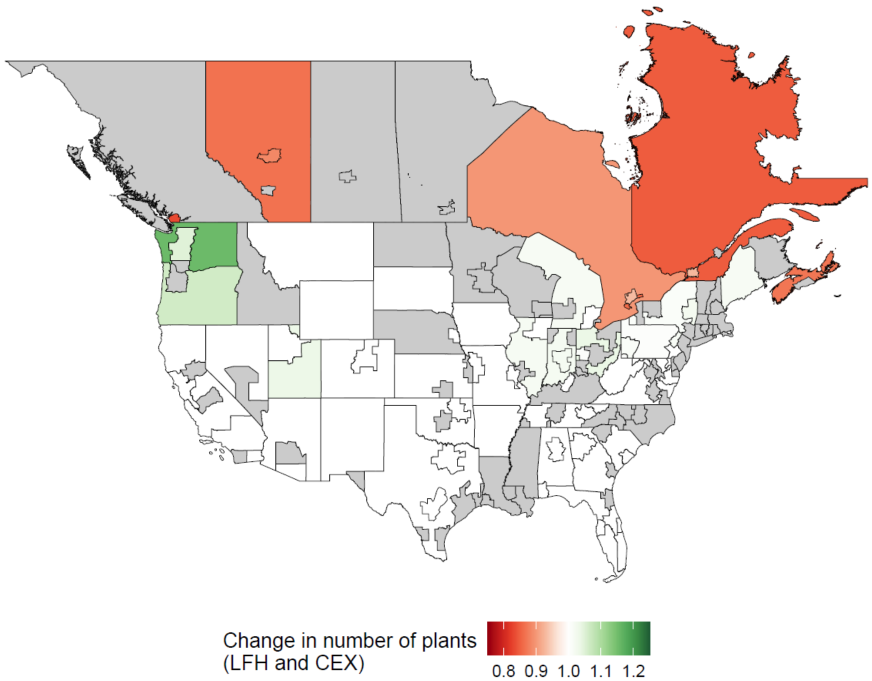
Augmenting the carbon tax on fuel with a BTA mitigates the loss of domestic market share to foreign producers, thus slowing the degree of relocation from Canada to the US. Comparing Figure 11 to Figure 10, the exit rate for Canadian plants decreases and fewer locations in the US are seen with significant plant entry. In British Columbia, less than 17% plants are closed, followed by Québec around 15%, and then Nova Scotia, Alberta and Ontario. Montana will no longer face plant increase, and relocation to Washington, Oregon, Utah and locations in eastern US are all declined. Table 10 also presents smaller change in entry probability compared to the case of fuel charge alone. Therefore, sufficient level of BTA is indeed effective in reducing production leakage

[46]Producer surplus is calculated combining all firms including the small ones operating in the sample market. However, small firms' locations are fixed. Therefore, their profit changes are solely an adjustment of market share due to the restructure of large oligopolists.

[47]The paper does not disentangle how the consumer losses are distributed downstream among ready-mix concrete plants, construction firms or end users. I leave that to future research.

through plant relocation. However, Canada, as a net exporter of cement, will not overturn the closure of cement plants since many of them were used to primarily serve the US markets.

Figure 11: Plant relocation with $50 carbon levy on fuel and 33% BTA in Canada



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

Finally, Canada suffers additional $10.5 million loss in welfare compared to the scenario without BTA, out of which the $1.77 million gain of producers cannot compensate the extra $12.26 million loss of consumers. However, the government receives more tax revenue, besides the $98.2 million from the carbon tax on domestic production. The calculation of tax revenue from BTA on cement from the US can be tricky without prediction on the trade value but volume. I abuse the estimated parameters here and use it as the change in trade value. A rough estimation of the border tax revenue is $10.7 million.[48] Combining the change in consumer surplus, producer surplus, and government revenues, the total loss from a carbon tax and BTA is about $280 million. Compared

[48]The 2016 export value of cement from the US to Canada is $69.8 million according to Trade Data Online from the Government of Canada.

to the previous case, the remedy itself saves \$1.5 million for Canada which may not be a significant amount considering the total loss. Nevertheless, it unintentionally increases carbon reduction to 4.6 million tonne through the firms' responses. Therefore, the threshold of the social cost of carbon, in order for Canada to benefit from the policies, reduces to \$60.9/tCO_2. On the other hand, the US loses \$530 thousand more from the unpreferable trade restrictions.[49]

Table 10: Counterfactual changes with \$50 carbon levy on fuel and 33% BTA in Canada

	Entry Probability Δ		Price Δ	Consumption $\Delta\%$	Production $\Delta\%$	Trade $\Delta\%$		CS Δ	PS Δ
	LFH	CEX				Canada	US		
Canada	-6.70	-2.00	32.24	-53.61	-57.04	-53.61	-94.65	-322.76	-66.27
US	0.08	0.15	0.75	-1.06	0.90	-53.61	0.99	-36.30	10.93

The columns on entry probability, price, consumer surplus and producer surplus refer to change in level in their respective unit. The unit of entry probability is in percentage. Price is US dollar per tonne. Consumer surplus and producer surplus are in millions of US dollars. The consumption, production and trade columns refer to percentage change in volume. As baseline, Canada consumes 8 million tonne of cement and the US consumes 88.83 million tonne. Canada produces 11.43 million tonne and the US 85.4 million tonne of cement. For trade, rows are origins and columns are destinations.

5.1.3 Output-based pricing system

I show in the previous section that sufficient level of BTA on top of carbon tax on fossil fuels is more likely to improve the welfare in Canada than leaving it out. However, BTAs may violate the rules by World Trade Organization because by design the trade restrictions apply differentially to certain countries. Therefore, an alternative strategy to compensate regulated firms and minimize carbon leakage risks is by imposing an output-based pricing system as adopted by the Act. OBPS works as a rebate (or production subsidy). Covered firms only pay for the excess amount beyond their emissions limit. Specifically for the cement industry, it is subjected to a output-based standard at 95% of the sector's average carbon intensity. Taking the industry average at 0.8tCO_2/tonne of cement, if a plant generates more emission than 76% of its cement output, it will face a marginal rate of \$50/tCO_2. Consistent with the Act, I also adjust the calculation to the coverage of OBPS including both combustion and non-combustion emissions, unlike only combustion for the fuel charge. In practice, I translate the marginal charge on carbon to a representative plant operates at the industry average emission intensity.[50] The OBPS is equivalent to a levy of \$2 per tonne of

[49] Counting the benefit of carbon reduction, the welfare of the US always improves if the welfare of Canada improves after Canada implementing carbon tax with and without BTA.

[50] Two details are missing from this simple OBPS counterfactual exercise. First, I assume that all firms are homogeneous. In reality, OBPS allows the clean firm with lower than limit emission to sell carbon credits to those that exceed the emission limit. Therefore, OBPS has distributional effects of allocating resources from heavy polluters to clean firms. Second and related to the first point is that I assume all firms emit at the industry average carbon emission

cement, beyond the average plant production cost of $60.22.

Figure 12 shows that OBPS triggers the least degree of plant relocation among the three carbon pricing schemes. Top two firms in maximum decrease 2.3% number of plants across all locations in Canada. Very few locations in the US are observed with large entry, and some locations such as Nevada even have plants exit due to expansion in nearby efficient area.

Figure 12: Plant relocation with OBPS in Canada

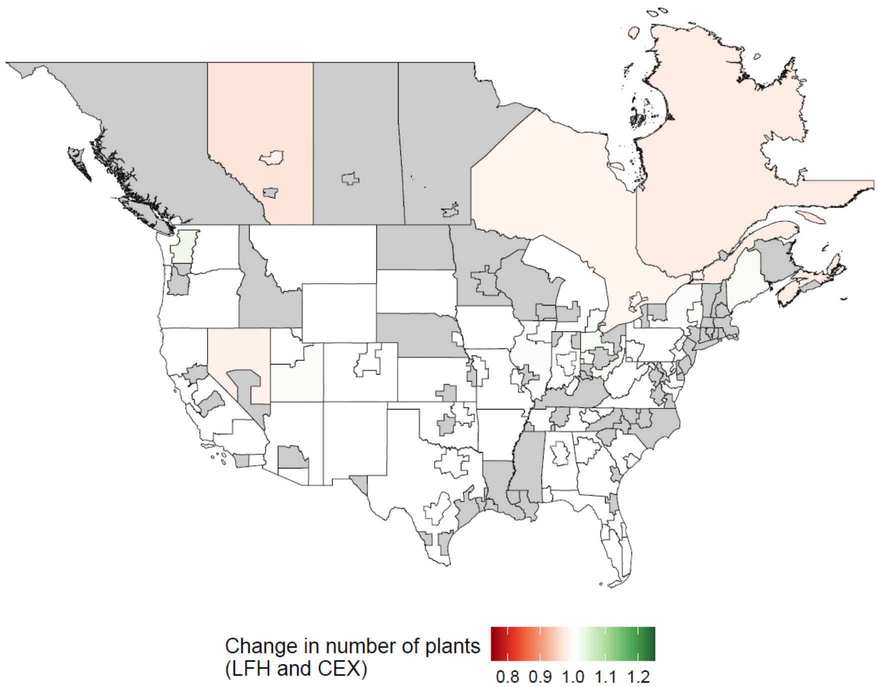


Table 11 tabulates results in various dimensions. The changes are not qualitatively different from those in Table 9, if any, smaller in magnitude. As expected, it provides relief from the fuel charge to emission-intensive and trade-exposed facilities. The number of plants, the amount of production, and the exports to the US, have all been restored nearer to the baseline level. The mitigation on production leakage is achieved at the sacrifice of weaker environmental effort. Carbon emission drops by 0.72 million tonne, which is less than one fifth of the reduction in the case of carbon tax.

