Demand Uncertainty, Capacity Decisions and the Irreversibility Effect. Empirical Evidence from the US Cement Industry, 1994-2006.*

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Abstract

Demand uncertainty is thought to influence irreversible capacity decisions. This paper examines some implications of this theory for the US cement industry. Firms in this sector deliver cement for local markets either from domestic plants or from imports. Since cement is costly to transport, the difference in marginal cost between local production and imports varies across local markets. In the presence of uncertain demand, capacity choices depend on whether firms are located on the coast or inland. We construct a model consistent with irreversibility theory embedding these industry characteristics. The properties of the model are then tested using industry data from 1994 to 2006. Consistent with our predictions, there is a negative relationship between the average level of excess capacity and demand uncertainty only for coastal areas. An increase in demand uncertainty is associated with an increase in excess capacity only in landlocked areas. More generally, the paper shows that the cost of imports relative to the cost of domestic production affects the relationship between uncertainty and domestic capacity levels. We briefly discuss the relevance of our results for multinationals' investment decisions and for the effects on US cement capacity of the introduction of a unilateral climate policy.

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1 Introduction

Several important theory papers investigate the relationship between the optimal level of capacity and demand uncertainty. Ordinarily the relationship is ambiguous. We study this relationship in the context of the US cement industry where firms may have access to two technologies: capital-intensive local production at a low marginal cost, and a flexible technology corresponding to importing at a higher marginal cost that includes transport costs. We ask whether variation in the cost of access to imports helps explain variation in the relationship between local demand uncertainty and the domestic capacity decisions made by cement producers in the US.

We show that there is a negative relationship between the level of excess cement production capacity and demand uncertainty in coastal regions in the US between 1994 and 2006, where the incremental marginal cost associated with importing cement is lower. In landlocked regions where the relative cost difference is greater, increases in demand uncertainty are associated with increases in excess capacity. The average plant size is also increasing with demand uncertainty within landlocked regions but not within coastal regions.

There are four major reasons why the US cement industry is an attractive industry in which to study the role of uncertainty in investment decisions. First, the industry is regionally segmented, and there are many plants located throughout the country across varying economic environments. Second, capacity decisions are the major firm-level decision in the industry since cement production is capital intensive. Third, demand for cement in each regional market is largely uncertain. It follows the general business cycle as well as the local cycles typical of the construction industry. Last, in recent decades, long-haul maritime imports have played an increasing role in absorbing fluctuations in US domestic demand. Importantly, a large fraction of the installed base of US cement capacity is controlled by the large multinational firms that dominate this industry worldwide. Following Kogut and Kulatilaka (1994), these firms may use their global production networks to adapt to the demand fluctuations in a given market.

The theoretical framework analyzing investment decisions under this type of uncertainty goes back to the Rothschild and Stiglitz papers (1970, 1971). These authors investigate the monotonicity property of an irreversible decision when risk increases. They provide a necessary and sufficient condition for such a property to hold, point out that this will rarely be the case, and indeed provide a number of economic examples in which it does not. This work can be related to the option value literature originating with Henry (1974), Arrow and Fisher (1974), and fully developed by Dixit and Pindyck (1992). These authors study the impact of a future learning phase on the current irreversible decision. As has been widely noted, the relationship between uncertainty in general and irreversible decisions is theoretically ambiguous (Boyer and Moreaux, 1989, 1997; Abel et al. 1996).

Our empirical analysis relies on an analytical model tailored to the US cement industry. In a setting of oligopolistic competition in a local market, each firm has to decide its capacity when facing uncertain demand. Once the level of demand in a given time period is revealed, the firm may use imports to complement domestic production if local capacity is saturated. In the context of our model, the predicted relationship between uncertainty and investment is unambiguous. The optimal capacity choice is monotonic with respect to the level of uncertainty, contingent on the cost of imports relative to the domestic production cost. Specifically, capacity is increasing with uncertainty if the cost of imports is relatively large, and decreasing if the cost of imports is relatively small. This contingent property is at the crux of our empirical analysis.

There are a number of papers which relate directly or indirectly to our work, the closest of which is Rob and Vettas (2003). In their model, as in ours, FDI and exports (domestic production and imports, respectively, in our model) will co-exist under some circumstances. Much of the prior existing theory on FDI offers only limited explanation of this empirical regularity, as noted by Blonigen (2001) and Head and Ries (2001). However, Rob and Vettas focus on the optimal strategy mix between FDI and exports as demand grows over time, while we focus on the optimal strategy mix (between domestic production and imports) when demand uncertainty varies across settings with differing variable costs of imports.

A number of theory papers have studied the impact of uncertainty on capacity decisions under a set of specific conditions. Demers (1991) analyses capacity choice in a dynamic oligopolistic Markov model. The author shows that the equilibrium capacity is decreasing with uncertainty. In his model the firm is constrained to always produce as much as its earlier capacity commitment, possibly more with a penalty cost, but never less. Gabszewicz and Poddar (1997) consider a two stage game and show that firms invest more with uncertainty. In their framework firms can produce less and not more than their capacity. In our model firms have access to two technologies: domestic production and imports. Demers' model can be viewed as similar to our analysis for coastal markets while Gabszewicz and Poddar's model could be compared to our analysis for landlocked markets. Our two-technology setting generates the contrasting predictions of our model for these two different geographic markets.

Capacity decisions may also be analyzed as a strategic entry barrier. Typically, a monopoly or an oligopoly may operate with excess capacity to deter entry. There have been many theoretical contributions that justify such strategic behavior, such as Spence (1977) and Dixit (1980). A number of empirical studies have tested this hypothesis in specific industry studies, for instance see Ghemawat (1984) and Mathis and Koscianski (1997). As noted by Lieberman (1987), the empirical results have in general failed to provide strong supporting evidence. Our focus in this paper is on the role played by uncertainty and we attempt to control for incentives for preemptive investment in the empirical work by controlling for local demand growth.

To sum up, we develop a model of capacity decisions designed for the US cement industry based on the general literature on the irreversibility effect. This model exhibits original monotonicity properties between capacity and uncertainty which vary depending on the relative cost of a second production technology. Empirical evidence from the US cement industry supports the model's predictions.

The significance of our empirical contribution comes from the observation that while the relationship between uncertainty and investment is a major focus of macroeconomic study, there is a limited amount of work at the micro level. Carruth et al. (2000) survey the existing empirical work. Studies of plant or firm-level variation in investment and uncertainty, including Leahy and Whited (1996) and Guiso and Parigi (1999), focus on the roles played by cross-industry variation in investment irreversibility and also, to a lesser extent, to the role of differences in market structure. Ghosal and Loungani (1996, 2000) study the influence of industry concentration and firm size on the relationship between investment and uncertainty. They find a negative relationship between investment and uncertainty that is substantially greater in industries with lower concentration ratios or industries dominated by small firms. Bloom et al. (2007) evaluate the predictions of a dynamic model about how uncertainty affects the responsiveness of investment to shocks to demand using firm-level data from the UK. Goldberg (1993) finds a negative relationship between investment and exchange rate variability in some sectors, but Campa and Goldberg (1995) find that exchange rate variability has no significant effect on investment levels in US manufacturing. There are even fewer industry-level studies. Notable exceptions include the studies of North Sea oil by Hurn and Wright (1994) and Favero et al. (1994). Bell and Campa (1997) find no relationship between product demand uncertainty at the country level and capacity investment in the chemical processing industry. Most micro-level empirical work is based on variation in the option value of delaying investment, dynamics and adjustment processes. Our approach is closer to the original perspective taken in Rothschild and Stiglitz in that we are interested in the impact of the level of demand uncertainty on irreversible decisions.

Our paper indirectly provides interesting insights into the "leakage" issue in the cement industry. A high unilateral carbon price increases the domestic cost of production relative to foreign imports, hence production and CO2 emissions may simply "leak" to other countries rather than decline overall. The model predicts that the implementation of a unilateral climate policy may have a negative long term impact on local investment levels, amplifying the short term competitiveness impact of higher production costs that is usually captured in static models. Our empirical findings provide an indirect way to test this prediction. In this study, landlocked districts are analogous to domestic countries prior to the imposition of a unilateral carbon price, and coastal districts reflect the ex-post case. Based on this analogy, our findings suggest that there is indeed a relocation effect of capacity due to a high domestic carbon price. We return to this point in the concluding section.

The paper is organized as follows: Section 2 provides some background on the cement industry and describes the data used in the study. The analytical model that sustains our empirical testing is described in Section 3. Section 4 develops the methodology employed and Section 5 describes the empirical results. General implications of these results are addressed in the concluding section.

2 The Cement Industry

2.1 General Characteristics of the Cement Industry

As described in D'Aspremont et al. (2000), demand for cement is more or less proportional to the density of the population. Production takes place in large plants and, once built, the capacity of a given plant cannot be increased without large re-investment. In addition, markets are horizontally differentiated. Quality-wise cement is a homogenous good, but a high transportation cost relative to the production cost creates strong spatial differentiation. This means there are a limited number of competitors in any one geographic location in the industry.

