Online Appendix:
Market-based Emissions Regulation and the Evolution of Market Structure

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A Equilibrium Equations

In each time period, firm i makes entry, exit, production, and investment decisions, collectively denoted by a_i. Since the full set of dynamic Nash equilibria is unbounded and complex, we restrict the firms' strategies to be anonymous, symmetric, and Markovian, meaning firms only condition on the current state vector and their private shocks when making decisions, as in Maskin and Tirole (1988) and Ericson and Pakes (1995).

Each firm's strategy, $\sigma_i(s, \epsilon_i)$, is a mapping from states and shocks to actions:

$$\sigma_i : (s, \epsilon_i) \to a_i, \tag{A.1}$$

where ϵ_i represents the firm's private information about the cost of entry, exit, investment, and divestment. In the context of the present model, $\sigma_i(s)$ is a set of policy functions which describes a firm's production, investment, entry, and exit behavior as a function of the present state vector. In a Markovian setting, with an infinite horizon, bounded payoffs, and a discount factor less than unity, the value function for an incumbent at the time of the exit decision is:

$$\begin{aligned} V_i(s; \sigma(s), \theta, \epsilon_i) = \bar{\pi}_i(s; \theta) + \max \Bigg\{ \phi_i, E_{\epsilon_i} \Bigg\{ \beta \int E_{\epsilon_i} V_i(s'; \sigma(s'), \theta, \epsilon_i) \; dP(s'; s, \sigma(s)) \\ + \max_{x_i^* \neq 0} \left[-\gamma_{i1} - \gamma_2 x_i^* + \beta \int E_{\epsilon_i} V_i(s'; \sigma(s'), \theta, \epsilon_i) \; dP(s_i + x^*, s'_{-i}; s, \sigma(s)) \right] \Bigg\} \Bigg\}, \end{aligned} \tag{A.2}$$

where θ is the vector of payoff-relevant parameters, E_{ϵ_i} is the expectation with respect to the distributions of shocks, and $P(s'; \sigma(s), s)$ is the conditional probability distribution over future state s', given the current state, s, and the vector of strategies, $\sigma(s)$.

Potential entrants must weigh the benefits of entering at an optimally-chosen level of capacity against their draws of investment and entry costs. Firms only enter when the sum of these draws is sufficiently low. We assume that potential entrants are short-lived; if they do not enter in this period they disappear and take a payoff of zero forever, never entering in the future.[1] Potential entrants are also restricted to make positive investments; firms cannot "enter" the market at zero capacity and wait for a sufficiently low draw of investment costs before building a plant. The value function for potential entrants is:

$$V_i^e(s; \sigma(s), \theta, \epsilon_i) = \max\left\{0, \max_{x_i^*>0}\left[-\gamma_{1i} - \gamma_2 x_i^{*2} + \beta \int E_{\epsilon_i} V_i(s'; \sigma(s'), \theta, \epsilon_i) dP(s_i + x^*, s'_{-i}; s, \sigma(s))\right] - \kappa_i\right\}. \quad \text{(A.3)}$$

Markov perfect Nash equilibrium (MPNE) requires each firm's strategy profile to be optimal given the strategy profiles of its competitors:

$$V_i(s; \sigma_i^*(s), \sigma_{-i}(s), \theta, \epsilon_i) \geq V_i(s; \tilde{\sigma}_i(s), \sigma_{-i}(s), \theta, \epsilon_i), \quad \text{(A.4)}$$

for all s, ϵ_i, and all possible alternative strategies, $\tilde{\sigma}_i(s)$. As we work with the expected value functions below, we note that the MPNE requirement also holds after integrating out firms' private information: $E_{\epsilon_i} V_i(s; \sigma_i^*(s), \sigma_{-i}(s), \theta, \epsilon_i) \geq E_{\epsilon_i} V_i(s; \tilde{\sigma}_i(s), \sigma_{-i}(s), \theta, \epsilon_i)$. Doraszelksi and Satterthwaite (2010) discuss the existence of pure strategy equilibria in settings similar to the one considered here. The introduction of private information over the discrete actions guarantees that at least one pure strategy equilibrium exists, as the best-response curves are continuous. However, there are no guarantees that the equilibrium is unique.

B Computation

Once the parameters have been estimated, the model can be computed to compare the market performance under market-based policy designs. In order to compute the equilibrium of the

[1] This assumption is for computational convenience, as otherwise one would have to solve an optimal waiting problem for the potential entrants. See Ryan and Tucker (2012) for an example of such an optimal waiting problem.

game, we make use of parametric approximation methods. In particular, we interpolate the value function using cubic splines. The reasons behind using parametric methods are twofold. First, the game has a continuous state space, given by the vector of capacities of the firms. By using parametric methods, we can allow firms to deterministically choose their capacity in a continuous space. Second, parametric approximation methods can be useful to improve computational speed. Previous work has already suggested the potential benefits of using parametric approximation methods (Pakes and McGuire, 1994).

Parametric value function methods have been explored in a single agent dynamic programming context.[2] However, they have not been widely used in dynamic games, particularly in games in which players take discrete actions, such as entry and exit (Doraszelski and Pakes, 2007). In our application, we find the method to perform well compared to a discrete value function method. In particular, this parametric method allows us to treat capacity as a continuous state, which improves the convergence properties of the game.[3]

The procedure we use is similar in spirit to the discrete value function iteration approach. In both methods, the value function is evaluated at a finite number of points. At each iteration and for a given guess of the value function, firms' strategies are computed optimally (*policy step*). Then, the value function is updated accordingly (*value function step*). This process is repeated until the value function and the policy functions do not change significantly.