Consumers and producers combined suffer $56 million loss in Canada. But the government collects $20.5 million proceeds from the firms' excess emission penalty. Calculating the social cost of carbon for the policy to be welfare-improving for Canada, the threshold should be $49.2 per tonne of CO_2. The break-even cost of carbon is very close to the $50 carbon price set by the

intensity. Firms are passive takers of the carbon charges but not active seekers for cleaner production technology. I leave more detailed treatment of OBPS to future research.

government and also the lowest among the three cases, meaning that OBPS is the best scheme so far. My analysis provides some justification for the government to adopt OBPS in the cement industry and to set the carbon price the level it is.

Table 11: Counterfactual changes with OBPS in Canada

	Entry Probability Δ		Price Δ	Consumption $\Delta\%$	Production $\Delta\%$	Trade $\Delta\%$		CS Δ	PS Δ
	LFH	CEX				Canada	US		
Canada	-1.00	-0.23	3.15	-8.65	-10.35	-8.79	-27.54	-46.36	-9.57
US	0.04	0.03	0.19	-0.29	0.33	11.75	0.31	-9.57	2.67

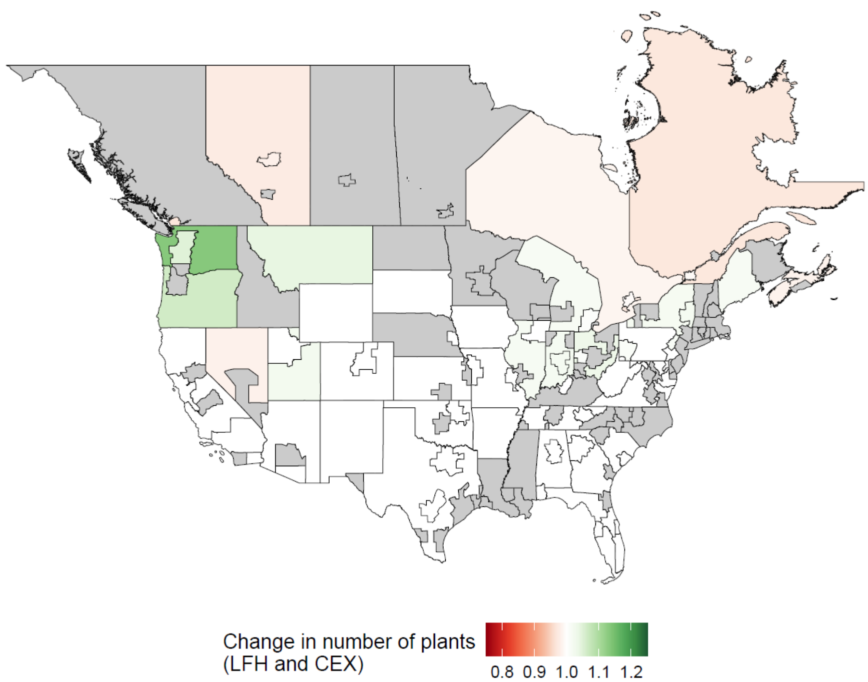
The columns on entry probability, price, consumer surplus and producer surplus refer to change in level in their respective unit. The unit of entry probability is in percentage. Price is US dollar per tonne. Consumer surplus and producer surplus are in millions of US dollars. The consumption, production and trade columns refer to percentage change in volume. As baseline, Canada consumes 8 million tonne of cement and the US consumes 88.83 million tonne. Canada produces 11.43 million tonne and the US 85.4 million tonne of cement. For trade, rows are origins and columns are destinations.

5.2 National protectionism

With the recent political unrest and the US-Canada tension on key manufacturing inputs such as aluminum, there is potential risk for unilateral increase in tariff. In this exercise, I show how the multi-plant firm model can be applied to a trade experiment. Given the cement consumption in Canada relies mostly on domestic production, changes to import tariff by Canada would not significantly affect firm dynamics. On the contrary, Canada exports around 30% of its cement production to the US, and it is also the largest foreign supplier for the U.S. cement industry. Unilaterally rise of import tariff by the US will shift plant location and trade pattern in the region. I hereby examine firm dynamics and welfare implications when the US raises import tariff by 20%, as most of the MFN rates in the cement industry fall below 20%.

Figure 13 shows the plant relocation from Canada to the US. Plant closure proportional to number of plants is most severe in British Columbia for about 3%, followed by Québec, Alberta, Nova Scotia, and Ontario. The number of new plants in Washington except for Seattle metro area actually accounts for 13% of its baseline level. Other area such as Oregon, Montana, Utah and some eastern states also face moderate degree of plant entry. However, accompanying plant entry in some US locations is exit in others where markets are crowded out by such expansion, namely Nevada. The first two columns in Table 12 quantify the overall change at national scale. A result contrasting with previous environmental policy experiments is that the US have more plants entered than the number of plants shut down in Canada, implying that the US demand of cement is large enough to support more players if prohibiting imports.[51] Another caveat is that the overall changes of plants number in absolute value for both Canada and the US are quite small, although locally the relative change is not trivial. Therefore, tariff can bring some plants back to the US and may even facilitate more entry beyond the degree of relocation, but the magnitude counting both is still not as large.

Figure 13: Plant relocation with 20% import tariff in the US



Looking at Table 12, the largest changes are found in the production of cement in Canada and the exports from Canada to the US. A 20% tariff rise leads to around 855 thousand tonne shrinkage in the Canadian cement production, and a fraction of it is now produced in the US. Export to the US decreases by about 85%, which makes the export intensity in Canada to be 5%, a much lower rate than the previous level of 30%.

In terms of welfare, Canada faces a \$2.2 million decrease, while the US loses \$22.4 million of which the negative effect on consumers is triple the gain by producers. The government's tariff revenue is roughly \$8.4 million and cannot offset the loss.[52] The huge reduction of welfare in the US driven by consumers is consistent with the traditional theory of trade but having the additional

[51]The top two firms combined increase the entry probability to any FAF zone in the US by 0.23%, multiplying 63 potential FAF zones results in 0.145 more plants. In contrast, the two firms decrease the entry probability to any FAF zone in Canada by 1.37%, multiplying 10 potential FAF zones results in 0.137 fewer plants.

[52]I estimate the percentage decrease in trade value using the change in trade volume. In 2016, Canada export cement to the US for a total of 274.7 million dollars.

power to decompose the aggregate outcome into various micro channels. A unilateral tariff rise does more damage to the US itself than to the opponent.

Table 12: Counterfactual changes with 20% import tariff in the US

	Entry Probability Δ		Price Δ	Consumption $\Delta\%$	Production $\Delta\%$	Trade $\Delta\%$		CS Δ	PS Δ
	LFH	CEX				Canada	US		
Canada	-1.00	-0.37	0.17	-0.43	-7.48	-0.43	-84.70	-2.55	0.36
US	0.10	0.13	0.66	-0.93	0.90	0.52	0.90	-31.81	9.45

The columns on entry probability, price, consumer surplus and producer surplus refer to change in level in their respective unit. The unit of entry probability is in percentage. Price is US dollar per tonne. Consumer surplus and producer surplus are in millions of US dollars. The consumption, production and trade columns refer to percentage change in volume. As baseline, Canada consumes 8 million tonne of cement and the US consumes 88.83 million tonne. Canada produces 11.43 million tonne and the US 85.4 million tonne of cement. For trade, rows are origins and columns are destinations.