Local demand tends to be quite volatile due to the ups and downs of the housing and infrastructure construction markets, generating significant regional differences between supply and demand. These differences need to be balanced with inter-regional flows, some from adjacent regions, others, in particular if the region is on the coast, through long haul flows.[1] The conditions for long haul transportation of cement changed drastically in the late seventies (Dumez and Jeunemaitre, 2000).

[1]While possible to stock limited quantities of clinker from month to month, particularly during the winter when cold temperatures may prohibit construction activity, producers do not stock finished cement from year to year. From 2002 to 2006 district-level cement stocks at year-end relative to annual production remained at around 7 to 8%, in high and low demand years.

Because of technological change, it became possible to transport cement in bulk quantities safely and cheaply in very large ocean-going vessels, which, however, remain too large to pass through the US river system. This triggered a major change for the US cement industry. The import of cement to areas such as Florida, California, New York, and Texas increased steadily, coming from South America, Europe, and Asia. It was also at this time that the world cement industry entered a phase of ownership concentration, indirectly driven by this enlargement of its strategic market. In 2007, as stated by analysts' reports, the top five cement firms accounted for approximately 20% total world market share. The world cement industry may be seen as a network of regional oligopolies, as described in Ghemawat and Thomas (2008).

Major cement firms such as Cemex, Holcim and Lafarge typically operate a large number of plants.[2] The existence of such networks allows these firms to optimize their sourcing of production at any point in time depending on local supply and demand conditions.[3] Their short term optimization depends on their available capacities in the various markets and on the relative production and freight costs. As such they have a competitive edge over smaller firms that are limited to a given regional market. Traders may also be active in complementing a lack of local capacities. These traders may indeed react quickly to an occasional disequilibrium but they do not have the long term efficiency to sustain long haul trade flows. They often prefer to sell the market positions obtained at peak demand to local players when the downturn comes.

2.2 The US Cement Industry

We now turn to the data on the US cement market used in this study, noting that demand fluctuates at the local level within the US. Our primary data is published by the U.S. Geological Survey (USGS) and summarized in the annual Minerals Yearbook.[4] In the data, the US is divided up into 23 regional districts, the boundaries and groupings of which differ slightly across years. We construct time series data by district for cement capacity, production, and demand, grouping together districts where necessary.[5] The data are summarized in Table 1 and pairwise correlation coefficients for the key

[2]According to their 2009 websites, Cemex operates in 79 plants (in 50 countries), Holcim 151 plants (in 70 countries, and Lafarge 166 plants (in 79 countries).

[3]It is quite difficult to obtain quantitative data on this subject since multinationals often use subsidiaries to make these long haul flows. The actual market share of the global players differs across countries, along with their involvement in the import/export flows. Multinationals' market share is typically higher in developed economies such as the US or in Europe than in emerging economies such as China or in South America. Our framework is designed for countries where multinationals dominate production. See Salvo (2010) for a discussion of the role of imports on domestic competition in Brazil.

[4]We are grateful to Hendrik G. van Oss for advice on interpreting this data.

[5]The district containing Alaska, Hawaii, Oregon, and Washington, the district containing Georgia, Virginia, West Virginia, South Carolina, and Maryland, and the district containing Michigan and Wisconsin, sometimes appear in

variables used in the study are given in Table 2.

District Number	District Name	Landlocked Indicator
1	Alabama	1
2	Alaska, Hawaii, Oregon, Washington	0
3	Arizona, New Mexico	1
4	Arkansas, Oklahoma	1
5	California, Northern	0
6	California, Southern	0
7	Colorado, Wyoming	1
8	Florida	0
9	Georgia, Virginia, West Virginia, South Carolina, Maryland	0
10	Idaho, Montana, Nevada, Utah	1
11	Illinois	1
12	Indiana	1
13	Iowa, Nebraska, South Dakota	1
14	Kansas	1
15	Kentucky, Mississippi, Tennessee	1
16	Michigan, Wisconsin	1
17	Missouri	1
18	New York, Maine	0
19	Ohio	1
20	Pennsylvania, Eastern	0
21	Pennsylvania, Western	1
22	Texas, Northern	1
23	Texas, Southern	0

Excerpt from Table 1: Classification of Districts

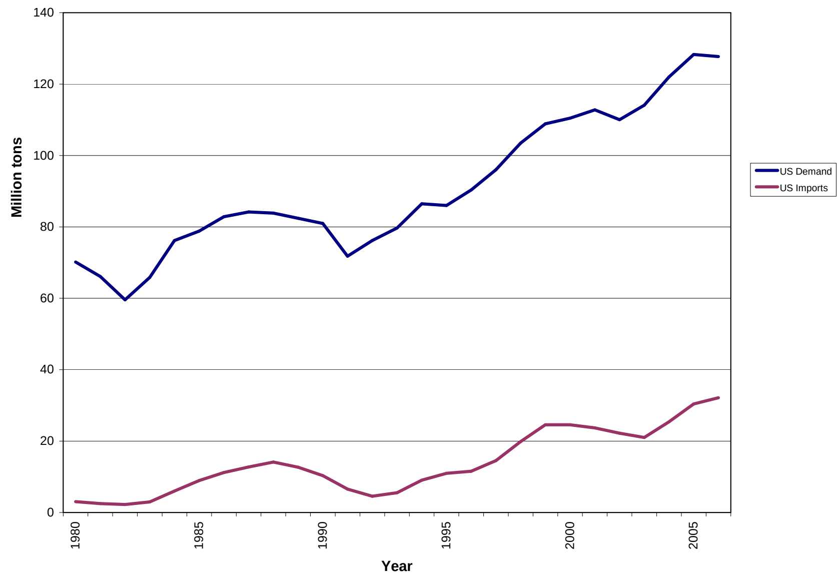
The USGS breaks down total imports of cement and clinker by customs district. Major import terminals include Tampa, FL, New Orleans, LA, Los Angeles, CA, Miami, FL, and Houston-Galveston, TX. Smaller import terminals are spread out over the East Coast of the US and include Baltimore, MD, New York City, NY, Norfolk, VA, and Philadelphia, PA.[6] In each year, there are also imports to Detroit, MI and other northern Midwestern districts from Canada. All of our results are robust to classifying both the Michigan and Wisconsin district and the Ohio district as coastal rather than landlocked, reflecting their accessibility via lake transport from Canada.[7]

Our study employs data from 1994 to 2006. Since the lifespan of a cement plant may exceed 40 years, it is important to study a relatively long time period to understand capacity decisions. Graph 1 presents the evolution of cement consumption and imports between 1980 and 2006.

the minerals yearbook broken up into different groupings.

[6]This list is not comprehensive. Annual statistics can be found in Table 18 of the Cement Yearbook.

[7]Alabama has limited imports from the terminal at Mobile, although the largest cities in this district are located relatively far inland. Arizona imports cement from Mexico at Nogales, an inland border crossing. Nonetheless, all our results are robust to classifying both or each of these districts as coastal rather than landlocked. These results and the results from other alternative district classifications are available from the authors on request.



Graph 1: Demand and imports in the US cement market, 1980-2006.

Over the first part of this time period, up to the early 1990s, the cement industry was considered a mature business (for a discussion on the US cement industry at that time, see Scherer's postface in Dumez and Jeunemaitre, 2000). A large fraction of the US industry was acquired by European (and Mexican) companies (this acquisition wave is discussed in Collomb and Ponssard, 1984). It is also at the beginning of this period that technical change made long haul imports feasible and relatively cheap. By the early 1990s, the US cement industry had been partly restructured and imports came in to the country largely via the new domestic players.[8] In the early 2000s, according to industry sources, global cement players such as Cemex, Holcim, Lafarge, and Lehigh (Heidelberger) operated import terminals located on the East Coast, and Lafarge, Lehigh (Heidelberger) and Taiheiyo on the West Coast. We may certainly hypothesize that the proposed adjustment process of domestic capacities to cope with demand fluctuations had taken place.

One further point is worth attention. Imports are indeed positively correlated with aggregate domestic consumption. The regression coefficient capturing this correlation (the "beta" of a regression of the percentage deviation from the mean level of imports on the equivalent for domestic demand) is computed to be 2.55, demonstrating both that imports are correlated with domestic

[8]Importers have been subject to antidumping charges brought against them by the US government, and antidumping duties were subsequently imposed. Cohen-Meidan (2010) shows that domestic production increased in the early 1990s, more significantly on the Pacific and the West Gulf Coasts than along the Mexican border, because of differential exit costs of importers. Because we focus on vertically integrated firms, we consider that the impact of these duties on our analysis is limited, particularly during the time period we study here. In addition, while duties may have affected the relative cost of imports, the relative price difference between local production and imports remained much greater for landlocked than for coastal districts.

consumption and tend to be more volatile. This suggests aggregate imports adjust to supply residual demand once domestic capacity is exhausted. We investigate local variation in the magnitude of residual demand due to endogenous local capacity choices.