The difference between the discrete value function iteration and our iterative approach is that we approximate the value function with a flexible parametric form. In particular, given a guess for the value function V^k at pre-specified grid points, we interpolate the value function with a multi-dimensional uniform cubic spline, which can be computed very efficiently (Habermann and Kindermann, 2007).[4] This interpolation defines an approximation of the value function in a continuous space of dimension equal to the number of active firms. For a given number of firms active N_A in the market, the value function at any capacity vector s is approximated as,

$$\hat{V}_i^k(s) = \sum_{j=1}^{(J+2)^A} \phi_{N_A,j} B_{N_A,j}(s), \tag{B.1}$$

[2]For a general treatment of approximation methods used in the context of dynamic programming, see Judd (1998). An assessment of these methods in a single agent model can be found in Benitez-Silva et al. (2000).

[3]This is mainly driven by the fact that firms take deterministic actions with respect to the continuous state.

[4]For a detailed treatment of splines methods, see de Boor (2001).

where J is the number of grid points, $\phi_{N_A,ij}$ are the coefficients computed by interpolating the values V^k when there are A active firms, and $B_{N_A,j}(s)$ is the spline weight given to coefficient $\phi_{N_A,j}$ when the capacity state equals s. This coefficient is the product of capacity weights for each of the incumbent firms, so that $B_{N_A,j}(s) = \prod_{i \in A} B_j(s_i)$.

In the *policy step*, optimal strategies are computed over this continuous function. For a given firm, we compute the conditional single-dimensional value function, given the capacity values of the other firms, $\hat{V}_i^k(s_i|s_{-i})$. This formulation allows us to represent the single-dimensional investment problem of the firm. The following expression defines the expected value function of the firm conditional on staying in the market and investing to a new capacity s_i'. Firms maximize,

$$\max_{s_i'} \quad \pi_i(s_i, s_i'|s_{-i}) + \sum_{s_{-i}' \in S_{-i}} Pr^k(s_{-i}'; \sigma^k(s)) \hat{V}_i^k(s_i'|s_{-i}'). \tag{B.2}$$

We compute the best-response of a firm by making use of the differentiability properties of the cubic splines, which allows us to compute the first-order conditions with respect to investment. Given that the cubic spline does not restrict the value function to be concave, we check all local optima in order to determine the best-response of the firm.[5] Conditional on optimal investment strategies, we then compute the new policy function with respect to the entry, investment and exit probabilities, which gives us an updated optimal policy σ^{k+1}. This allows us to compute a new guess for the value function V^{k+1} in the *value function step*.

The process is iterated until the strategies for each of the firms and the value function in each of the possible states do not change more than an established convergence criterion, such that $\| \sigma^{k+1} - \sigma^k \| < \epsilon_\sigma$ and $\| V^{k+1} - V^k \| < \epsilon_V$.

Strengths and Limitations Our methodology has the advantage that it treats the state space as continuous. This allows us to consider a continuous range of optimal policies for the firm's capacity, without imposing a coarse discretization of states. If the policy functions are continuous and well-behaved, a limited number of spline knots will suffice to approximate them.

As a limitation, and common with the literature, there might be multiple equilibria that are consistent with the model (Besanko et al., 2010; Borkovsky et al., 2010). To compute the equilibrium, we pick a particular starting point and let the algorithm converge. In particular,

[5] Taking the actions of other firms as given, the cubic spline is defined by a cubic polynomial at each of the grid intervals, which implies that at most there will be $2(J-1)+2$ candidate local optima, where J is the number of grid points.

we initialize firms' value function to zero. We have experimented with alternative starting points and we have not found our results to be sensitive to these choices.

Finally, we compute over 1,600 counterfactuals, some of which are quite similar to each other except for minor modifications to the fundamental parameters (e.g. different carbon prices, different elasticities, etc.). Inspecting the counterfactuals, we find that results across similar experiments appear to be smooth and well-behaved, which reassures us about the stability of the algorithm.

C Construction of Emissions Rates

Under the umbrella of the Cement Sustainability Initiative (CSI) of the World Business Council for Sustainable Development (WBCSD), a number of leading cement companies have collaborated on a methodology for calculating and reporting CO_2 emissions: the Cement CO_2 Protocol. The basic calculation methods are compatible with guidelines issued by the Intergovernmental Panel on Climate Change (IPCC). We use this protocol as a guide when estimating kiln-specific CO_2 emissions rates in this study (WBC, 2011).

Over half of the emissions from clinker production come from the chemical reaction that occurs when the calcium carbonate in limestone is converted into lime and carbon dioxide. To measure carbon dioxide emissions from calcination accurately at the kiln level, we would need to measure CaO and MgO contents of the clinker produced. We cannot, unfortunately, access this detailed plant-level information. Instead, we use the recommended default rate of 0.51 metric tons of carbon dioxide/metric ton of clinker (WBC, 2011).

CO2 is also emitted during the calcination of cement kiln dust (CKD) in the kiln. The lost CKD represents additional CO_2 emissions not accounted for in the clinker emissions estimate. The CO_2 from the lost CKD is generally equivalent to about 2-6 percent of the total CO_2 emitted from clinker production. It is therefore recommended that the estimate of CO_2 emissions from clinker production be scaled up (in percentage terms) to account for the CO_2 from the lost, calcined CKD (Gibbs et al., 2000). We thus increas our default rate to 0.525 metric tons of carbon dioxide/metric ton of clinker.