5.3 Merger and acquisition

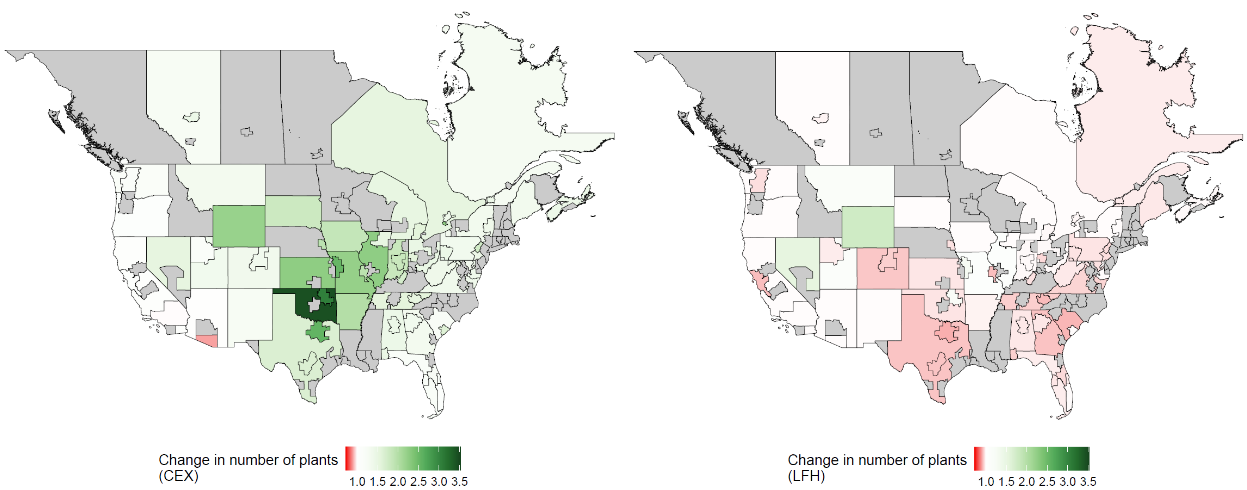
In the last counterfactual exercise, I apply the estimated multi-plant firm model to demonstrate how the framework can be handy in answering a central question of competition policy design. I simulate an acquisition of a medium-sized firm in the group of fringe by the second largest firm in the markets, Cemex. The target chosen in this experiment is the leading US cement producer, Eagle Materials Inc, which owns six US cement plants in 2016 and headquartered at Dallas in Texas.[53] The acquisition is assumed to bring cost synergy to the Mexican firm, Cemex, such that fixed costs of establishing plants in the US are going to be lower with detailed local knowledge. The reduction in fixed costs is reflected through every location's proximity to firm headquarter as Monterrey in Mexico pre-acquisition and Dallas in the US post-acquisition.

Holding the estimated parameters the same, I let LafargeHolcim and Cemex to re-optimize their plant sets and fully adjust to a more efficient Cemex and also a smaller pool of fringe firms. The left panel in Figure 14 displays significant plant entry for Cemex post acquisition, radiating from the headquarter Dallas and most severely affecting Oklahoma, Kansas, Illinois, Missouri, and Wyoming. In total, Cemex would have 54% more plants in the US. The positive spillover continues to Canada where Cemex would also build around 38% more plants despite that the acquired entity does not own plants there. The expansion of Cemex within the US and cross-border is attributed to fixed costs synergies and exacerbated by the production advantage gained through adding plants

[53] Eagle Materials Inc was the second largest locally owned cement manufacturer in 2016, just following Ash Grove Cement Company which owned eight US plants. However, Ash Grove Cement Company was acquired by CRH plc, an international building materials group, at the end of 2017. Eagle Materials Inc, remaining to be independent, is now the largest US owned cement producer in 2020.

at efficient places. However, comparing the post entity to Cemex and Eagle Materials combined before, I find that Cemex internalizes some plants after acquisition because markets of the two separate firms overlap at southern states. On the other hand, the competitor, LafargeHolcim, faces plant exits in numerous places across Canada and the US, especially south of the US where Cemex surges in market presence. With plant redistribution generally follows the expectation, not every location has Cemex rising and LafargeHolcim shrinking. For example, what happens at Wyoming, Nevada and Tucson metro area in Arizona imply that changes in market structure outside of these area affect the internal redistribution due to the interdependency across plants.

Figure 14: Plant relocation when Cemex acquires a small firm



(a) Cemex post-acquisition

(b) LafargeHolcim

Table 13 shows that the total number of plants increases in Canada and decreases in the US represented by summation of entry probabilities. However, they both experience lower prices. To reconcile the discrepancy, one has to realize that there are two channels in which the market price would change in the multi-plant firm model. One is that more competing firms intensify the head-to-head competition and put downward pressure to the market price. The other is that more plants owned per firm indicate cost advantage and pass on to a lower price. In Canada, the number of firms does not change since Eagle Materials Inc is not present prior to acquisition. After acquisition, Cemex expands its active set of plants in Canada at a degree larger than the shrinkage of LafargeHolcim. Therefore, total number of plants increases and the second price channel dominates. As for the US, the number of firms declines after Eagle Materials is acquired, and thus imposes an upward pressure to the cement price. However, the number of plants per firm increases on average with a "larger" Cemex and a slightly smaller LafargeHolcim, which leads to lower price. The declining total number of plants in the US is a result of fewer firms and internalization of Cemex post acquisition, whereas the drop in price is a result attributed to the dominant role of "larger" firms on average. Therefore, we would also see the change in price is smaller in the US with two countervailing forces.

Following the price drop is the higher consumption and production of cement for 0.8 million tonne more. Unintentionally, this is equivalent to 0.64 million tonne of carbon emissions. Trade also adjust accordingly with more active cross-border trade.

Overall, acquisition of the medium-sized US firm by Cemex generates pro-competitive effects, conditional on the significant cost synergies and asymmetry between the first and second largest player in the markets. LafargeHolcim owns twice the number of plants than Cemex and expansion of the second largest player closes the gap for more intense competition. Both countries gain overall although producers loose. Decomposing the total change in producer surplus, I find Cemex benefits while all other firms loose. Across country, US improves welfare by \$14.42 million and Canada by \$2.1 million. If one concerns about the side effect - rise in carbon emissions, an external cost of more than \$25.8/tCO_2 will undermine all the gains. The analysis provides a theoretical ground to rationalize the industry consolidation during the recent decades. Nevertheless, one should be careful in generalizing the quantitative results to M&A activities of other firms. The multi-plant firm framework and its estimation are what can be broadly used in examining different cases.

Table 13: Counterfactual changes when Cemex acquires a small firm

	N. Plants Δ	Price Δ	Consumption $\Delta\%$	Production $\Delta\%$	Trade $\Delta\%$		CS Δ	PS Δ
					Canada	US		
Canada	0.22	-0.22	0.63	0.89	0.63	3.72	2.95	-0.85
US	-0.45	-0.01	0.88	0.82	1.18	0.82	22.82	-8.40

The columns on number of plants, price, consumer surplus and producer surplus refer to change in level in their respective unit. The number of plants is the summation of entry probabilities for the two large firms and fringe firms, and thus need not be integer. Price is US dollar per tonne. Consumer surplus and producer surplus are in millions of US dollars. The consumption, production and trade columns refer to percentage change in volume. As baseline, Canada consumes 8 million tonne of cement and the US consumes 88.83 million tonne. Canada produces 11.43 million tonne and the US 85.4 million tonne of cement. For trade, rows are origins and columns are destinations.

6 Conclusions

In this paper, I have developed a multi-plant oligopoly model with endogenous and interdependent location decisions. The model nests previous findings for single-plant firms, and also extends to capture firms strategically decide sets of production locations. The framework points to the importance of spatial correlation and a production-trading network. It further relaxes the assumption of zero measure firms in standard trade theory by allowing granularity of firms engaging in oligopolistic competition. Most notably, despite having a generalized model, it earns tractable solutions on market outcomes that can be easily estimated in two steps. The framework goes quite far in matching data on U.S. and Canada cement industry. The estimation encloses key costs faced by cement plants, including marginal cost of production, trade cost and fixed cost of entry. Using the structurally estimated parameters, I can quantitatively evaluate the effects of environmental regulation, trade policies, and change in market structure on firm dynamics and market aggregates.