District-level capacity is measured in our data as the finish grinding capacity in thousands of metric tons, and is based on the grinding capacity required to produce a plant's normal output mix, including both portland and masonry cement, allowing for downtime for routine maintenance. Production, also in thousands of metric tons, includes cement produced using imported clinker. The USGS Minerals Yearbook also includes data on the number of active plants by district – which allows us to measure average plant size in each year – and the percentage of plants that are dry and wet process.[9] Table 1 summarizes the levels of capacity investment in each district in 1994 and 2006. There was an increase of 26% in the total metric tonnage of cement capacity in the US over this time period. The total number of plants declined by 5 to 113 in 2006, meaning that the average plant size increased by 31%. There was also a 15% increase in the percentage of plants that used the relatively efficient dry process (or both wet and dry) rather than wet process technology.

These aggregate measures mask substantial variation across districts. The standard deviation of the percentage change in capacity is 29%. Three districts – Ohio, and Eastern and Western Pennsylvania – saw declines in capacity. Northern Texas and the district containing Georgia, Virginia, West Virginia, South Carolina, and Maryland saw the largest absolute increases in capacity. The percentage increases were largest in Kansas, the district containing Kentucky, Mississippi, and Tennessee, Northern Texas, and Florida, at 85%, 74%, 68%, and 67%, respectively. The largest increases in average plant size took place in the Colorado and Wyoming district, which also saw a plant closure. Other large increases were seen in Kansas and Northern Texas. There were no decreases in average plant size in any district. 7 of the 23 districts had 100% dry or both wet and dry process plants in 1994, 10 of the remaining 16 districts saw an increase in the percentage of dry process plants, and two districts saw a decline.[10]

The demand data is aggregated by the USGS up from the state-level cement shipments to final customers. It includes cement produced from imported clinker and imported cement shipped by domestic producers and importers. Table 1, panel A, also summarizes the demand data by district in 1994 and 2006. Much of the variation in capacity across districts corresponds with variation in

[9]The statistics for the percentage of plants that are dry or wet process come from Table 5 of the USGS annual yearbook which details the technology in clinker plants only. The data on the total number of plants in each district used in the study are taken from Table 3 each year which details all white cement plants by district.

[10]While regulation may play a role in capacity decisions, it is more likely to act as a very local constraint and unlikely to matter differently in landlocked and coastal districts.

regional economic growth, and so to understand the roles played by demand uncertainty we must also control for the role of demand growth in explaining these patterns. We measure demand growth as the average percentage change in the level of demand over the prior four years.

To measure demand uncertainty for each district, we construct a measure of the variance in demand levels over the past four years and the current year. To avoid overstating uncertainty we de-trend the data to account for changes in demand levels that are consistent with patterns that are arguably predictable. Since this measure of variation will be a function of the level of demand, we also normalize our uncertainty measure to facilitate comparison of uncertainty across districts of different sizes. To do this, we regress demand by district over the past five years on a constant. The residuals of this de-trending process measure the difficulty of predicting the current year demand from demand levels over the previous five years. To find the average difficulty of predicting current demand in recent years, we then take the standard deviation of the residual values over the current year and the prior 4 years, divided by the mean demand level over these five years. This normalized standard deviation summarizes the extent of recent demand uncertainty. Our intent is to capture the plant manager's view about the difficulty in predicting the demand level using past information.[11] Panel B of Table 1 lists the district level mean demand growth and demand uncertainty over the data period.

We note that our measure of uncertainty is backwards-looking since it is constructed using district-level data from previous years. Any increase in uncertainty is due to the level of demand in the current year being less similar to the level of demand for the past three years than is the level of demand four years ago to the prior three years. As will be described in Section 4, we also classify districts into high and low demand uncertainty districts, capturing whether the level of uncertainty is higher or lower than the mean level across districts over the entire time period.[12]

3 The Analytical Model applied to the US Data

Our model features a local oligopoly that faces fluctuating demand. Each firm may source its production from plants in two areas, some directly located in the market, i.e. "home" plants, and some located abroad, i.e. "foreign" plants from which it may import. Home plants have a

[11]All of our results are robust to assuming the plant manager looks back at the residuals (measuring the difficulty of predicting a given year's demand) for the past 3 years or the past 5 years, in assessing the extent of overall demand uncertainty.

[12]Carruth et al. (2000) contain a discussion about the relative merits of different measures of uncertainty. Guiso and Parigi (1999) is one of very few studies that uses survey data on manager's certainty about future demand as a measure of firm-level uncertainty.

lower variable cost and are capacity constrained. Foreign plants have a higher variable cost, when including the cost of transport to the home market, and are not capacity constrained because there are many of them that can potentially export to this home market.

We focus on the dependence of the home capacity decisions on import costs as demand uncertainty increases. Imports will be required at peak demand levels, given the home capacity constraint. Consequently, the optimal capacity depends on the relative import versus domestic production costs and on the level of demand uncertainty. Clearly, the lower the import cost the more beneficial it is to import and the lower the optimal capacity should be. However, for a given import cost, the irreversibility effect of a larger demand uncertainty on the capacity choice is ambiguous a priori. It will be proved that this irreversibility effect is positive if the import cost is higher than some threshold and negative if it is lower. This result, which is key in our empirical analysis, can be related to the original paper by Rothschild and Stiglitz (1971) (example D in Section 2) in which a rigid input (capital) may be combined with a flexible one (labor). There, the choice of capacity depends on the relative elasticity of substitution between the two inputs.

The inverse demand function is assumed to be linear: $p = a + \lambda\theta - bq$, in which p is the price, q the quantity on the market, and a and b are two positive parameters. Uncertainty is introduced through the random variable θ, assumed to be uniformly distributed on the interval $[-1; +1]$ with density 1/2. The parameter λ measures the range of demand variation, the case of no uncertainty corresponds to $\lambda = 0$.

N firms are assumed to operate in the home market. The cost function for the home technology consists of two terms: a linear investment cost c_k relative to a capacity choice denoted K, and a linear production cost c_h.[13] The cost function for the foreign technology involves a linear production cost c_f and no investment cost. In the case of no uncertainty, the home technology is preferred to the foreign one, $c_h + c_k < c_f$ and demand is high enough to make production worthwhile, $a > c_h + c_k$. Furthermore, λ is limited so that in all realized demand states, it is worth producing with the home technology: $0 < \lambda < a - c_h$.

The decision process takes place in three stages. First, the firms decide their capacity K relative to the home technology. Second, uncertainty is resolved for the time period in question, and the realized value of θ is revealed to the firm. Third, the production decisions (q_h, q_f) using respectively the home and foreign technologies are made by the firm. It is explicitly assumed that the production decisions of any given firm do not depend on the capacity of its competitors. This assumption means

[13]The introduction of a fixed component in the investment cost is immaterial for the analysis.

that firms do not select their capacity to preempt competitors, but only to face demand fluctuations optimally. The firms maximize their expected profit, with no risk aversion.

Under these assumptions, the equilibrium capacity can be derived and its properties discussed, in particular with respect to c_f, λ, and N. The equilibrium capacity is denoted $K^*(c_f, \lambda, N)$.

Since $c_h + c_k < c_f$, the equilibrium capacity in the case of no uncertainty $K^*(c_f, 0, N)$ is independent of c_f. It is simply the equilibrium quantity in the standard symmetric Cournot-Nash model. With a linear demand and a constant variable cost it is straightforward to observe that:

$$K^*(c_f, 0, N) = \frac{2K^*(c_f, 0, 1)}{(N+1)}$$

Our model has the appealing feature that this property holds for all values of λ (all proofs are in appendix 1).

Proposition 1 *Whatever the level of uncertainty λ, we have*

$$K^*(c_f, \lambda, N) = \frac{2K^*(c_f, \lambda, 1)}{(N+1)}$$

Observe that the capacity of an individual firm $K^*(c_f, \lambda, N)$ is a decreasing function of the number of competing firms N. Let $k^*(c_f, \lambda, N) = \frac{K^*\left(c_f, \lambda, N\right)}{K^*\left(c_f, 0, N\right)}$. This is the optimal capacity with uncertainty relative to the optimal capacity without uncertainty. Because of Proposition 1, this ratio does not depend on N, and hence will be denoted as $k^*(c_f, \lambda)$ and referred to as the excess capacity ratio.