The other major source of carbon dioxide emissions from clinker production is fossil fuel combustion. The preferred approach to estimating CO_2 emissions from fuel combustion requires data on fuel consumption, heating values, and fuel specific carbon dioxide emission factors. Although the Portland Cement Association (PCA) does collect plant level data regarding fuel inputs and fuel efficiency (i.e. BTUs per ton of cement), the disaggregated data are not publicly available. We do have data aggregated by kiln type and vintage. We use these data (reported in 2006), together with average carbon dioxide emissions factors, provided by the U.S. Department of Energy, to estimate kiln technology specific emissions intensities.

We consider three classes of kilns in particular: wet process kilns (i.e. older, less efficient technology), dry process kilns with preheater/precalciner, and a best practice energy intensity benchmark (Coito et al., 2005).[6]

Because of the dominant role played by coal/pet coke, our benchmark emissions calculations use coal/petcoke emissions factors. We assume an emissions factor of 0.095 metric tons carbon dioxide/mmbtu.[7] Alternative fuels, including alternative or waste fuels, can either directly reduce plant-level CO_2 emissions or may be allowed to be deducted from reported combustion emissions because they are lower in carbon content per unit heat, the fuels are considered to be carbon-neutral (certain biofuels), or because credits may be allowed for their use (certain waste fuels).

Our kiln technology-specific estimates of combustion emissions rates are explained below.

Wet process In 2006, there were 47 wet process kilns in operation. On average, wet kilns produced 300,000 tons of clinker (per kiln) per year. The PCA 2006 Survey reports an average fuel efficiency of 6.5 mmbtu/metric ton of clinker equivalent among wet process kilns. The relevant conversion is then 0.095 metric tons carbon dioxide/mmbtu * 6.5 mmbtu/metric ton of clinker equivalent = 0.62 tons carbon dioxide/ton clinker. When added to process emissions, we obtain our estimate of 1.16 tons carbon dioxide/ton clinker.

Dry process In 2006, there were 54 dry kilns equipped with precalciners with an average annual output of 1,000,000 tons of clinker per year. The PCA 2006 Survey reports an average fuel efficiency of 4.1 mmbtu/metric ton of clinker equivalent among dry process kilns with precalciners. Thus, 0.095 metric tons carbon dioxide/mmbtu * 4.1 mmbtu/metric ton of clinker equivalent = 0.39 tons carbon dioxide/ton clinker. Adding this to process emissions

[6] The industry has slowly been shifting away from wet process kilns towards more fuel-efficient dry process kilns. On average, wet process operations use 34 percent more energy per ton of production than dry process operations. No new wet kilns have been built in the United States since 1975, and approximately 85 percent of U.S. cement production capacity now relies on the dry process technology.

[7] Fuel-specific emissions factors are listed in the Power Technologies Energy Data Book, published by the US Department of Energy (2006). The emissions factors (in terms of lbs CO_2 per MMBTU) for petroleum coke and bituminous coal are 225 and 205, respectively. Here we use a factor of 210 lbs CO_2/MMBTU (or 0.095 metric tons CO_2/MMBTU). This is likely an overestimate for those units using waste fuels and/or natural gas.

results in the estimate for dry-process kilns: 0.93 tons carbon dioxide/ton clinker.

Frontier technology To establish estimates for new entrants, a recent study (Coito et al., 2005) establishes a best practice standard of 2.89 mmbtu/ metric ton of clinker (not clinker equivalent). The calculation is then: 0.095 metric tons carbon dioxide/mmbtu * 2.89 mmbtu/metric ton of clinker equivalent= 0.275 tons carbon dioxide/ton clinker. Adding this to process emissions obtains in 0.81 tons carbon dioxide/ton clinker for new kilns.[8]

D The Social Cost of Carbon

In 2013, 12 government agencies, working in conjunction with economists, lawyers, and scientists, produced an updated set of standards for establishing the social cost of carbon (SCC) (Working Group on Social Cost of Carbon, 2013). The goal of this exercise was to ensure consistency in the values of SCC used across various government agencies to inform policy and conduct cost-benefit analyses. Table D.1 enumerates the resulting range of SCC values. The SCC increases over time because future emissions are expected to produce larger incremental damages as physical and economic systems become more stressed. In light of disagreements about how to assign a social discount rate, three different discount rates are used (corresponding to the first three columns). The final schedule (fourth column) corresponds to a scenario with extreme (95th percentile) economic costs from climate change.

In our analysis, we consider values ranging from \$0 to \$65 per ton. In our policy simulations, neither the carbon price nor the SCC changes over time.

E Sample Value Functions

In the main text, we focus the analysis on equilibrium outcomes along the equilibrium path, across policy regimes and carbon price levels. We report here sample value functions, which show equilibrium strategies at each possible state. These can be useful to understand the forces behind equilibrium outcomes. Given the high dimensionality of the state space, we focus on a small market with only two potential firms. Comparative statics are similar for bigger markets, although the state space becomes larger.

[8] This is very similar to the CO_2 emissions rate assumed in analyses carried out by California's Air Resources Board in 2008 under a best practice scenario that does not involve fuel switching. If fuel switching is assumed, best practice emissions rates drop as low as 0.69 MT CO_2/ MT cement. See NRDC Cement GHG Reduction Final Calculations.