An increase in carbon tax would result in firms to relocate production to nearby "pollution haven". Specifically, the output-based pricing system for the cement industry implemented by the Canadian federal government balances the effort of reducing carbon emissions and protecting domestic competitiveness. The social benefit of carbon reduction need not be tremendously high in order for the policy to be welfare improving. In addition, examination of unilateral tariff changes confirms the long-existing consensus that countries gain from free trade. Lastly, the acquisition simulation provides a case of pro-competitive effects of M&A, which justifies the major consolidation process happened in the cement industry.

To save computational cost, this paper ignores endogenous entry and exit of small firms, while using a static model and a screen shot of data to infer equilibrium. In principle one could extend my model to allow for dynamic interaction and incorporate endogenous small firms. Such extensions remain topics for future research. But the model in this paper has already gone much further than previous work in capturing firm entry, trade, competing and pricing decisions in a spatial network.

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Appendices

A Model details

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

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

$$\begin{aligned} F_{12,m}(z_1, z_2; \ell^*, f^*) &= \Pr\left(\tilde{Z}_{1m}(j) \leq z_1, \tilde{Z}_{2m}(j) \leq z_2 \mid \tilde{Z}_{1m}(j) > V\right) \\ &= \Pr\left(\tilde{Z}_{1m}(j) \leq z_2 \mid \tilde{Z}_{1m}(j) > V\right) \\ &\quad + \Pr\left(z_2 \leq \tilde{Z}_{1m}(j) \leq z_1, \tilde{Z}_{2m}(j) \leq z_2 \mid \tilde{Z}_{1m}(j) > V\right), \end{aligned} \tag{17}$$

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

The distribution of S is

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

And the distribution of V is

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

The first part of equation (17) can be simplified as

$$\begin{aligned} \Pr\left(\tilde{Z}_{1m}(j) \leq z_2 \mid \tilde{Z}_{1m}(j) > V\right) &= \frac{\Pr\left(V < \tilde{Z}_{f^*\ell^*m}(j) \leq z_2\right)}{\mathbb{P}_{f^*\ell^*m}} \\ &= \frac{\Phi_m}{\phi_{\ell^*m}} \int_0^{z_2} \left[\tilde{F}_{\ell^*m}^{draw}(z_2) - \tilde{F}_{\ell^*m}^{draw}(V)\right] dF_m^V(V; \ell^*, f^*) \\ &= \exp\left(-\Phi_m z_2^{-\theta}\right). \end{aligned} \tag{18}$$

Next, the second part of equation (17) is equal to

$$\begin{aligned} &\frac{\Pr\left(z_2 \leq \tilde{Z}_{f^*\ell^*m}(j) \leq z_1, \tilde{Z}_{2m}(j) \leq z_2, \tilde{Z}_{f^*\ell^*m}(j) > V\right)}{\mathbb{P}_{f^*\ell^*m}} \\ &= \frac{\Pr\left(z_2 \leq \tilde{Z}_{f^*\ell^*m}(j) \leq z_1, \tilde{Z}_{2m}(j) \leq z_2, \tilde{Z}_{f^*\ell^*m}(j) > S\right)}{\mathbb{P}_{f^*\ell^*m}}, \end{aligned}$$

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

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

The second part of equation (17) is therefore

$$
\Pr\left(z_2 \leq \tilde{Z}_{1m}(j) \leq z_1, \tilde{Z}_{2m}(j) \leq z_2 \mid \tilde{Z}_{1m}(j) > V\right) = \frac{\Phi_m}{\Phi_{f^* m}} \left(e^{-(\Phi_m - \Phi_{f^* m}) z_2^{-\theta}} e^{-\Phi_{f^* m} z_1^{-\theta}} - e^{-\Phi_m z_2^{-\theta}}\right). \tag{19}
$$

Summing equation (18) and (19), the joint distribution of highest two cost-adjusted productivities conditional on f^* from ℓ^* selling to j 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 a project j in market m is

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

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

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

Derive each component, I have the firm term

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

and the second term

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

Combining the two and subtracted by one, I get the price distribution exactly equals to equation (8).

A.3 Markup distribution

The markup equals

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

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

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

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

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

The conditional markup distribution is then

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

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

The markup distribution is truncated at the monopoly markup,

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

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

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

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

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

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

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

A.4 Expected revenue

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

Gamma Lemma:

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

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

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

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

The conditional expected revenue is

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

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

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

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

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

The second term can be simplified to

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

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

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

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

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

A.5 Costs

The conditional expected cost of a firm is

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

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

$$\mathbb{E}\left[\frac{p_m(j)^{1+\eta}}{\mu}\right] = \underbrace{\int_0^\infty \int_{\frac{z_1}{\bar{\mu}}}^{z_1} \left(\frac{1}{z_2}\right)^{1+\eta} \frac{z_2}{z_1} f_{12,m}(z_1,z_2)dz_2dz_1}_{\text{T1}} + \underbrace{\int_0^\infty \int_0^{\frac{z_1}{\bar{\mu}}} \left(\frac{\bar{\mu}}{z_1}\right)^{1+\eta} \frac{1}{\bar{\mu}} f_{12,m}(z_1,z_2)dz_2dz_1}_{\text{T2}}.$$

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

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

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

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

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

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

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

where

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

The unconditional expected cost is therefore

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

B Model extensions

B.1 Adding project demand

Recall that there are a continuum of projects in every market, each demanding certain amount of the good. In the baseline model, I characterize the aggregated market demand instead of the project demand. Here, I add more details to the demand side by modeling each project's demand of the product in the context of construction projects and their use of cement.

The construction projects use cement and other intermediate materials, such as steel, wood, and glass, to produce final output (buildings, bridges, roads, etc). Suppose a project's final good production function follows constant elasticity of substitution,

$$Y_m(j) = B_m(j) \left(\sum_i \xi_i^{\frac{1}{\sigma}} q_m(j,i)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

where $B_m(j)$ indicates the efficiency to build project j in market m. The distribution and substitution between cement and other materials are governed by ξ_i and σ respectively, with $0 < \xi_i < 1$ and $\sigma > 1$.

The factor demand is then

$$q_m(j,i) = \xi_i B_m(j)^{\sigma-1} \left(\frac{c_m(j)}{p_m(j,i)}\right)^{\sigma} Y_m(j),$$

where the unit cost of producing final output for the project is $c_m(j) = \frac{1}{B_m(j)} \left(\sum_i \xi_i p_m(j,i)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$, and $p_m(j,i)$ is the price of intermediate material i for project j in market m. Specifically for cement ($i = \mathcal{C}$), its project-level demand is

$$q_m(j,\mathcal{C}) = \xi_{\mathcal{C}} B_m(j)^{\sigma-1} \left(\frac{c_m(j)}{p_m(j,\mathcal{C})}\right)^{\sigma} Y_m(j).$$

Aggregating the expenditure on cement across projects in market m and combining with equation (1), I have the market-level cement spending as

$$
\begin{aligned}
P_m Q_m &= \int_0^1 p_m(j,\mathcal{C}) q_m(j,\mathcal{C}) dj \\
A_m P_m^{\eta+1} &= \xi_{\mathcal{C}} \int_0^1 \frac{c_m(j) Y_m(j)}{(B_m(j) c_m(j))^{1-\sigma}} p_m(j,\mathcal{C})^{1-\sigma} dj,
\end{aligned}
$$

where $A_m = \exp(\alpha_m)$. The market price index for cement is a composite of cement price for each project,

$$
P_m = \left(\int_0^1 \frac{\xi_{\mathcal{C}}}{A_m} \frac{c_m(j) Y_m(j)}{(B_m(j) c_m(j))^{1-\sigma}} p_m(j,\mathcal{C})^{1-\sigma} dj \right)^{\frac{1}{\eta+1}}.
$$

Mathematically, if $\eta = -\sigma$ and denote $\gamma_m(j,\mathcal{C}) \equiv \frac{\xi_{\mathcal{C}}}{A_m} \frac{c_m(j) Y_m(j)}{(B_m(j) c_m(j))^{1-\sigma}}$, the market price index for cement resembles what derives from maximizing a representative consumer's constant elasticity of substitution (CES) utility,

$$
P_m = \left(\int_0^1 \gamma_m(j,\mathcal{C}) p_m(j,\mathcal{C})^{1-\sigma} dj \right)^{\frac{1}{1-\sigma}},
$$

where the CES utility over cement consumed by every projects is in the form of

$$
U_m = \left(\int_0^1 \gamma_m(j,\mathcal{C})^{\frac{1}{\sigma}} q_m(j,\mathcal{C})^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}}.
$$

The substitution parameter σ which is used to represent the substitution across different construction materials, also governs the substitution across different projects. One can think of the representative consumer as a social planner in market m. Maximizing the utility subject to budget constraint, the planner decides the optimal set of cement used for various projects and subsequently the level of various infrastructure services provided in the market. The demand parameter $\gamma_m(j,\mathcal{C})$ is isomorphic in the CES setup to have consumers demand more of a project conditional on price because it is higher quality in some objective sense or because they just like it more. For example, a planner may demand more bridges if the market is water-borne and the technology for building bridges is already mature, i.e. $B_m(j) > B_m(j^{'})$ for $j =$bridges.