Proposition 2 *The following comparative static properties hold for the excess capacity ratio*

1. *For all c_f, $\frac{\delta k^*\left(c_f, \lambda\right)}{\delta c_f} \geqslant 0$*

2. *For all $c_f \geq 2c_k + c_h$, $\frac{\delta k^*\left(c_f, \lambda\right)}{\delta \lambda} \geqslant 0$*

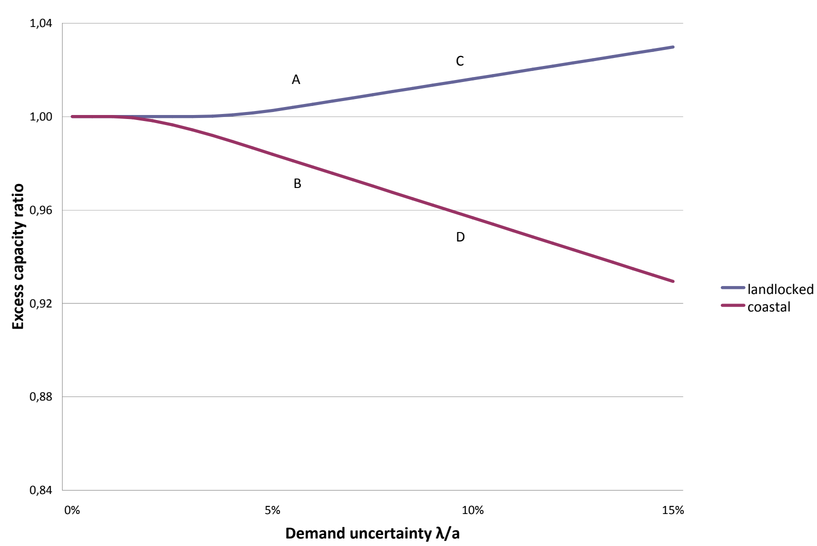
3. *For all $c_f \leqslant 2c_k + c_h$, $\frac{\delta k^*\left(c_f, \lambda\right)}{\delta \lambda} \leqslant 0$*

4. *For all c_f and λ, $\frac{\delta^2 k^*\left(c_f, \lambda\right)}{\delta c_f \delta \lambda} \geqslant 0$*

Proposition 2 (2) and (3) provides a clear cut answer to the usual ambiguous impact that ordinarily prevails in the literature regarding the irreversibility effect. In our model, consistent with intuition, uncertainty leads to higher capacity when imports are expensive and leads to lower capacity when they are cheap

Together, Propositions 1 and 2 provide simple and direct predictions that can be tested. Proposition 1 says that the excess capacity ratio does not depend on the actual level of competition in the market, which would be difficult to assess empirically. Proposition 2 (4) says that the higher the import cost the higher the impact of uncertainty, which generates a clear differentiation between coastal and landlocked markets.

Indeed, suppose that for a coastal district we have $c_f \leqslant 2c_k + c_h$, while the reverse is true for a landlocked district. Graph 2 shows how the respective excess capacity ratios would evolve. Proposition 2 (4) implies that the difference between C and D is larger than the difference between A and B. This is the first prediction to be tested. The second prediction relates to the slopes of the excess capacity ratios in the two types of districts. According to Proposition 2 (2)-(3), the excess capacity ratio should be increasing for landlocked districts and decreasing for coastal districts. Ordinarily, competition is more intense in the coastal district than in the landlocked one because of the presence of marginal traders. The equilibrium capacity of a firm decreases as competition becomes more intense, as shown in Proposition 1.[14] Consequently the ranking of ABCD is preserved when one substitutes K^* for k^* in Graph 2 since the two curves move further apart. Our third prediction relates to the fact that the absolute individual level of capacity is higher in landlocked versus coastal districts, and that the difference increases with uncertainty.



Graph 2: The excess capacity ratio in landlocked and coastal districts as a function of demand uncertainty.

[14]To be more precise the model should be extended to consider firms heterogeneity

We make a number of simplifications, now discussed in turn, in applying the model to the US cement industry.

The market is the US district, and we are assuming symmetric firms while in reality firms are heterogeneous. The extent of heterogeneity may not be large in terms of investment since cement production technology is fairly mature. A dynamic model would be one way to capture this heterogeneity, but would complicate the analysis considerably. Second, our classification of districts into two types, coastal and landlocked, is coarse and could be refined. For example, districts of each type differ in the cost of importing cement, depending on the existence of deep water harbors, their proximity to the US river system, and local demand density.

In our assessment of import costs, we have implicitly assumed that adjacent markets follow similar business cycles so the balance of supply and demand mostly comes from long haul flows, or from a ripple effect.[15] This appears to be borne out in the data. The mean district pair-wise correlation in deviations from mean excess capacity between 1994 and 2006 is positive, and the mean pair-wise correlation for geographically proximate districts tends to be more strongly positively correlated.[16]

We now turn to the evaluation of the model's predictions using the US data. The optimal capacity under no uncertainty is not observable. As a proxy for the excess capacity ratio, we use the difference between current capacity and the mean production level over the entire time period divided by the current capacity for the districts in each of four categories. This ratio is also independent of the number of firms.[17] These four categories mirror Graph 2: landlocked and coastal districts and low and high uncertainty districts. The table below (an excerpt from Table 3) presents the corresponding statistics (mean and standard deviation) for 2006. We see that the excess capacity in low demand uncertainty districts is similar across coastal and landlocked districts; on average, there is around 25% excess capacity in these district groups. Among high demand uncertainty districts, however, coastal districts have much lower levels of excess capacity than landlocked districts.

[15] This explains why in the model firms do not export from their domestic production capacity. We note that US exports remain a very low percentage of US annual production – at around 1% between 2002 and 2006.

[16] We measured the pairwise correlation coefficient in deviations from mean capacity over production for each pair of districts. Of the 253 correlation coefficients, the mean is 0.12 and only 95 of the coefficients are negative. We grouped the districts into 7 regions and found the average within each group. In only one group was the average correlation less than the overall average (0.109 in the Midwestern group). This was due to a relatively large negative correlation between the Arkansas and Oklahoma and the Iowa, Nebraska, and South Dakota districts. We note that these two districts, while close, are separated by Kansas and Missouri.

[17] Numerical simulations available from the authors show that the ratio used here has similar comparative statics properties in the model as the excess capacity ratio.

	Low volatility	High Volatility
Landlocked	0.25 (0.05)	0.27 (0.11)
Coastal	0.26 (0.13)	0.12 (0.15)

Excerpt from Table 3: Excess Capacity ((Capacity-Production)/Capacity) by District Group in 2006.

As noted in the preceding section, it is likely that the phenomenon under study appeared during the early 1990s, as the availability of cheap long haul transportation developed and industry concentration increased. Table 3 also shows the change in the average excess capacity in each of the four categories between 1994 and 2006. These overall trends support our first and second predictions.

If we consider that the plant efficient scale has increased over time, our third prediction says that it makes more sense to increase average plant capacity in a landlocked district than in a coastal one. In a similar way, since we expect that dry kilns are more efficient than wet kilns, there are more investment opportunities to make this technological change in a landlocked district than in coastal one. Table 3 demonstrates that this indeed seems to be the case.

We see large percentage increases in excess capacity, average plant size, and percentage dry process plants in high uncertainty landlocked districts. We see the smallest percentage increases (or largest percentage decrease) in high uncertainty coastal districts. These broad patterns are consistent with the predictions of the model. But, since the growth rates of these variables are clouded by variation in demand growth, we now look at cross sections of the data at different points in time.

Excess Capacity ((Capacity-Production)/Capacity)

Change 1994-2006

	Low volatility	High Volatility
Landlocked	0.16 (0.17)	0.31 (0.23)
Coastal	0.13 (0.14)	0.08 (0.21)

Average Plant Size

Percentage Change 1994-2006

	Low volatility	High Volatility
Landlocked	28.628 (15.86)	56.65 (30.98)
Coastal	18.77 (21.37)	17.59 (16.21)

% Dry Process

Percentage Point Change 1994-2006

	Low volatility	High Volatility
Landlocked	5% (10%)	14% (12%)
Coastal	15% (22%)	-2% (3%)

Excerpt from Table 3: Change in capacity measures between 1994 and 2006.

We analyze the relationship between demand uncertainty and the excess capacity ratio at the start of our data sample, in 1994, and at the end, in 2006. We regress this measure of excess capacity in each district on an indicator variable for whether the district is high uncertainty over the time period, an indicator variable for whether it is landlocked, and the interaction of these two indicator variables. We also control for whether the district experiences high growth over the data period, and the interaction of the high growth and landlocked indicator variables. Table 4 presents these results for 1994 and 2006.

In panel B of Table 4, the tests of significance of the relevant linear combinations of coefficients reveal that in 1994 higher demand uncertainty districts have significantly lower levels of excess capacity than low demand uncertainty districts, across both landlocked and coastal districts. There is no significant difference in the extent of excess capacity between coastal and landlocked districts. By 2006, the average level of excess capacity in high uncertainty coastal districts has fallen even further. There was no corresponding reduction in the extent of excess capacity in landlocked districts. This suggests the relationship between demand uncertainty and excess capacity has evolved differently in coastal and landlocked districts over this time period as the model would predict.