Table D.1: Environmental parameters

	(1)	(2)	(3)	(4)
Social discount rate $(1 - \beta_S)$	5.0%	3.0%	2.5%	3.0%
Year	Avg	Avg	Avg	95th
SCC 2010	11	33	52	90
SCC 2015	12	38	58	109
SCC 2020	12	43	65	129
SCC 2030	16	52	76	159
SCC 2050	27	71	98	221

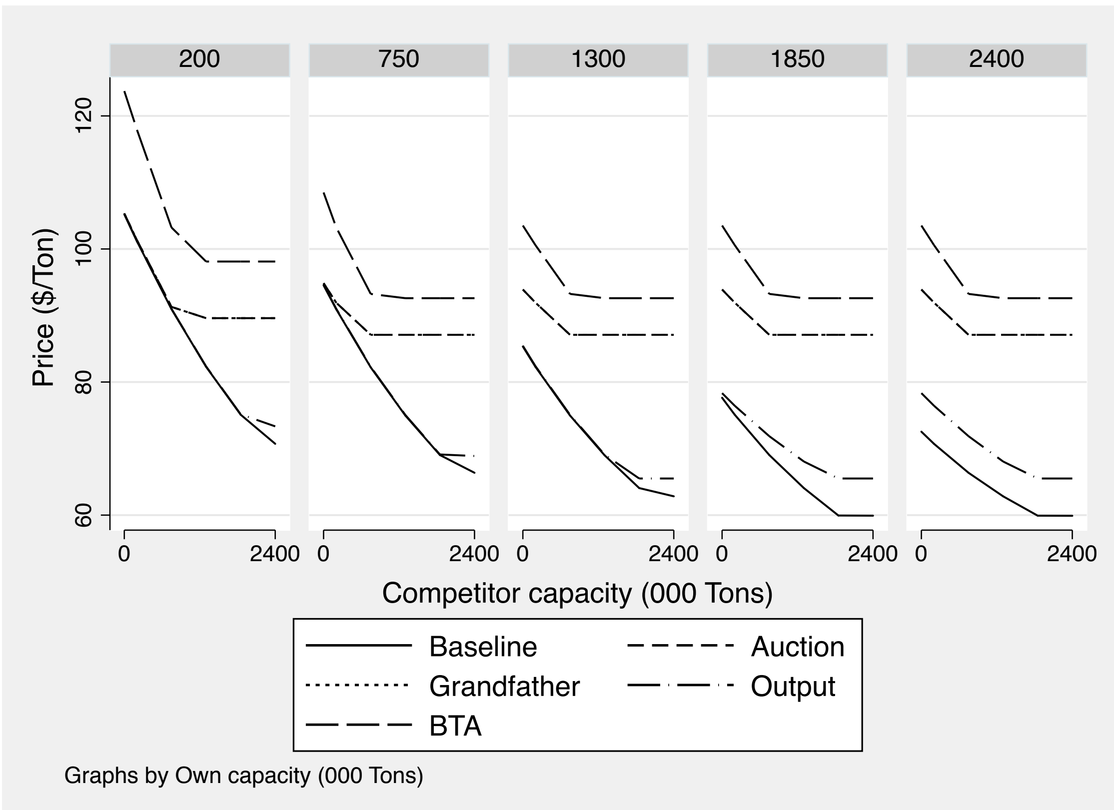
Source: Working Group on Social Cost of Carbon (2013). All values for the social cost of carbon in given as $ per metric ton of carbon dioxide in $2007.

We consider the case of an incumbent firm with dry-technology facing either a potential entrant or an active firm with state-of-the-art technology. Figure E.1 plots the static equilibrium price as a function of own capacity. The information is depicted in blocks to capture the three-dimensional nature of this object. Each block represents a given capacity level of the incumbent firm. For each block, the other firm's capacity ranges from 0 to 2,400. For example, at the first observation in the block of 750 thousand tons, the other firm is a potential entrant.

Figure E.1 represents the equilibrium price at different states. It is useful to highlight some key points. First, as mentioned in the main text, auctioning and grandfathering have the same static prices at a given state. Second, capacity is binding when total market capacity is not too large. This can be observed quite vividly for the case of output-based updating. Because the effective tax is relatively small, equilibrium prices are in many states equivalent to the case with no tax. In those states and from a static perspective, the output-based tax only represents a net transfer from firms to the government. Finally, capacity is eventually not binding, specially when firms face the full tax and stronger competition, and equilibrium prices flatten.