The equalization of material substitution parameter and projects substitution parameter is not surprising. The elasticity of demand at market level depends on how projects are aggregated and the trade-off between cement and outside options (i.e. other intermediate materials). For the elasticity of market demand exactly equals to the elasticity of substitution across materials ($\eta = -\alpha$), it must be that the projects are aggregated in the same way.

B.2 Adding core productivity differences at firm level

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

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

where $Z_\ell(j)$ 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 $\tilde{Z}_{f\ell m}(j) = \frac{Z_\ell(j)}{w_\ell \tau_{\ell m}/Z_f}$ is then

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

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

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

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

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

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

Transforming the sourcing probabilities into the gravity-type regression, one gets the same form as in equation (14), but with the location fixed effects being $\text{FE}_\ell = \ln \left(T_\ell w_\ell^{-\theta} \sum_f \mathbb{I}_{f\ell} Z_f^\theta\right)$. Therefore, one can no longer separately identify the location characteristics $T_\ell w_\ell^{-\theta}$ from the firm productivities Z_f without the help of additional firm-level data.

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

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

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

C Estimation details

C.1 Asymptotic standard deviation

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

$$V_0 = \sum_{\ell' \in R_\ell} \mathbb{E}\big[m(\delta_0; \mathbf{X}_\ell, \hat{\eta}, \hat{\theta}, \hat{\beta}^\tau) m(\delta_0; \mathbf{X}_{\ell'}, \hat{\eta}, \hat{\theta}, \hat{\beta}^\tau)'\big],$$

and its sample analogue is

$$\hat{V} = \frac{1}{L} \sum_{\ell} \sum_{\ell' \in R_\ell} \big[\hat{m}(\delta; \mathbf{X}_\ell, \hat{\eta}, \hat{\theta}, \hat{\beta}^\tau) \hat{m}(\delta; \mathbf{X}_{\ell'}, \hat{\eta}, \hat{\theta}, \hat{\beta}^\tau)'\big],$$

where R_ℓ is the set of locations belong to the same region as location ℓ.[54]

Adjusted for spatial correlation, the asymptotic distribution is

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

where the $K \times P$ gradient matrix $G_0 = \mathbb{E}\big[\nabla_{\delta'} m(\delta_0)\big]$ and S is the number of simulation for the fixed cost draws. In practice, I take 600 simulation draws from a van der Corput sequence for a good coverage. However, in the case of small samples, the standard asymptotic reasoning may be inappropriate. I instead report the bootstrapped standard errors in the baseline estimation. Nevertheless, Table C.1 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

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

I show in the Table C.1 column (3), (6) and (9) the 2-step estimators, where the first step is per-

[54]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.

formed using identity weight on moments and then compute the optimal weight using the first-step estimates to be fed in the second-step estimation. In most cases, the 2-step estimates are more efficient than the identity weighted estimates. The estimates themselves are consistent and close.

Table C.1: Robustness check: estimation of fixed costs

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

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

C.2 Submodularity across plant locations

I now prove that the profit function in my model satisfies the Single Crossing Differences condition, in particular submodularity due to the negative competition effect. Hence, applying the Arkolakis-Eckert Repetitive algorithm to solve for the equilibrium location set is valid.

Denote the vector of firm f location set $\{\mathbb{I}_{f1}, \mathbb{I}_{f2}, ..., \mathbb{I}_{f\ell}, ...\}$ as $\mathbf{I}_f$, and the number of plants in every location $\{N_1, N_2, ..., N_\ell, ...\}$ as $\mathbf{N}$. Note that $\mathbf{I}_f^{'} > \mathbf{I}_f$ if and only if $\mathbb{I}_{f\ell}^{'} \geq \mathbb{I}_{f\ell}$ for all ℓ with at least one ℓ that the inequality holds strictly. Analogously for $\mathbf{N}$. Recall that by definition $\Phi_m = \Phi_{fm} + \Phi_{-fm}$, where $\Phi_{-fm} = \sum_{f' \neq f} \Phi_{f'm}$ is the sum of production capability for all firms except for f. The production capability of firm f for market m, Φ_{fm}, rises in $\mathbf{I}_f$. The sourcing capability of market m from all firms, Φ_m, rises in $\mathbf{N}$. Therefore, for what follows, only the changes with respect to Φ_{fm} and Φ_{-fm} will be discussed, and those to the location strategy sets $\mathbf{I}_f$ and $\mathbf{I}_{-f}$ will remain the same direction. The advantage for investigating the properties of profit function through Φ_{fm} and Φ_{-fm} instead of the discrete location choices is that the derivatives can be derived using a continuous domain. I focus on the curvature of expected variable profits because fixed costs enter the total expected profits linearly. Exploiting the additive separability across variable profits obtained across markets, I can also analyse $\mathbb{E}\big[\pi_{fm}\big]$ only since according to Lemma 1 in Eckert et al. (2017), the submodularity of $\mathbb{E}\big[\sum_m \pi_{fm}\big]$ would follow from each separable component. I now show that it is submodular over the entire domain under one condition of the parameter θ and η.

First, I explore the changes in profit with respect to a firm's own strategy. One can easily prove that the conditional joint productivity distribution $F_{12,m|f}$ decreases in Φ_{fm} by taking the first-order derivative, which means when $\mathbf{I}_f^{'} > \mathbf{I}_f$, $F_{12,m|f}(z_1, z_2; \mathbf{I}_f^{'})$ first-order stochastically dominates (FOSD) $F_{12,m|f}(z_1, z_2; \mathbf{I}_f)$. Since the price distribution $F_{m|f}^P(p; \mathbf{I}_f)$ is an increasing function of p, it implies $F_{m|f}^P(p, \mathbf{I}_f^{'}) > F_{m|f}^P(p, \mathbf{I}_f)$ or $F_{m|f}^P(p, \mathbf{I}_f)$ FOSD $F_{m|f}^P(p, \mathbf{I}_f^{'})$. This corroborates our main finding that a firm with more plants lowers the price. Given the elastic demand, revenue decreases with price and increases with markets' sourcing probability from the firm. Price in turn decreases with the number of plants owned by the firm and the sourcing probability increases with the number of plants owned by the firm. Therefore, revenue rises with the firm's plant entry. Combining with the ranking of price distribution, the cumulative distribution of revenue $F_{m|f}^R(r, \mathbf{I}_f^{'})$ FOSD $F_{m|f}^R(r, \mathbf{I}_f)$.[55] From proposition 2, we know that markup is an increasing function of the firm's number of plants. The share of profit (Lerner index), therefore, increases with the number of firm's plants as well. I have showed that the marginal expected variable profit increases with the firm's own plants. The second-order derivative of the expected variable profit function with respect to one's own strategy is negative if $\theta > -\eta - 1$.

An increasing and concave expected variable profit function implies that the expected total profit $\mathbb{E}\big[\Pi_f\big]$ features decreasing differences in location choices, and therefore the marginal gain from adding a new location within the same firm to its active locations is decreasing. This case happens when productivities across plants are less dispersed than the elasticity of demand such that the reduction in expected costs dominates the change in price but slower with more locations adding in.

On the other hand, the expected variable profit function monotonically decreases with respect to competing firms' production capability, $\Phi_{-fm} = \sum_{f \neq f} \Phi_{fm}$ when $\theta > -\eta - 1$. The conditional joint productivity distribution $F_{12,m|f}$ again decreases in Φ_{-fm} and therefore when $\mathbf{I}_{-f}^{'} > \mathbf{I}_{-f}$, $F_{12,m|f}(z_1, z_2; \mathbf{I}_{-f}^{'})$ FOSD $F_{12,m|f}(z_1, z_2; \mathbf{I}_{-f})$. The price distribution $F_{m|f}^P(p; \mathbf{I}_{-f})$ FOSD $F_{m|f}^P(p; \mathbf{I}_{-f}^{'})$ because the second-lowest cost firm is more binding for firm f's price given that firm f still supplies to the project. The price drops when competing firm builds more plants. The expected revenue is affected by two opposing forces: upward pressure from a lower price and downward pressure from lower probability of supply. When the existing market share in

[55] One can also proof by taking the first-order derivative of $\hat{R}_{fm}$ with respect to Φ_{fm}.

terms of the sourcing probability is small for competitors, the price effect dominates and revenue increases. When competitors have grown to to some degree, one more competing plant will significantly decrease the probability of firm f supplies to the market and the latter dominates, revenue drops. From the markup distribution, the firm's markup decreases with competitors' plants entry. If $\theta > -\eta - 1$, the decrease in markup dominates the rise of revenue even when competing firms are small, and hence, the expected profit declines whenever competing plants enter. The reason is that when plants are rather homogeneous, any addition to the competitors' active plant set will significantly reduce the existing firm's market share, tighten the room for markup, which is more than the additional demand brought by a lower price.