4 Estimation Strategy

We now turn to analyze the patterns revealed in Table 4 in more detail. We investigate variation at the district level in the excess capacity ratio (measured as yearly capacity less mean production divided by yearly capacity). Using the mean production by district over the time period 1994-2006 in the numerator of the dependent variable ensures that any variation in a district over time reflects firms' decisions related to capacity choices rather than yearly fluctuations in production, which will vary systematically with annual local demand. We regress this dependent variable on district-level demand growth, demand uncertainty, and the interaction of each of these measures with an indicator for whether the district is landlocked or coastal. We include the landlocked indicator variable and year fixed effects as control variables. This specification reveals how variation in excess capacity is related to variation in local demand conditions in cross section.

The estimated equation is:

$$y_{i,t} = \alpha + \beta_G G_{i,t} + \beta_V V_{i,t} + \gamma_G \left(G_{i,t} * L_i\right) + \gamma_V \left(V_{i,t} * L_i\right) + \mu L_i + i.Year + \varepsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is the measure of excess capacity in district i in year t, $G_{i,t}$ and $V_{i,t}$ are the yearly values of district demand growth and uncertainty, respectively, and L_i is the landlocked indicator variable.

As is common in the analysis of panel data, the observations are likely to be correlated within groups – in our case, within districts. In addition to the clustering problem arising from the fact that we might expect observations within a district to share some unobserved variable, our measure of demand uncertainty is based on the variance in local demand levels over this year and the past four years. This introduces serial correlation in the observations from a given district. We estimate equation (1) using OLS regression, and use two different corrections to the standard errors, $\varepsilon_{i,t}$, to mitigate these concerns.

First, we report Newey-West standard errors with a maximum lag order of correlation within a district of four years (Newey and West, 1987). This correction addresses serial correlation in the errors resulting from the definition of demand uncertainty. Second, we report the standard errors produced by a non-parametric bootstrap estimation, drawing district groups with replacement to allow for correlation within a district. This bootstrapping approach does not preserve the serial correlation structure present in the data. While neither correction fully addresses both issues, the inferences made about the significance of individual coefficients and linear combinations of coefficients are robust to which is chosen. We draw inference about the statistical significance of linear combinations of the estimated coefficients, and about the difference between linear combinations, using the bootstrapped standard errors.[18]

We test whether differences in the estimated coefficients are significantly different from zero, and significantly different from each other, in ways that support the predictions of the model. Starting with the group of coastal districts, we test whether there is a significant difference in excess capacity for districts at the 5th and 95th percentiles of district-level demand uncertainty. We do the same for the group of landlocked districts. We then ask whether there is a significant difference in levels of excess capacity between coastal and landlocked districts at the 5th percentile of demand uncertainty and at the 95th percentile of demand uncertainty.

The estimation described in equation (1) does not include district fixed effects and so district-level factors other than whether the district is landlocked may be contributing to the results. The second specification we estimate includes district fixed effects in equation (1), and hence omits non-time varying district characteristics. This specification tells us whether changes in demand growth or uncertainty within a district are associated with changes in the level of excess capacity which, since the denominator is time-invariant, corresponds to changes in the level of capacity within-district. Once again, we present the results with both Newey-West and bootstrapped standard errors.

Using the output from this specification, we ask whether a change in capacity is associated with an increase in uncertainty for different district groups, using the bootstrapped standard errors for inference. The impact of the change in uncertainty is restricted to be constant at all levels of growth or uncertainty in this linear specification. Hence, to test whether a change in demand uncertainty is associated with a change in the level of excess capacity in coastal districts, we examine the significance of the coefficient estimate for demand uncertainty. To test whether a change in demand uncertainty is associated with a change in capacity in landlocked districts, we test whether the linear combination of the coefficients on demand uncertainty and the interaction of demand uncertainty and the landlocked indicator is significantly different from zero. We then test whether changes in demand uncertainty are associated with significantly different changes in excess capacity in coastal versus landlocked districts.

Last, we note that our data contains some information on the quality of capacity by district. We know that, in this industry, larger plants are on average more efficient and also that dry process

[18] The bootstrapped standard errors are larger than the Newey-West standard errors in the specifications that include district fixed effects, and using these estimates for inference is hence more conservative. Clustering standard errors by district is inappropriate since we have only 23 districts.

plants are more efficient than wet process plants. The model has similar predictions for upgrading the quality of capacity as for the amount of capacity. Accordingly, we examine whether plant size and the percentage of dry process capacity within-district are related to demand uncertainty in a way consistent with the predictions of the model. We estimate equation (1) including district fixed effects with the average plant size and the percentage of dry process capacity as the dependent variables.

5 Results

Panel A of Table 5 presents the results from the first regression specification, equation (1). Columns 1 and 2 reveal that, on average, greater uncertainty is associated with lower levels of excess capacity controlling for demand growth and production levels. This appears to contradict previous models which consider only one production technology and predict a positive association between demand uncertainty and capacity. Higher levels of demand growth are positively associated with excess capacity, but not significantly so. Columns 3 and 4 show that the negative relationship between demand uncertainty and excess capacity varies across districts by separating the data into coastal and landlocked districts and investigating whether the relationship holds in each subgroup.

We see that higher uncertainty is associated with lower excess capacity only in coastal districts. Panel B of Table 5 constructs the linear combinations of relevant coefficient estimates for different groups of districts. The level of excess capacity is significantly lower in coastal districts with higher demand uncertainty than in coastal districts with lower demand uncertainty. For landlocked districts, where high transport costs allows firms access to only one production technology, the difference in excess capacity between high and low uncertainty districts is not significantly different from zero. Moreover, we note that excess capacity in high uncertainty coastal districts is significantly lower than excess capacity in high uncertainty landlocked districts.

The results for the second specification, equation (1) including district fixed effects, are given in Table 6. Changes in capacity are positively associated with changes in demand uncertainty on average, although the relationship is not significant with the bootstrapped standard errors. Columns 3 and 4 show that there is a significant positive coefficient on the interaction of demand uncertainty and the variable indicating that a district is landlocked. Panel B of the table contains the linear combinations of estimated coefficients and the analysis of significant differences. We see that there is a positive relationship between changes in uncertainty and changes in capacity in landlocked districts that is significant at the 5% level. There is also a significant difference in the response to changes in uncertainty between landlocked and coastal districts – the relationship is significantly more positive in landlocked districts.

Table 7 contains the results for the estimation of equation (1) including district fixed effects with average plant size and the percentage of dry process plants as the dependent variables. The findings for average plant size are consistent with the model's predictions. An increase in demand uncertainty is, on average, associated with an increase in the average plant size in a district. This positive relationship is, however, limited to landlocked districts. The tests of significance of the linear combinations of the coefficients reveal that the slope of the relationship between average plant size and demand uncertainty is significantly more positive for landlocked than for coastal districts.

The corresponding results in Table 7 for the percentage of dry process plants offer no empirical support of the model's predictions. On average, there is a positive relationship between demand uncertainty and the percentage dry process, but the estimated coefficient is not significantly different from zero and there is no significant difference in the nature of the relationship across coastal and landlocked districts. We note, though, that many districts began the data period with 100% dry process plants, as shown in Table 1, and offer no variation throughout the period from which to draw inference. Further, we discussed our results with industry sources who suggested our lack of consistent findings related to the percentage dry variable could be due to the coarseness of this technology classification in the data. The efficiency gains associated with dry kilns require that the dry technology is used in combination with a pre-calcinator and pre-heater. Our data does not distinguish between when these complementary processes are present or absent from a given cement plant.

6 Concluding Comments

This paper provides some empirical evidence about the theory of irreversible decisions under uncertainty at the micro-level. It shows that the capacity decisions of US cement firms are consistent with the theory: the amount of domestic excess capacity over an uncertain business cycle depends on the relative cost of imports, which varies from coastal to landlocked markets. The positive relationship between demand uncertainty and investment predicted by theory models with only one technology is present in landlocked districts where imports are prohibitively costly. The paper also provides a new rationale to explain the coexistence of home production and imports in the US cement market by large multinational firms. Adding demand uncertainty to the proximity-concentration trade-off described in Brainard (1997) can explain why we see imports and domestic production – even in the long run – in districts where the variable cost of imported cement is not too much greater than domestic production. The greater the demand uncertainty in these districts, the larger the average ratio of imports to FDI.

Specifically, we show that coastal districts with high demand uncertainty have significantly lower levels of excess capacity than coastal districts with low demand uncertainty, controlling for the level of demand and recent demand growth. Landlocked districts look very different. Investment in capacity, and the average plant size, both increase with demand uncertainty in these districts.