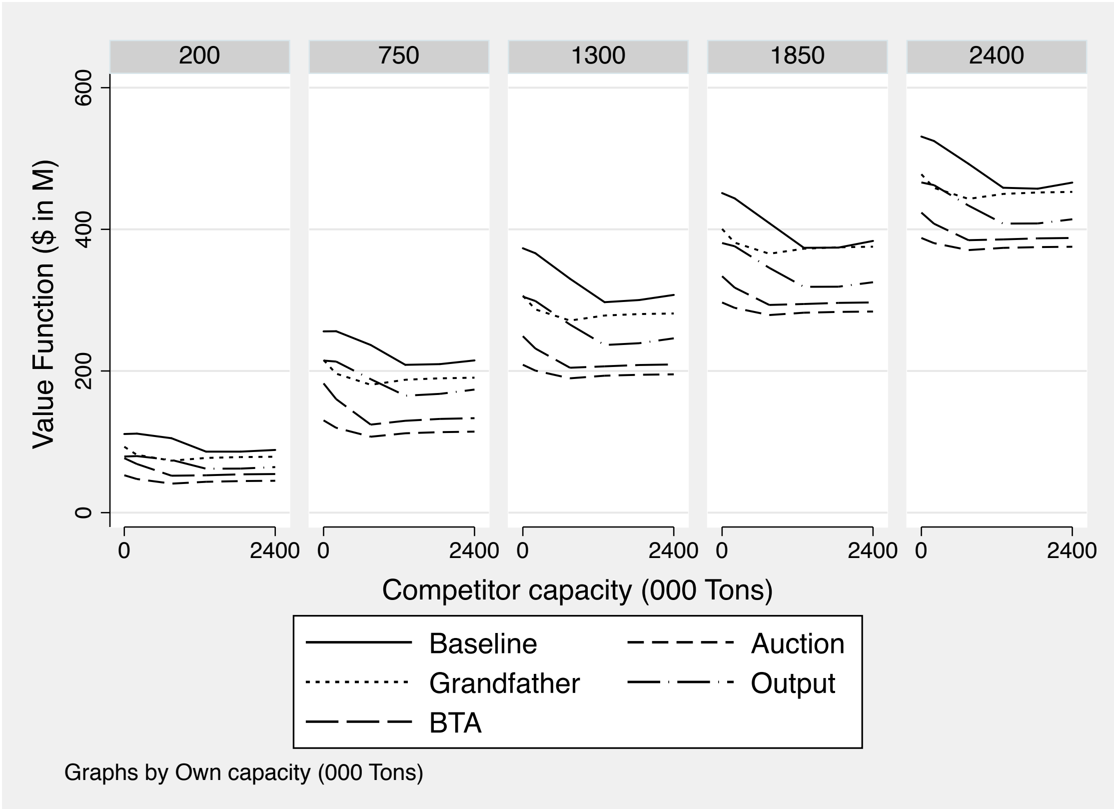
When we account for dynamics, the net present value of being at a particular state becomes different across mechanisms, even for those states with equivalent static prices. Figure E.2 represents the value function at different states. First, auctioning and grandfathering are no longer equivalent, as firms are receiving free permits when grandfathered. In fact, the value function is always larger for the grandfathering case. Second, dynamically the baseline equilibrium and the output based one have substantially different values, even if prices were the same across a wide range of states. Finally, even though prices flatten out, there is some

Figure E.1: Prices for Minneapolis at Carbon Price $35



Note: Equilibrium static prices with an incumbent firm with dry-technology facing a potential entrant or active firm with state-of-the-art technology. For each capacity level of the incumbent firm (200, 750, 1300, 1850 and 2400), capacities of the other firm are evaluated. A capacity of zero (first point in a given block) implies that the other firm is a potential entrant.

Figure E.2: Value function for Minneapolis at Carbon Price $35

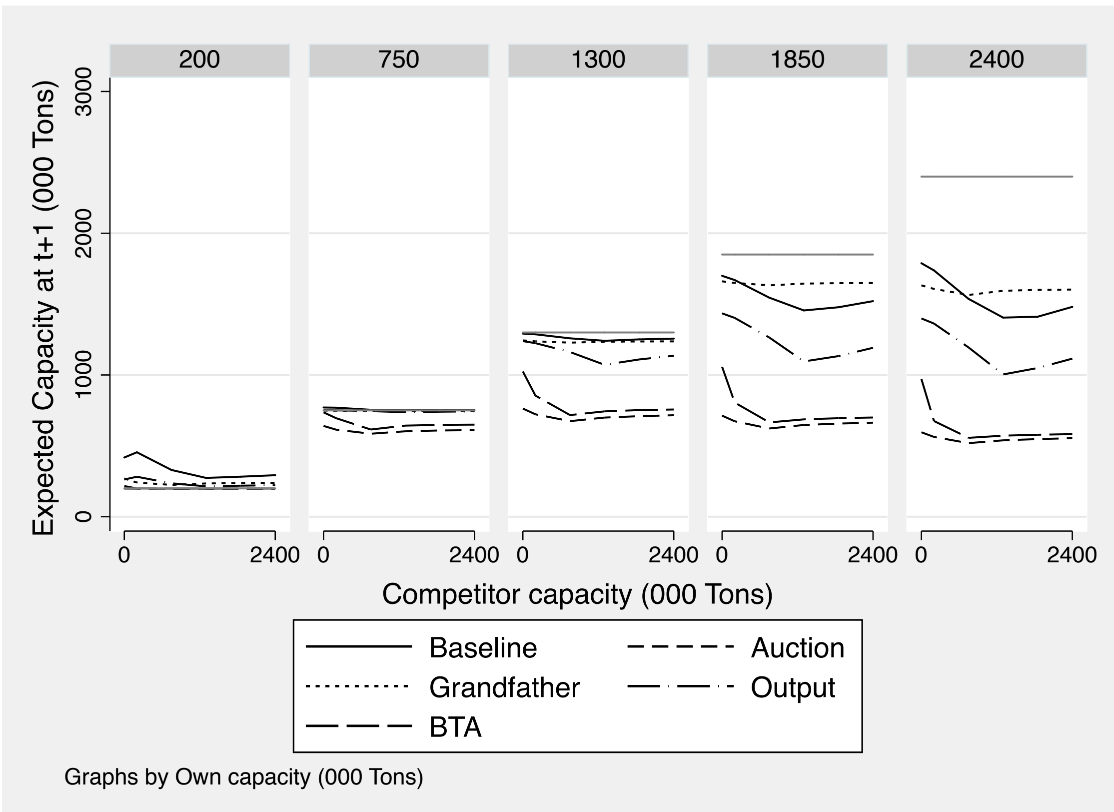


Note: Equilibrium value function for incumbent firm with dry-technology facing a potential entrant or active firm with state-of-the-art technology. For each capacity level of the incumbent firm (200, 750, 1300, 1850 and 2400), capacities of the other firm are evaluated. A capacity of zero (first point in a given block) implies that the other firm is a potential entrant.

value to being larger. This can be either because firms can deter entry or because they have more capacity to sell off.