To examine the submodularity property across the entire domain of location choices, what left is to calculate the cross derivative of the profit function with respect to within-firm locations and across-firm locations. When $\theta > -\eta - 1$, the cross derivative is negative featuring the negative spillover across plants. Therefore, the entire entry game is submodular, as the expected variable profit and therefore expected total profit function has decreasing differences in both own strategy and joint strategy space.

C.3 Best-response potential game

A best-response potential game is where potential functions infer the difference in the payoff due to unilaterally deviation of each player to the best response. It is introduced in work of Monderer and Shapley (1996) and later on developed in Voorneveld (2000). Under the condition of a finite game where the number of players is finite and each of them has a finite strategy space, a best-response potential game always has pure strategy Nash equilibrium and more interestingly, every learning process based on best-response of the players converges to an Nash equilibrium. Specifically, if there exists an ordinal potential function $P : \mathcal{L}_1 \times \ldots \mathcal{L}_n \to R$ such that for every firm f and every location configuration in the finite strategy space $\mathbf{I}_{-f} \in \mathcal{L}_{-f}$ and $\mathbf{I}'_f, \mathbf{I}_f \in \mathcal{L}_f$,

$$\mathbb{E}\big[\Pi_f(\mathbf{I}'_f, \mathbf{I}_{-f})\big] - \mathbb{E}\big[\Pi_f(\mathbf{I}_f, \mathbf{I}_{-f})\big] > 0 \text{ iff } P(\mathbf{I}'_f, \mathbf{I}_{-f}) - P(\mathbf{I}_f, \mathbf{I}_{-f}) > 0,$$

then the location configuration $\{\mathbf{I}^*_f, \mathbf{I}^*_{-f}\}$ that maximizes $P(\mathbf{I}_f, \mathbf{I}_{-f})$ is a pure strategy equilibrium.

For the payoff function in our strategic substitutes game, equation (11) can be decomposed into an additively separable firm-specific part containing only the firm f's locations, $h_f(\mathbf{I}_f)$, and a common part containing all firms' location decisions, $g(\mathbf{I}_f, \mathbf{I}_{-f})$. The payoff for each firm depends upon her action and an aggregate of other players' actions. The game is then best-response potential with potential function,

$$P(\mathbf{I}_f, \mathbf{I}_{-f}) = g(\mathbf{I}_f, \mathbf{I}_{-f}) + \sum_f h_f(\mathbf{I}_f).$$

If firm f obtains a higher profit by unilaterally deviate from a strategy to another one, the potential function increases with this deviation as well. Solving the strategic game in the paper is then equivalent to finding the equilibrium of a coordination game. A pure strategy Nash equilibrium is guaranteed.

Moreover, starting from any arbitrary location decisions, if players simultaneously deviates to their unique best replies in each period, the process terminates in a Nash equilibrium after finite number of steps. Swenson and Kar (2017) found that the convergence rate is exponential. By solving the game 1000 times using the sample data and randomized parameters, Table C.2 shows the maximum number of rounds to find an equilibrium is three. When the potential number of locations is larger and therefore the strategy space is larger, it takes longer to find an equilibrium but still converges to a solution relatively fast.

Table C.2: Convergence Rate Check of Best-Response Potential Game

	Number of locations	Average time (seconds)	Average number of BR rounds	Max number of BR rounds
Mountain and Pacific North	10	0.0934	1.1230	3
Mountain and Pacific South	9	0.0596	1.1830	3
West North Central	7	0.0429	1.1010	2
West South Central	7	0.0494	1.0190	2
East North Central	12	0.0963	1.1980	2
East South Central	6	0.0198	1.0830	3
New England and Middle Atlantic	10	0.1275	1.1130	2
South Atlantic	12	0.1753	1.0780	2

C.4 Additional tables

Table C.3 provides alternative specifications for the first-step gravity-type regression using the country-level sample. Table C.4 presents the first-stage results of the demand estimation using the price survey data. Table C.5 provides details in computing fuel costs for the carbon tax on fossil fuel counterfactual exercise.

Table C.3: Estimation of Trade Costs at Country Level

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

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

Table C.4: First-Stage Regression for Demand Estimation

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

First-stage regression for the column (3) in Table 4. Price is from the data based on survey regions and then assigned to the 149 FAF zones. $d_{\ell m}$ is the distance between a location-market pair. The regression include year fixed effects from 2012 to 2016. Variables other than the number of building permits and population are excluded instruments. Robust standard errors in parentheses. Significance levels: ^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01.

Table C.5: Fuel Costs and Energy Content

	Usage Breakdown (%)	Energy Content	Price, 2016 ($/mBTU)	Price, 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	12.2232	$0.1593/L

Based on the Portland Cement Association's US and Canadian Portland Cement Labor-Energy Input Survey, the amount of energy required to produce one tonne of cement is 4.432 million BTU. The rest of fuel used in the cement production is 7% waste fuels and 11% electricity which are not covered by the carbon tax.
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.

D Data appendix

D.1 Implied trade across FAF zones

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

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

Since some parts of cement trade data is implied from trade in nonmetallic minerals, I validate that the trade coefficients are not significantly different between this two group using country-level data as shown in Table D.1. Other products included in the nonmetallic minerals category are glass, bricks, and ceramic products. The result is not unreasonable given that product characteristics of cement and other nonmetallic minerals are similar, such as both being heavy to trade.

D.2 Regions

Map in Figure D.1 and Table D.2 shows the division of sample to 8 districts and an overview of cement market. The area greyed out in the districts map are FAF zones without cement production. Consumption and production are roughly the same for each district, indicating smaller share of trade with outside. Explicitly, Figure D.2 shows the distribution of FAF zones trading within the same district. Out of the 73 producing zones, all of them export at least 50% to other FAF zones within the same district and more than three quarters export more than 80% within the same district. As for the importing cement markets, the distribution is a little dispersed. But still, three quarters of the 149 markets import more than 80% from FAF zones located within the same district and more than 90% of the markets import at least half of their cement consumption within the district. Trade flow validates my assumption of districts being relatively separated from one another. The competition among plants across districts is negligible.

D.3 Locations of limestone deposits and cement plants

Figure D.3 maps the distribution of cement plants versus limestone resources. The information is obtained from US Geological Survey. There are 2909 limestone quarries in the US and 40 in Canada. Most of the FAF zones studied in my sample have at least one limestone quarry available. Obvious exceptions are Saskatchewan and North Dakota where no limestone is available and neither cement plants. These locations where access to limestone is limited are out of the potential set of locations to set up cement plants in my study.

Another issue is that large cement firms such as LafargeHolcim and Cemex typically use lime-