We are able to infer significant differences in the relationship between excess capacity and demand uncertainty between coastal and landlocked districts even though our analysis is based on fairly aggregated data and covers only 12 years. A simple regression with 23 observations of the average district-level excess capacity on indicator variables for whether the district is landlocked, whether it has high demand uncertainty on average over the entire period, and the interaction of the two, while allowing for the effect on capacity of demand growth to vary with whether the district is coastal or not, reveals that within coastal districts, high demand uncertainty districts have significantly lower levels of excess capacity on average than low demand uncertainty districts. There is no similar relationship for landlocked districts. This suggests to us that our more detailed analysis is capturing meaningful correlations in the data.

A number of other caveats should be made. Some important features of the industry are not taken into account explicitly in the model or the empirical work. These include the existence of independent importers (pure traders, grinding stations, ready mix companies. . .), strategic behavior for preemption purposes, and further local variation in geography of each market (large urban areas or other types of markets). Extending the model to incorporate these features is left to future research. It may also be interesting to extend the empirical analysis to other cement markets. Preliminary analysis using data from the industry source Cembureau reveals that coastal countries, such as the UK, have significantly lower levels of excess capacity than landlocked countries such as Switzerland. A country like Spain exhibits both landlocked and coastal markets and, as such, is a good candidate for inclusion in a further test, but detailed regional data is less readily available for Spain than for the US.

From a policy perspective, this paper provides a contribution to the current debate on the impact of unilateral climate policies. The EU implemented a unilateral policy in 2004 with a cap and trade scheme for carbon intensive industry (such as cement production, electricity, glass, oil refineries, steel…). Other industrialized countries such as the US may engage in similar policies in the future. This has triggered an intense debate about the effectiveness of unilateral policies in sectors that are subject to international competition, which includes most of the carbon intensive sectors except electricity (Grubb and Neuhoff, 2006). In theory, we expect a reduction in market share and a decline in investment from home producers, and a concomitant increase in imports from countries with no similar climate policy (for a discussion in the cement case see for instance Demailly and Quirion, 2006 or Ponssard and Walker, 2008). This would reduce the efficiency of unilateral policies in curbing worldwide emissions through the so-called leakage effect – an increase in foreign emissions substituting for any decrease in domestic emissions.

So far, there is very little empirical evidence to support the conclusions derived from analytical models of the impacts of climate policies (Ellerman et al., 2010). Still, the debate remains open since existing empirical work cannot yet capture long run effects. This paper provides an important indirect contribution. It substantiates that there are indeed long term effects on investment levels associated with a change in the relative costs of imports when demand is subject to uncertainty. The recent failure of the United Nations Climate Change Conference in Copenhagen to agree to implement a uniform carbon tax across international markets reinforces the importance of these considerations.

7 Appendix 1: Proofs

7.1 The monopoly capacity

We first establish the monopoly capacity $K^*(c_f, \lambda, 1)$, and then consider the oligopoly case.

Lemma 1 *The monopoly capacity* $K^*(c_f, \lambda, 1)$ *is:*

Case 1: if $0 \leq \lambda \leq \min\{c_k, c_f - (c_h + c_k)\}$ *then*

$$K^* = [a - (c_h + c_k)] / 2b. \tag{2}$$

Case 2: if $c_f \geq 2c_k + c_h$ *and* $c_k \leq \lambda \leq (c_f - c_h)^2/4c_k$ *then*

$$K^* = \left[a - c_h + \lambda - 2\left(\lambda c_k\right)^{1/2}\right] / 2b. \tag{3}$$

Case 3: if $c_f \leq 2c_k + c_h$ *and* $c_f - (c_h + c_k) \leq \lambda \leq (c_f - c_h)^2 / 4(c_f - c_h - c_k)$ *then*

$$K^* = (a - c_f - \lambda) / 2b + [\lambda(c_f - c_k - c_h)]^{1/2} / b. \tag{4}$$

Case 4: If $\lambda \geq \max\{(c_f - c_h)^2/(4c_k), (c_f - c_h)^2 / 4(c_f - c_h - c_k)\}$ *then*

$$K^* = [a - (c_h + c_f)/2 + \lambda\left(1 - 2c_k/(c_f - c_h)\right)] / 2b. \tag{5}$$

Proof. We denote q_h (resp. q_f) the local production (resp. the quantity imported). The firm's profit is

$$\pi = \frac{1}{2}\int_{-1}^{+1} \max_{(q_h \leq K, q_f)} [pq - c_h q_h - c_f q_f]\, d\theta - c_k K \tag{6}$$

In each demand state θ, the firm maximizes its short term revenue: $pq - c_h q_h - c_f q_f$ subject to the constraint $q_h \leq K$. Three situations can arise, let us denote two thresholds states: $\theta^- = \max\{-1, (2bK + c_h - a)/\lambda\}$ and $\theta^+ = \min\{1, (2bK + c_f - a)/\lambda\}$, then

- if $\theta \leq \theta^-$, $q_h = (a - c_h + \lambda\theta)/2b$ and $q_f = 0$;
- if $\theta^- < \theta \leq \theta^+$, $q_h = K$, and $q_f = 0$;
- if $\theta^+ \leq \theta$, $q_h = K$ and $q_f = (a - c_f + \lambda\theta)/2b - K$.

In the long term, the monopoly chooses its capacity to maximize its profit (6). The profit of the firm is concave; the optimal capacity is the solution of the first order condition

$$\int_{\theta^-}^{\theta^+} [a+\lambda\theta - 2bK - c_h]d\theta + \int_{\theta^+}^{1} (c_f - c_k)d\theta. \tag{7}$$

Several cases should be distinguished depending on whether, at equilibrium, θ^- (resp. θ^+) is equal or larger (resp. lower) than -1 (resp. 1); that is, whether in some demand states the firm has excess capacity ($\theta^- > -1$) or imports ($\theta^+ < 1$). For sufficiently large λ, both situations happen and

$$\theta^- = (2bK^* + c_h - a)/\lambda \tag{8}$$

$$\theta^+ = (2bK^* + c_f - a)/\lambda. \tag{9}$$

We will only consider this case (4 in lemma 1) for the sake of exposition but similar calculations could be done to obtain the expression of K^* and boundary conditions in other cases.

By substituting (8) into (7):

$$\begin{aligned} 2c_k &= \int_{\theta^-}^{\theta^+} \lambda(\theta - \theta^-)d\theta + [1-\theta^+](c_f - c_h) \\ &= \lambda(\theta^+ - \theta^-)^2/2 + \left(1-\theta^+\right)(c_f - c_h) \end{aligned} \tag{10}$$

and, from (9) and (8), $\theta^+ - \theta^- = (c_f - c_h)/\lambda$, substituting into (10) gives

$$\theta^+ = 1 + (c_f - c_h)/2\lambda - 2c_k/(c_f - c_h)$$

and replacing θ^+ by (9) gives:

$$K^* = [a - (c_f + c_h)/2 + \lambda(1 - 2c_k/c_f - c_h)]/2b. \tag{11}$$

Finally, we have to check that the expressions (8) and (9), used for θ^- and θ^+ are consistent with the capacity (11); that is, that the right hand side of (8) (resp. 9) is larger than -1 (resp. lower than 1). The monopoly capacity is given by (11) if and only if

$$\lambda \geq \max\left\{(c_f - c_h)^2/4(c_f - c_h - c_k), (c_f - c_h)^2/4c_k\right\}. \tag{12}$$

To find the expression of the equilibrium capacity in case 2, we have to use the expression (8) together with $\theta^+ = 1$, and, in case 3, the expression (9) together with $\theta^- = -1$; finally, for small λ (case 1), $\theta^- = -1$ and $\theta^+ = 1$. ■

Proof of proposition 1

In order to limit the introduction of notation, only a brief sketch of the proof is provided here. A more detailed one can be obtained from the authors on request.

We assume that there are N firms with $N \in \mathbb{N}^*$. Each firm simultaneously chooses its capacity and a production plan $(q_h(\theta), q_f(\theta))$. There is a unique symmetric equilibrium of this game, the individual equilibrium capacity is $K^*(c_f, \lambda, N) = 2K(c_f, \lambda, 1)/(N+1)$.

This relationship between the quantities in oligopoly and in monopoly holds in a standard Cournot game with linear demand and costs. This property is preserved here because of the linearity of the framework (demand, cost, and uncertainty) and because we do not consider the strategic effect of a firm's capacity on its rivals' production.