Figure E.3 provides more insights on how firms are changing their capacities in a dynamic environment. The figure plots expected capacity in the next period, taking into account investment probabilities and investment policies. One can see that, given the small size of this market, for most states firms either maintain their capacity or decrease their size. In the presence of the carbon tax, firms decrease their size substantially. Importantly, this is quite different for the grandfathering case, as in some instances firms maintain a capacity level even larger than in the baseline. The intuition behind this effect is that grandfathering creates pervasive incentives to remain in the market and receive free permits.

Figure E.3: Expected Next Period Capacity for Minneapolis at Carbon Price $35



Note: Equilibrium expected next period capacity for incumbent firm with dry-technology facing a potential entrant or active firm with state-of-the-art technology. For each capacity level of the incumbent firm (200, 750, 1300, 1850 and 2400), capacities of the other firm are evaluated. A capacity of zero (first point in a given block) implies that the other firm is a potential entrant. The gray line depicts current capacity for easier comparison.

F Additional Tables and Figures

Table F.1: Dynamic Cost Estimates for Alternative Discount Factors

	$\beta = 0.85$	$\beta = 0.90$	$\beta = 0.95$
Investment Estimates			
Capacity Investment Cost ($/Ton)	106	171	347
Adjustment Fixed Cost ($000)	35,230	48,525	78,783
Adjustment Fixed Cost SD (($000)	20,263	28,536	48,057
Adjustment Fixed Cost, 4% Draw	-244	-1,433	-5,350
Adjustment Total Cost, 1.4 MT addition, 4% Draw	148,046	237,895	479,916
Entry Estimates			
Entry Fixed Cost ($000)	50,253	75,032	139,578
Entry Fixed Cost SD ($000)	18,961	27,948	46,837
Entry Fixed Cost, 2% Draw	11,312	17,633	43,386
Entry Total Cost, Plant 1 MT, 2% Draw	117,234	188,582	390,004
Exit Estimates			
Exit Scrap Value ($000)	-105501	-151825	-238026
Exit Scrap Value SD ($000)	61,244	89,231	148,559
Exit Scrap Value, 2% Draw	20,279	31,434	67,076
Exit Total Scrap, Plant 1 MT, 2% Draw	126,201	202,382	413,694

Notes: Bootstrapped standard errors in parenthesis.

Table F.2: Marginal Cost Estimates for a Range of Elasticity Parameters

	$\eta = 1$	$\eta = 1.5$	$\eta = 2$	$\eta = 2.5$	$\eta = 3$	$\eta = 3.5$
Marginal cost ($/000 Ton)	31.71	42.36	46.99	45.67	45.18	43.90
Capacity cost ($/Extra % Utilization)	944.67	785.04	803.65	706.37	802.97	785.18
Utilization Threshold Estimate	1.87	1.73	1.89	1.67	1.76	1.70
Implied Utilization % Threshold	0.87	0.85	0.87	0.84	0.85	0.85

Notes: Bootstrapped standard errors in parenthesis.

Table F.3: Dynamic Cost Estimates for a Range of Elasticity Parameters

	$\eta = 1$	$\eta = 1.5$	$\eta = 2$	$\eta = 2.5$	$\eta = 3$	$\eta = 3.5$
Investment Estimates						
Capacity Investment Cost ($/Ton)	298	210	171	177	179	186
Adjustment Fixed Cost ($000)	49,960	49,371	48,525	51,445	53,061	54,846
Adjustment Fixed Cost SD ($000)	32,418	29,929	28,536	30,146	31,006	32,082
Adjustment Fixed Cost, 4% Draw	-6,793	-3,025	-1,433	-1,331	-1,221	-1,321
Adjustment Total Cost, 1.4 MT addition, 4% Draw	409,727	290,587	237,895	246,388	249,428	259,622
Entry Estimates						
Entry Fixed Cost ($000)	70,355	72,091	75,032	77,134	79,717	81,200
Entry Fixed Cost SD ($000)	25,432	26,834	27,948	28,517	29,299	29,692
Entry Fixed Cost, 2% Draw	18,123	16,982	17,633	18,567	19,544	20,221
Entry Total Cost, Plant 1 MT, 2% Draw	315,638	226,704	188,582	195,510	198,579	206,608
Exit Estimates						
Exit Scrap Value ($000)	-134,248	-146,139	-151,825	-158,871	-164,271	-168,636
Exit Scrap Value SD ($000)	78,789	85,403	89,231	93,743	97,310	100,104
Exit Scrap Value, 2% Draw	27,565	29,257	31,434	33,654	35,579	36,953
Exit Total Scrap, Plant 1 MT, 2% Draw	325,079	238,979	202,382	210,596	214,614	223,340

Notes: Bootstrapped standard errors in parenthesis.