Table D.1: Trade Estimates for Cement and Nonmetallic Minerals

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

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

Figure D.1: Districts Map

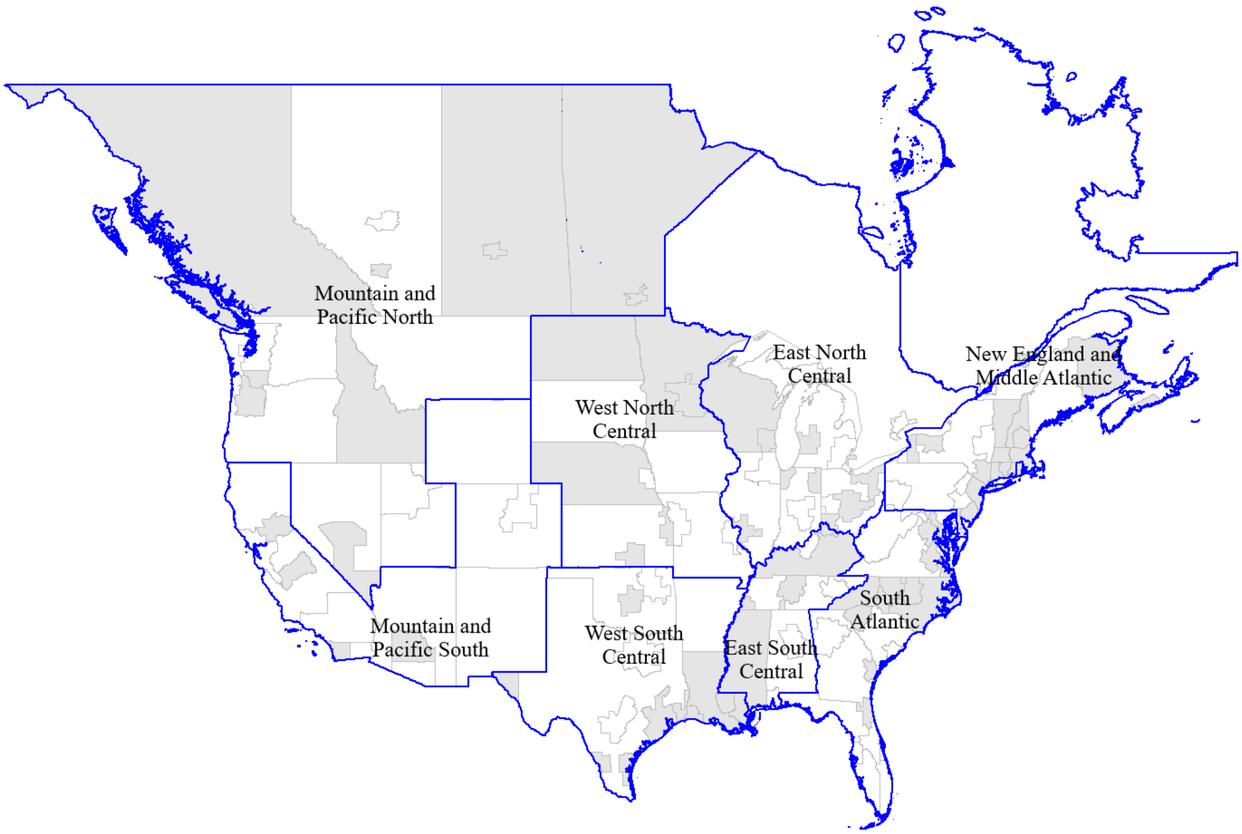
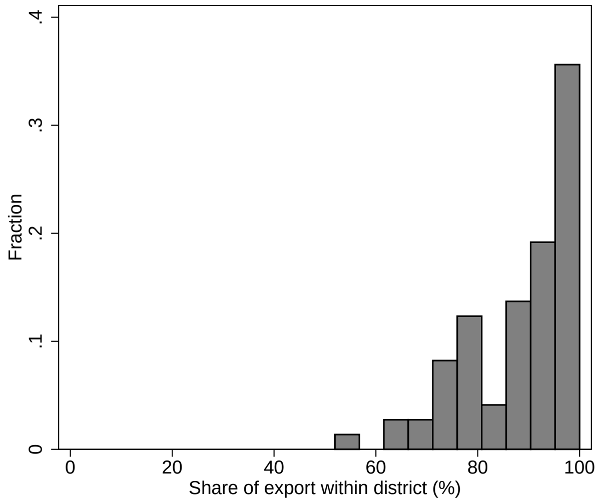


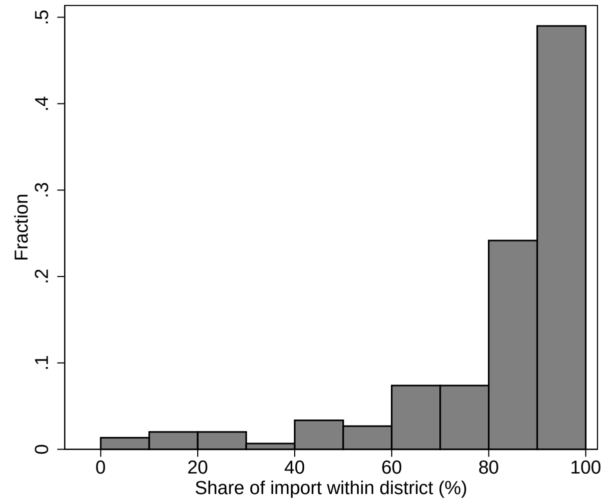
Table D.2: Summary Statistics of Districts

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

Figure D.2: Trade within the Same District



(a) Exports



(b) Imports

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

E Comparison to separate entry decisions

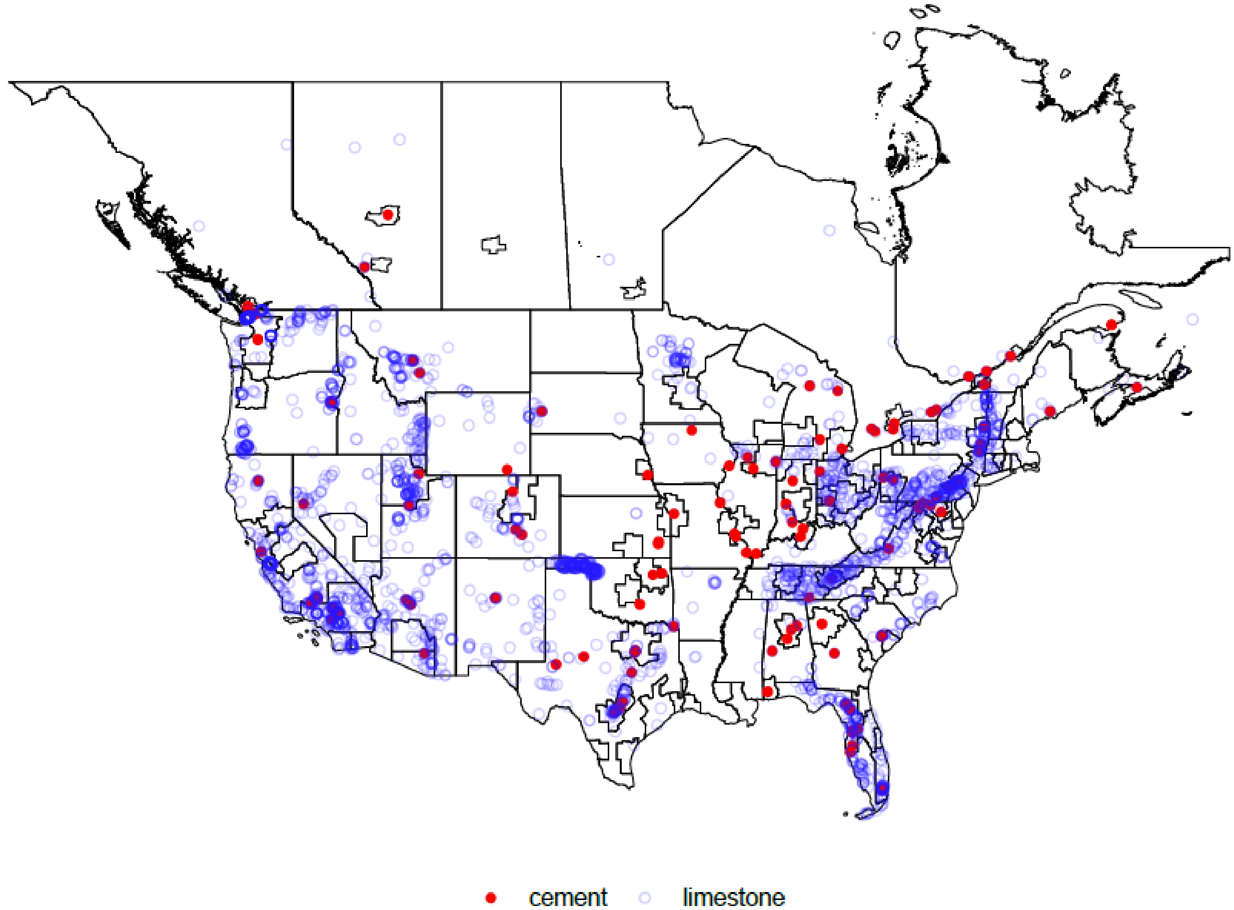
This section examines the difference in estimation and counterfactual results of having multi-plant firms making interdependent plant location choices versus entering each location separately.