Proof. At an equilibrium: in each demand state, firms play a constrained Cournot game with two technologies available, and, each firm capacity is a solution of a first order equation that equalizes the capacity cost c_k with expected short term marginal profit. Any equilibrium is symmetric because the expected marginal short term profit of two firms is equal if and only if their capacities are equal (this is related to the absence of a strategic effect of capacity on a competitor's production). Then, the only possible equilibrium is symmetric and the individual equilibrium capacity $K^*(c_f, \lambda, N)$ is the unique solution of equation

$$\int_{\theta^-(N,K)}^{\theta^+(N,K)} (a - c_h + \lambda\theta - (N+1)bK)\, d\theta + \int_{\theta^+(N,K)}^{1} (c_f - c_h) d\theta - 2c_k = 0 \tag{13}$$

where $\theta^-(N,K)$ and $\theta^+(N,K)$ are :

$$\theta^- = \max \left\{ \left((N+1)bK + c_h - a \right) / \lambda, -1 \right\}, \tag{14}$$

$$\theta^+ = \min \left\{ \left((N+1)bK + c_f - a \right) / \lambda, +1 \right\}, \tag{15}$$

and equilibrium production levels are the constrained Cournot production levels:

$$\begin{aligned} 0 \leq \theta \leq \theta^- &: \; q_h = (a + \lambda\theta - c_h)/(N+1)b \text{ and } q_f = 0; \\ \theta^- \leq \theta \leq \theta^+ &: \; q_h = K^* \text{ and } q_f = 0; \\ \theta^+ \leq \theta \leq 1 &: \; q_h = K^* \text{ and } q_f = (a + \lambda\theta - c_f)/(N+1)b - K^* \end{aligned} \tag{16}$$

With these expressions, it is possible to reproduce the calculations done in the monopoly case. The expressions (14) and (15) of threshold states are functions of $(N+1)K^*$, the first integrand of the equation (13) is also a function of $(N+1)K^*$, therefore, by substituting the expressions (14) and (15) into (13), it appears that $(N+1)K^*(c_f, \lambda, N)$ solves the same equation as $2K^*(c_f, \lambda, 1)$ and

$$K^*(c_f, \lambda, N) = 2K^*(c_f, \lambda, 1)/(N+1). \tag{17}$$

And finally, the capacity (17) and production levels (16) are equilibrium strategies because the individual profit of each firm is concave and the first order conditions are satisfied. ■

Proof of proposition 2

Without demand variation, $\lambda = 0$, the situation is similar to a Cournot game with marginal cost $c_h + c_k$. The equilibrium capacity is :

$$K^*(c_f, 0, N) = (a - (c_h + c_k))/(N+1). \tag{18}$$

Consequently, $k^*(c_f, \lambda, N) = K^*(c_f, \lambda, N)/K^*(c_f, 0, N)$ is independent of N, i.e.,

$$k^* = K^*(c_f, \lambda, 1)/K^*(c_f, 0, 1).$$

The denominator is independent of both c_f and λ.

We detail calculations only for case 4 of Lemma 1 but the results could be obtained in all cases.

- By differentiating the expression (11),

$$\frac{\partial k^*}{\partial c_f} = (2\lambda c_k/c_f - 1/2) \, / \, (a - c_h - c_k)$$

  which is non-negative from (12).

- From (11)

$$\frac{\partial k^*}{\partial \lambda} = \left[1 - 2c_k/(c_f - c_h)\right] / \left(a - c_h - c_k\right),$$

which is non-negative (resp. non-positive) if $c_f \geq 2c_k + c_h$ (resp. $c_f \leq 2c_k + c_h$).

- From the derivative obtained above,

$$\frac{\partial^2 k^*}{\partial c_f \partial \lambda} = \frac{1}{a - c_h - c_k} \frac{2c_k}{(c_f - c_h)^2} \geq 0.$$

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Tables

Table 1: Summary Statistics

Panel A

		1994					2006				
District Number	District Name	Demand 000 metric tons	Active Plants* #	Capacity 000 metric tons	Average Plant Size 000 metric tons	Percentage Dry (or Wet and Dry)* %	Demand 000 metric tons	Active Plants* #	Capacity 000 metric tons	Average Plant Size 000 metric tons	Percentage Dry (or Wet and Dry)* %
1	Alabama	1432	5	4573	914.6	100%	1798	5	6036	1207.2	100%
2	Alaska, Hawaii, Oregon, Washington	3168	4	2295	573.8	75%	4307	4	2540	635.0	67%
3	Arizona, New Mexico	2823	3	2288	762.7	100%	5511	3	3310	1103.3	100%
4	Arkansas, Oklahoma	1994	4	2694	673.5	50%	2730	4	3260	815.0	50%
5	California, Northern	2872	3	2776	925.3	100%	4761	3	2853	951.0	100%
6	California, Southern	5328	8	7933	991.6	100%	9549	8	10238	1279.8	100%
7	Colorado, Wyoming	2021	4	2377	594.3	75%	3107	3	3450	1150.0	100%
8	Florida	5623	6	4382	730.3	50%	11180	7	7301	1043.0	100%
9	Georgia, Virginia, West Virginia, South Carolina, Maryland	9461	11	8586	780.5	60%	14716	10	11636	1163.6	78%
10	Idaho, Montana, Nevada, Utah	3112	6	2422	403.7	33%	5443	6	3750	625.0	50%
11	Illinois	3593	4	3217	804.3	100%	4555	4	3420	855.0	100%
12	Indiana	1876	4	2867	716.8	50%	2173	4	3720	930.0	75%
13	Iowa, Nebraska, South Dakota	3112	6	5758	959.7	100%	4182	5	6048	1209.6	100%
14	Kansas	1277	4	1801	450.3	50%	1546	4	3329	832.3	75%
15	Kentucky, Mississippi, Tennessee	3794	4	2128	532.0	50%	4765	4	3700	925.0	75%
16	Michigan, Wisconsin	5992	5	6532	1306.4	67%	6578	5	7328	1465.6	67%
17	Missouri	2386	5	5059	1011.8	60%	2626	5	6958	1391.6	60%
18	New York, Maine	3691	5	4141	828.2	20%	5207	5	4203	840.6	50%
19	Ohio	3482	3	1588	529.3	50%	3727	2	1304	652.0	50%
20	Pennsylvania, Eastern	1967	8	4878	609.8	71%	2172	7	4530	647.1	67%
21	Pennsylvania, Western	2529	4	2009	502.3	25%	3030	3	1770	590.0	33%
22	Texas, Northern	3817	6	4512	752.0	50%	6499	6	7594	1265.7	67%
23	Texas, Southern	5759	6	5529	921.5	100%	10668	6	5850	975.0	100%

Panel B

		1994-2006				
District Number	District Name	Landlocked Indicator	High Demand Growth Indicator	High Demand Volatility Indicator	Mean Demand Growth 1994-2006	Mean Demand Volatility 1994-2006
1	Alabama	1	0	0	0.020	0.024
2	Alaska, Hawaii, Oregon, Washington	0	0	0	0.020	0.012
3	Arizona, New Mexico	1	1	0	0.059	0.024
4	Arkansas, Oklahoma	1	0	1	0.031	0.037
5	California, Northern	0	1	0	0.053	0.027
6	California, Southern	0	1	1	0.064	0.032
7	Colorado, Wyoming	1	1	1	0.043	0.041
8	Florida	0	1	0	0.061	0.023
9	Georgia, Virginia, West Virginia, South Carolina, Maryland	0	1	0	0.033	0.021
10	Idaho, Montana, Nevada, Utah	1	1	0	0.037	0.025
11	Illinois	1	0	0	0.021	0.028
12	Indiana	1	0	0	0.014	0.028
13	Iowa, Nebraska, South Dakota	1	0	0	0.026	0.016
14	Kansas	1	0	1	0.011	0.030
15	Kentucky, Mississippi, Tennessee	1	0	1	0.013	0.032
16	Michigan, Wisconsin	1	0	0	0.014	0.026
17	Missouri	1	0	1	0.018	0.030
18	New York, Maine	0	0	0	0.029	0.026
19	Ohio	1	0	0	0.008	0.025
20	Pennsylvania, Eastern	0	0	1	0.016	0.044
21	Pennsylvania, Western	1	0	1	0.023	0.042
22	Texas, Northern	1	1	1	0.054	0.046
23	Texas, Southern	0	1	0	0.048	0.028

** We take the number of plants from Table 3 of the USGS Minerals Survey in each year. The percentage dry technology is taken from Table 5, which is based on the number of white cement plants. The total number of white cement plants is on occasion less than the total number of plants. This means the percentage dry technology does not reflect a percentage of the total number of plants.*

Table 2: Pairwise Correlations in 1998 and 2006

(Earliest year is 1998 since demand growth and volatility are first measured for this year, based on data from 1994-1998)

1998	Demand	Number of Plants	Capacity	Production	Average Plant Size	Percentage Dry (or Wet and Dry) Process	Demand Growth	Demand Volatility
Demand	1							
Number of Plants	0.59	1						
Capacity	0.67	0.81	1					
Production	0.62	0.79	0.98	1				
Average Plant Size	0.37	0.09	0.65	0.62	1			
Percentage Dry (or Wet and Dry) Process	0.02	0.05	0.26	0.30	0.40	1		
Demand Growth	0.37	0.26	0.27	0.26	0.14	0.34	1	
Demand Volatility	-0.24	-0.01	-0.15	-0.04	-0.27	-0.28	-0.10	1