Table F.4: Bootstrap Simulation Welfare Comparisons

	W1 (M$)	W2 (M$)	W3 (M$)	Price ($/000t)	Market K (000t)	Profit (M$)	Num. Firms
Auctioning							
$\tau = 15.0$	-4,965	-3,197	-3,643	92.0	1744.2	753.2	1.5
	(849)	(689)	(759)	(7.2)	(418.6)	(96.6)	(0.2)
$\tau = 30.0$	-9,949	-3,893	-5,638	104.0	979.3	377.2	1.4
	(1,616)	(765)	(1,001)	(4.1)	(255.2)	(74.2)	(0.2)
$\tau = 45.0$	-12,983	-1,937	-5,238	113.4	673.9	221.9	1.3
	(2,337)	(576)	(768)	(2.1)	(107.3)	(51.2)	(0.3)
$\tau = 60.0$	-15,206	1,144	-3,956	120.4	593.3	150.0	1.2
	(2,568)	(1,110)	(658)	(2.1)	(92.2)	(52.5)	(0.2)
Grandfather							
$\tau = 15.0$	-2,769	-1,514	-1,814	86.8	2102.9	1037.1	1.5
	(580)	(373)	(426)	(7.3)	(431.2)	(125.0)	(0.2)
$\tau = 30.0$	-5,667	-1,264	-2,317	95.0	1854.0	894.1	1.4
	(1,082)	(448)	(485)	(5.6)	(483.5)	(155.3)	(0.2)
$\tau = 45.0$	-9,484	212	-2,280	103.5	2066.1	990.3	1.4
	(1,613)	(857)	(724)	(3.7)	(644.4)	(246.4)	(0.2)
$\tau = 60.0$	-12,986	3,061	-1,328	112.9	2552.4	1366.8	1.4
	(2,360)	(1,194)	(697)	(2.3)	(450.2)	(217.5)	(0.2)
Output							
$\tau = 15.0$	-1,044	-570	-668	81.1	2598.0	1152.0	1.6
	(232)	(201)	(219)	(8.4)	(566.5)	(133.9)	(0.2)
$\tau = 30.0$	-1,866	-164	-477	83.9	2388.2	999.7	1.6
	(400)	(387)	(408)	(8.3)	(535.8)	(116.2)	(0.2)
$\tau = 45.0$	-2,834	797	84	87.0	2193.5	879.0	1.6
	(691)	(740)	(810)	(8.1)	(525.2)	(104.8)	(0.2)
$\tau = 60.0$	-4,110	2,347	954	90.1	2009.2	774.6	1.6
	(702)	(1,154)	(1,165)	(7.5)	(515.4)	(99.4)	(0.2)
BTA							
$\tau = 15.0$	-3,275	-1,838	-1,784	93.4	1970.7	883.6	1.5
	(814)	(615)	(641)	(7.3)	(424.9)	(103.4)	(0.2)
$\tau = 30.0$	-6,210	-1,514	-1,258	107.8	1434.2	603.5	1.5
	(1,462)	(779)	(792)	(4.8)	(315.4)	(80.9)	(0.2)
$\tau = 45.0$	-8,946	18	590	123.2	1058.4	428.5	1.5
	(2,128)	(1,046)	(980)	(3.1)	(247.7)	(71.6)	(0.2)
$\tau = 60.0$	-10,997	2,601	3,589	136.0	840.8	315.7	1.4
	(2,747)	(1,387)	(1,039)	(2.0)	(181.6)	(68.5)	(0.3)

Notes: Table reports mean and standard deviation of simulation outcomes for a sample of 50 bootstrap estimates using a subset of regional markets with three or less firms (Cincinnati, Detroit, Minneapolis, Pittsburgh, Salt Lake City, Seattle).

Table F.5: Welfare difference with respect to baseline (W3) (**demand elasticities**)

Demand elasticity	1.0	1.5	2.0	2.5	3.0	3.5
$\tau = 5.0$						
Auctioning	-1,186	-1,442	-1,640	-1,779	-1,786	-1,844
Grandfather	-713	-825	-916	-1,015	-1,066	-1,177
Output	-271	-326	-377	-421	-374	-423
BTA	-608	-876	-1,071	-1,224	-1,275	-1,347
$\tau = 15.0$						
Auctioning	-3,336	-3,807	-4,197	-4,431	-4,535	-4,680
Grandfather	-1,760	-2,041	-2,244	-2,323	-2,269	-2,289
Output	-697	-765	-842	-820	-688	-668
BTA	-1,385	-1,867	-2,280	-2,511	-2,659	-2,817
$\tau = 25.0$						
Auctioning	-5,343	-5,592	-5,936	-6,103	-5,854	-5,606
Grandfather	-2,490	-2,597	-2,691	-2,635	-2,575	-2,495
Output	-871	-598	-697	-602	-488	-426
BTA	-1,606	-1,843	-2,082	-2,120	-2,128	-2,251
$\tau = 35.0$						
Auctioning	-7,309	-7,094	-6,434	-5,588	-4,815	-4,188
Grandfather	-2,851	-2,735	-2,691	-2,394	-1,996	-1,736
Output	-263	-468	-547	-375	-136	63
BTA	-1,262	-1,058	-1,160	-1,188	-842	-546
$\tau = 45.0$						
Auctioning	-8,782	-7,157	-5,939	-4,584	-3,354	-2,375
Grandfather	-3,195	-2,761	-2,478	-1,836	-1,135	-530
Output	-246	-281	-290	55	472	836
BTA	-572	-266	-270	605	1,508	2,408
$\tau = 55.0$						
Auctioning	-8,953	-6,801	-4,922	-3,265	-1,744	-360
Grandfather	-3,600	-2,619	-1,855	-729	614	1,882
Output	-304	-125	72	710	1,380	1,917
BTA	272	705	1,719	3,079	4,554	5,794
$\tau = 65.0$						
Auctioning	-9,002	-6,175	-3,931	-1,490	621	2,341
Grandfather	-4,149	-2,523	-764	1,394	3,335	4,937
Output	34	310	728	1,671	2,626	3,418
BTA	1,081	2,415	3,960	5,953	7,817	9,348