Because the price distribution for every plant owned by the same firm is the same, the expected variable profit for a particular plant is its fraction of market supplied out of all the markets captured by its parent firm, multiplied by the firm's expected variable profit. Therefore, the expected total profit of a plant owned by firm f at location ℓ is

$$\mathbb{E}\left[\Pi_{f\ell}\right] = \mathbb{E}\left[\pi_{f\ell}\right] - FC_{f\ell} = \sum_m \frac{\phi_{\ell m}}{\Phi_{fm}} A_m \kappa \left(\hat{R}_{fm} - \hat{C}_{fm}\right) - FC_{f\ell}. \tag{20}$$

Suppose an economist ignores the interdependency of plant location choices within a multi-plant firm, he then mistakenly treats the probability of plant entry as the probability that expected profits of having a plant owned by firm f at location ℓ exceed fixed costs of building it. An alternative interpretation is that managers of the firm are delegated to make myopic decisions

Figure D.3: Cement and limestone resources location distribution



on entry although they know that prices after entering are still coordinated by the headquarter. Preserving the parametric assumption that fixed costs follow a log normal distribution shifted by proximity to firm headquarter, and then taking logs of the plant entry condition $\mathbb{E}\big[\pi_{f\ell}\big] > FC_{f\ell}$, I obtain the the following myopic version of probability of plant entry in empirical form:

$$\Pr\big[\mathbb{I}_{f\ell} = 1\big] = \Phi\left(\frac{1}{\sigma^F}\ln\mathbb{E}\big[\pi_{f\ell}\big] - \mathbf{X}'_{f\ell}\frac{\beta^F}{\sigma^F}\right). \tag{21}$$

Inverting the coefficient of the calculated profitability of plant (f, ℓ) gives a direct estimate of the standard deviation of log fixed costs, σ^F. I estimate equation (21) as a binary probit with the constructed $\ln\mathbb{E}\big[\pi_{f\ell}\big]$ on the right-hand side, together with the distance between location and firm headquarter in logarithm and a constant.

The estimated fixed cost is significantly different as seen in Table E.1.The standard deviation of the fixed costs distribution is calculated to be $\sigma^F = 1.63$. The mean parameters of the fixed costs distribution are $\beta^F_{dist} = 0.605$ and $\beta^F_{cons} = 0.338$. Scaling these estimates to monetary term, the average fixed costs of building a LafargeHolcim plant is \$61 million and those of a Cemex plant is \$54 million. Comparing with the accounting costs or baseline estimates taking into account for interdependencies across plant locations, the fixed costs here are much lower. The reason is that multi-plant firms benefit from having more plants, and thus entry to a particular location can be profitable at firm level but not at plant level. Neglecting parent firm's coordination but only the head-to-head competition among plants leads to fewer entry. Therefore, in order to match the same number of plants, the fixed costs estimated based on separated entry need to be smaller than those for interdependent entry. Econometrically, the probit regression at plant level is no longer i.i.d, I may need to use the spatial interdependent probit models in Franzese and Hays (2008) to correct for the bias.

Table E.1: Estimation of entry without interdependency

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

Robust standard errors in parenthesis.

The differences in estimates cause departure in counterfactual policy evaluations. Table E.2 tabulates results by using the myopic fixed costs estimates for calculating the market equilibrium in the baseline and counterfactual using the multi-plant firm model. Comparing Table E.2 to Table 9, the degree of plant relocation is stronger when fixed costs are low. Subsequently, average price in Canada faces a steeper increase with more concentrated market. Price in the US, however, increases to a smaller amount facing more domestic competition. The welfare loss and carbon leakage in Canada are both more severe than the baseline scenario. On the contrary, the loss of US is milder.

Figure E.1 further compares plant relocation in two scenarios with and without considering interdependent plant locations. Each dot indicates the probability of at least one player from the top two enters the location. Myopic decisions of separate entry generate larger deviation from 45 degree line, indicating larger exit rate in Canada and entry rate in the US.

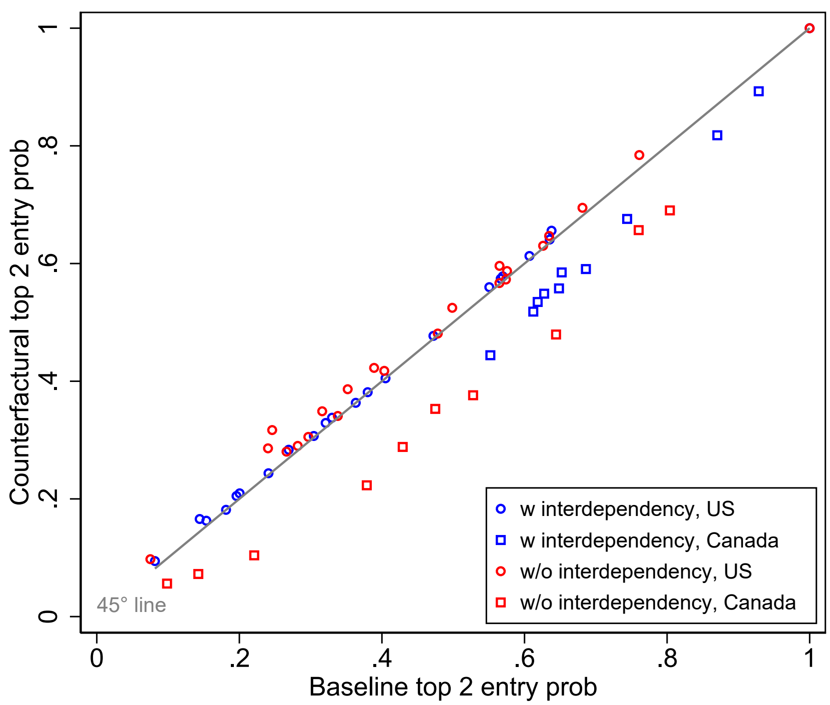
Similar comparison can be done for all counterfactual analysis which is working in progress for now.

Table E.2: Counterfactual changes with \$50 carbon levy on fuel in Canada without interdependency

	Entry Probability Δ		Price Δ	Consumption $\Delta\%$	Production $\Delta\%$	Trade $\Delta\%$		CS Δ	PS Δ
	LFH	CEX				Canada	US		
Canada	-9.27	-6.93	27.91	-54.08	-59.53	-56.52	-95.09	-316.81	-65.42
US	0.52	0.34	0.48	-0.67	1.56	259.51	1.11	-24.39	7.97

The columns on entry probability, price, consumer surplus and producer surplus refer to change in level in their respective unit. The unit of entry probability is in percentage. Price is US dollar per tonne. Consumer surplus and producer surplus are in millions of US dollars. The consumption, production and trade columns refer to percentage change in volume.

Figure E.1: Plant relocation with and without interdependency for \$50 carbon levy on fuel



F Collusion among firms

A concern that one may have about the cement industry is that firms could collude. Literature indeed finds that cement cartels exist in many countries and historically in the US (Chicu et al., 2013). In this section, I examine a limiting case where all firms collude, including the largest two and small firms. This can be seen as a mega multi-plant firm owning all the plants in the US and Canada and charging monopoly price to consumers. This case is nested in my baseline model, and the mega firm's expected variable profit is

$$\mathbb{E}\big[\pi\big] = \kappa\bar{\mu}^{\eta}(\bar{\mu}-1)\sum_{m} A_m \Phi_m^{\frac{-\eta-1}{\theta}},$$

where $\kappa = \Gamma\left(\frac{\theta+\eta+1}{\theta}\right)$. And every entity in the cartel earns

$$\mathbb{E}\big[\pi_f\big] = \kappa\bar{\mu}^{\eta}(\bar{\mu}-1)\sum_{m} A_m \Phi_m^{\frac{-\eta-1}{\theta}-1}\Phi_{fm}.$$

The market price index is

$$P_m = \Gamma\left(\frac{\theta+1}{\theta}\right)\bar{\mu}\Phi_m^{-1/\theta}.$$

Table F.1 presents changes of the market equilibrium if all firms collude at charging the monopoly markup, holding the spatial distribution of plants fixed at baseline. Compared to the baseline average price in Canada at \$96.29 per tonne of cement, the price increases by more than a third. For the US, the average price in the baseline scenario is \$107.21 per tonne of cement, the increase in price is even larger. The cement cartel significantly jeopardises consumer surplus in both countries, which only 40% can be offset by the gain of producers. Cement production in both countries shrinks by almost 60%.

Table F.1: Counterfactual changes with collusion among all firms

	Price Δ	Consumption $\Delta\%$	Production $\Delta\%$	Trade $\Delta\%$		CS Δ	PS Δ
				Canada	US		
Canada	35.42	-57.99	-58.17	-57.97	-60.36	-344.71	139.31
US	42.74	-59.30	-59.28	-59.95	-59.28	-1914.70	791.74

The columns on price, consumer surplus and producer surplus refer to change in level in their respective unit. Price is US dollar per tonne. Consumer surplus and producer surplus are in millions of US dollars. The consumption, production and trade columns refer to percentage change in volume.