2006	Demand	Number of Plants	Capacity	Production	Average Plant Size	Percentage Dry (or Wet and Dry) Process	Demand Growth	Demand Volatility
Demand	1							
Number of Plants	0.71	1						
Capacity	0.71	0.87	1					
Production	0.67	0.89	0.99	1				
Average Plant Size	0.31	0.32	0.71	0.68	1			
Percentage Dry (or Wet and Dry) Process	0.29	0.15	0.31	0.33	0.47	1		
Demand Growth	0.56	0.31	0.36	0.38	0.30	0.48	1	
Demand Volatility	-0.25	-0.05	-0.09	0.00	-0.06	-0.26	0.10	1

Table 3: Capacity-related Variables by District Group, 1994, 2006, and 1994-2006
(Standard Deviations, across districts in each group, in parentheses)

Excess Capacity ((Capacity-Production)/Capacity)

	1994		2006		Change 1994-2006	
	Low Volatility	High Volatility	Low Volatility	High Volatility	Low Volatility	High Volatility
Landlocked	0.10 (0.15)	-0.04 (0.15)	0.25 (0.05)	0.27 (0.11)	0.15 (0.17)	0.31 (0.23)
Coastal	0.13 (0.07)	0.04 (0.06)	0.26 (0.13)	0.12 (0.15)	0.13 (0.14)	0.08 (0.21)

Average Plant Size ('000 metric tons)

	1994		2006		Percentage Change 1994-2006	
	Low Volatility	High Volatility	Low Volatility	High Volatility	Low Volatility	High Volatility
Landlocked	800 (276)	645 (191)	1006 (293)	996 (284)	28.62 (15.86)	56.65 (30.98)
Coastal	793 (132)	801 (270)	935 (181)	963 (447)	18.77 (21.37)	17.59 (16.21)

% Dry Process

	1994		2006		Percentage Point Change 1994-2006	
	Low Volatility	High Volatility	Low Volatility	High Volatility	Low Volatility	High Volatility
Landlocked	75% (28%)	51% (15%)	80% (23%)	66% (21%)	5% (10%)	14% (12%)
Coastal	68% (31%)	86% (20%)	82% (21%)	83% (24%)	15% (22%)	-2% (3%)

Table 4: Excess capacity, in high and low volatility districts, landlocked and coastal. 1994 and 2006.*

Panel A: Regression Output

COEFFICIENT	Excess Capacity 1994	Excess Capacity 2006
High Demand Growth Indicator	-0.08**	0.09
	[0.04]	[0.07]
High Demand Volatility Indicator	-0.11***	-0.13*
	[0.03]	[0.07]
Landlocked * High Demand Growth	-0.03	-0.01
	[0.09]	[0.08]
Landlocked * High Demand Volatility	-0.03	0.14
	[0.08]	[0.08]
Landlocked	-0.06	0.03
	[0.06]	[0.04]
Constant	0.19***	0.20***
	[0.03]	[0.03]
Observations	23	23
R-squared	0.372	0.298

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

**The dependent variable is yearly capacity less the mean production level for the district divided by the yearly capacity level.*

Panel B: Tests of significance of the differences in excess capacity across district groups, based on bootstrapped standard errors.

1994	**Coastal**	**Landlocked**	Significant difference across columns?
Low volatility	0	-0.06 (0.06)	No
High volatility	-0.11*** (0.03)	-0.19** (0.08)	No
Significant difference across rows?	Yes***	No	

2006	**Coastal**	**Landlocked**	Significant difference across columns?
Low volatility	0	0.03 (0.04)	No
High volatility	-0.13* -0.07	0.04 (0.06)	No
Significant difference across rows?	Yes*	No	

Table 5: Cross Section. Excess Capacity.*

Panel A: Regression Output

	1	2	3	4
VARIABLES	Excess Capacity	Excess Capacity	Excess Capacity	Excess Capacity
Demand Growth	0.10	0.10	-0.03	-0.03
	[0.47]	[0.58]	[0.72]	[0.79]
Demand Volatility	-0.64	-0.64	-2.89***	-2.89***
	[0.79]	[0.83]	[1.05]	[0.83]
Landlocked * Demand Growth			0.13	0.13
			[0.75]	[0.87]
Landlocked * Demand Volatility			3.53**	3.53***
			[1.39]	[1.30]
Landlocked			-0.10*	-0.10**
			[0.06]	[0.05]
Constant	0.26***	0.26***	0.34***	0.34***
	[0.03]	[0.04]	[0.05]	[0.04]
Year Fixed Effects	Y	Y	Y	Y
Standard Errors	Newey-West	Bootstrapped	Newey-West	Bootstrapped
Observations	207	207	207	207
R-squared		0.19		0.22

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

**The dependent variable is yearly capacity less the mean production level for the district divided by the yearly capacity level. Any changes over time within a district hence reflect changes in capacity.*

Panel B: Tests of significance of the differences in excess capacity across district groups, based on bootstrapped standard errors.

From column 4

	Coastal	**Landlocked**	Significant difference across columns?
5th percentile volatility	-0.03*** [0.01]	-0.10** [0.04]	No
95th percentile volatility	-0.16*** [0.05]	-0.07 [0.04]	Yes**
Significant difference across rows?	Yes***	No	

Table 6: Panel, Excess Capacity.*

Panel A: Regression Output

VARIABLES	1 Excess Capacity	2 Excess Capacity	3 Excess Capacity	4 Excess Capacity
Demand Growth	0.318	0.318	0.049	0.049
	[0.408]	[0.514]	[0.336]	[0.481]
Demand Volatility	1.449	1.449	-0.808	-0.808
	[0.885]	[1.014]	[0.569]	[0.957]
Landlocked * Demand Growth			0.445	0.445
			[0.597]	[0.772]
Landlocked * Demand Volatility			3.470***	3.470**
			[1.117]	[1.433]
Constant	0.155***	0.155**	0.131***	0.131*
	[0.037]	[0.063]	[0.041]	[0.079]
Year Fixed Effects	Y	Y	Y	Y
District Fixed Effects	Y	Y	Y	Y
Standard Errors	Newey-West	Bootstrapped	Newey-West	Bootstrapped
Observations	207	207	207	207
R-squared		0.55		0.57

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in brackets

**The dependent variable is yearly capacity less the mean production level for the district divided by the yearly capacity level. Any changes over time within a district hence reflect changes in capacity.*

Panel B: Tests of significance of the differences in excess capacity across district groups, based on bootstrapped standard errors.

From column 4

	Coastal	**Landlocked**	**Significant difference across columns?**
Demand Volatility	-0.02	0.08**	Yes**
	[0.03]	[0.03]	

Table 7: Panel, Average Plant Size and Percentage Dry Process (Measures of Capacity Quality)

Panel A: Regression Output

VARIABLES	1 Average Plant Size	2 Average Plant Size	3 Average Plant Size	4 Average Plant Size	5 Percentage Dry Technology	6 Percentage Dry Technology	7 Percentage Dry Technology	8 Percentage Dry Technology
Demand Growth	196.028	196.028	55.385	55.385	-0.033	-0.033	0.782	0.782
	[498.790]	[650.627]	[416.344]	[548.821]	[0.373]	[0.500]	[0.567]	[0.773]
Demand Volatility	1,637.829	1,637.829	-889.933	-889.933	0.930*	0.930	1.851*	1.851
	[1,054.225]	[1,065.010]	[806.857]	[1,173.838]	[0.510]	[0.647]	[1.049]	[1.631]
Landlocked * Demand Growth			241.497	241.497			-1.304**	-1.304**
			[719.719]	[989.445]			[0.528]	[0.661]
Landlocked * Demand Volatility			3,875.910***	3,875.910**			-1.465	-1.465
			[1,455.057]	[1,633.823]			[1.300]	[1.962]
Constant	1,081.996***	1,081.996***	1,057.342***	1,057.342***	1.015***	1.015***	1.031***	1.031***
	[37.256]	[157.001]	[39.747]	[146.078]	[0.027]	[0.153]	[0.026]	[0.165]
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
District Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Standard Errors	Newey-West	Bootstrapped	Newey-West	Bootstrapped	Newey-West	Bootstrapped	Newey-West	Bootstrapped
Observations	207	207	207	207	207	207	207	207
R-squared		0.870		0.876		0.898		0.902

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in brackets

Panel B: Tests of significance of the differences in capacity quality across district groups, based on bootstrapped standard errors.

	From column 4. Average Plant Size.			From column 8. Percentage Dry Process.		
	Coastal	**Landlocked**	Significant difference across columns?	**Coastal**	**Landlocked**	Significant difference across columns?
Demand Volatility	-25.8 [31.02]	86.55** [37.28]	Yes**	0.05 [0.05]	0.01 [0.02]	No