Notes: Table reports average differences in our most comprehensive welfare measure (W3) for the subset of regional markets with three or less firms (Cincinnati, Detroit, Minneapolis, Pittsburgh, Salt Lake City, Seattle).

Table F.6: Welfare difference with respect to baseline (W3) (**import elasticities**)

Import Elasticity	1.5	2.0	2.5	3.0	3.5	4
$\tau = 5.0$						
Auctioning	-1,364	-1,366	-1,414	-1,375	-1,313	-1,281
Grandfather	-855	-815	-843	-776	-733	-705
Output	-272	-259	-298	-278	-252	-245
BTA	-862	-823	-845	-779	-721	-694
$\tau = 15.0$						
Auctioning	-3,151	-3,282	-3,486	-3,565	-3,665	-3,761
Grandfather	-1,968	-1,984	-2,050	-2,013	-1,981	-1,952
Output	-637	-620	-678	-628	-589	-548
BTA	-1,479	-1,496	-1,569	-1,547	-1,515	-1,485
$\tau = 25.0$						
Auctioning	-4,415	-4,716	-5,211	-5,724	-6,023	-6,234
Grandfather	-2,284	-2,350	-2,499	-2,537	-2,599	-2,681
Output	-493	-481	-550	-495	-500	-489
BTA	-1,255	-1,264	-1,357	-1,341	-1,334	-1,328
$\tau = 35.0$						
Auctioning	-5,312	-5,704	-5,980	-6,080	-6,163	-6,225
Grandfather	-2,185	-2,388	-2,688	-2,876	-3,053	-3,202
Output	-405	-424	-548	-549	-551	-543
BTA	-717	-644	-706	-677	-660	-625
$\tau = 45.0$						
Auctioning	-4,977	-5,211	-5,528	-5,729	-5,909	-6,039
Grandfather	-1,923	-2,297	-2,800	-3,183	-3,485	-3,815
Output	-284	-356	-526	-560	-598	-618
BTA	281	254	141	157	280	341
$\tau = 55.0$						
Auctioning	-4,191	-4,514	-4,950	-5,398	-5,773	-5,929
Grandfather	-1,491	-1,965	-2,579	-3,089	-3,341	-3,313
Output	-86	-211	-438	-515	-587	-639
BTA	1,904	1,854	1,691	1,675	1,678	1,707
$\tau = 65.0$						
Auctioning	-3,195	-3,908	-4,478	-4,662	-4,803	-4,906
Grandfather	-1,044	-1,642	-1,978	-1,931	-1,832	-1,702
Output	396	201	-101	-249	-386	-482
BTA	3,629	3,591	3,413	3,421	3,430	3,458

Notes: Table reports average differences in our most comprehensive welfare measure (W3) for the subset of regional markets with three or less firms that are trade exposed (Cincinnati, Detroit, Minneapolis, Seattle).

Table F.7: Prices and Welfare Comparisons for Alternative Samples

	Prices ($/ton)			Changes in Welfare (W3)		
	3-Firm	4-firm	5-firm	3-Firm	4-firm	5-firm
Auctioning $\tau = 15.0$	91.9	90.6	89.3	-3,557	-7,364	-12,180
$\tau = 30.0$	104.1	102.8	101.2	-5,806	-10,132	-16,512
$\tau = 45.0$	115.0	114.6	111.9	-4,845	-7,853	-12,890
$\tau = 60.0$	119.6	129.2	124.7	-3,107	-4,261	-7,375
Grandfather $\tau = 15.0$	86.5	85.1	83.6	-1,842	-3,778	-5,801
$\tau = 30.0$	94.4	92.3	90.6	-2,088	-3,708	-6,663
$\tau = 45.0$	103.3	102.0	99.9	-2,124	-1,978	-5,839
$\tau = 60.0$	113.8	113.4	110.7	-1,589	1,322	-1,818
Output $\tau = 15.0$	80.4	79.7	78.5	-657	-1,737	-2,418
$\tau = 30.0$	83.4	82.8	81.6	-410	-1,122	-1,901
$\tau = 45.0$	85.8	85.6	84.5	315	882	619
$\tau = 60.0$	89.4	89.2	88.0	1,425	3,977	4,947
BTA $\tau = 15.0$	93.4	91.8	90.3	-1,663	-4,318	-6,095
$\tau = 30.0$	106.7	105.5	104.3	-805	-2,943	-4,121
$\tau = 45.0$	125.8	122.3	120.1	883	1,609	3,150
$\tau = 60.0$	136.7	142.1	138.6	4,086	7,666	13,268

Notes: Each N-Firm column includes all markets with N firms or less. For the 3-, 4- and 5-Firm cases, six, twelve and sixteen markets are included, respectively.

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