

# Why is Productivity Correlated with Competition?\*

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## Abstract

The positive correlation between average establishment-level productivity and measures of competitiveness is oft-observed but still controversial, despite its implications for competition policy and its centrality in the debate over the origins of the productivity effect of trade liberalization. This paper considers two competing explanations for the existence of the correlation: a causal relationship between productivity and competition, also known as X-inefficiency, and a market-level dynamic selection story that has gained ground in the trade literature. This paper demonstrates that the two effects are econometrically separable. Two empirical approaches are developed: a quantile response model and a selection correction procedure derived from a model of Markov-perfect industry dynamics. Both are applied to the ready-mix concrete industry, where it is found that X-inefficiency is the stronger explanation.

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# 1 Introduction

There is a perennial paper in the productivity literature which presents the following empirical result, updated for contemporary innovations in attitudes towards data and econometrics: *firms that are in more competitive markets are also more efficient*. In the era of cross-sectional, cross-industry regressions, the correlation was straightforward to measure (Green and Mayes (1991) Caves and Barton (1990)). As panel methods became more prominent, the empirical result stood out in still more clarity (Hay and Liu (1997), Nickell (1996), Pavcnik (2002)). Finally, when cross-industry regressions became suspect, though finding an appropriate industry and instrument became a challenge, the correlation was robust (Berger and Hannan (1998), Syverson (2004), Schmitz (2005), Dunne, Klimek, and Schmitz (2010)).

The existence of a correlation between competition on productivity is significant both for anti-trust as well as trade policy. As Williamson (1968) noted in the case of horizontal merger evaluation, for deadweight loss to outweigh alleged productive synergies the estimated percentage change in price would have to be several times larger than the percentage efficiency gain. Efficiency losses from market concentration, however, which affect not only all firms in the market but operate on *infra*-marginal sales, could potentially overturn that result. If measurable, these rectangles may be a much stronger argument for worrying about mergers than deadweight loss triangles, famously found to be so diminutive by Harberger (1954). Moreover, trade economists have been quick to adopt measured efficiency gains as one of the central arguments for gains from trade, a Pantheon formerly dominated by allocative efficiencies and Ricardo's argument from comparative advantage.

No consensus exists, however, regarding the explanation for such a correlation. There are two main hypotheses: First, that competition has a direct effect on productivity. This hypothesis was originally introduced as a black box under the name "X-inefficiency" by Leibenstein (1966) and has since received considerable theoretical development. A second hypothesis has emerged from the trade literature on productivity gains from trade liberalization: that more competitive markets select more aggressively on productivity. Even in the absence of a direct causal relationship, this implies that the selected sample in more competitive markets will be, on average, more productive than that in less competitive markets.<sup>1</sup> The

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<sup>1</sup>This is related, but not identical, to the selection issue treated in the third stage of Olley and Pakes's (1996) structural production function estimator. In their paper there is only one market, and therefore market structure is fully controlled for by allowing the propensity score estimator to vary nonparametrically in time. Even given consistent estimator of the productivity residual, however, reduced-form estimates of

two hypotheses will be referred to here as X-inefficiency and dynamic selection.<sup>2</sup>

The conflation of these two effects is not unknown, and some of the papers documenting the correlation between productivity and competition have included reduced-form efforts to control for dynamic selection. Pavcnik (2002) applies Olley and Pakes (1996) to obtain productivity residuals, and then uses a regression framework with exit dummies to control for the selection effect. Alternatively, Schmitz (2005) adopts a decomposition approach to measure the relative effects of exit and within-firm change. Both papers find evidence in favor of the within-firm, X-inefficiency story.

This paper endeavors to disambiguate the two stories in a way that is structurally consistent and requires minimal appeal to parametric form beyond the original derivation productivity residuals. Identification is formulated two way— first, by thinking about the effect on the ergodic distribution of types; though the predictions of X-inefficiency on the distribution of types is ambiguous, the dynamic selection story implies the correlation of productivity quantiles and competition should be decreasing in quantile, since it operates primarily on the left tail. Second, an explicit model of the firm’s decision problem is formulated in order to derive a selection correction procedure which isolates the effect of X-inefficiency by controlling completely for dynamic selection. While the first approach has the appealing feature of offering a direct visual test, the latter is used to generate numerical estimates of the relative contribution of the two stories. Both confirm the dominance of X-inefficiency.

The natural setting for applying these identification techniques is ready-mix concrete. One of the difficulties of studying the correlation between productivity and competition is generating sufficient cross-sectional variance in competitive structure. High transportation costs make ready-mix concrete markets local in character; these local markets permit the measurement of just such variance. Second, the availability of homogeneous output measures in physical, rather than revenue terms, allows one to estimate physical productivity entirely separately from market power. This paper builds on Syverson’s (2004) pioneering study of productivity dispersion in ready-mix concrete, though here the first rather than the second

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the within-firm increase in productivity will be influenced upwards by dynamic selection, as survivors in an increasingly competitive market are more likely to have had a favorable innovation in productivity.

<sup>2</sup>A third hypothesis emerges if the object of interest is revenue-weighted average productivity; more competitive markets may better allocate demand to higher productivity firms, a hypothesis that comes out strong in Olley and Pakes (1996). This paper pre-empts the third hypothesis by focusing on unweighted productivity, not because allocation is unimportant, but because it is beyond the scope of the paper— the focus here is to disambiguate the empirical consequences of X-inefficiency and dynamic selection. Moreover, due to data exclusion issues described below, the data is poorly suited to measuring the reallocation effect.

moment is under consideration,<sup>3</sup> and this first moment is leveraged to examine the underlying model. Also closely related is Collard-Wexler (2011), which studies the determinants of establishment survival in ready-mix concrete markets.

There is also an extensive related literature on the use of decomposition methods in the study of changes in aggregate productivity. Here, a regression framework is used instead of decomposition for two reasons: to begin with, the objective is to take advantage of cross-sectional variation in order to map the changes in productivity onto a continuous explanatory variable, an index of competition. Decomposition methods are most apposite to the study of time-series variation and discrete policy changes, as in Olley and Pakes (1996). Moreover, the dynamic selection story posited as an alternative to X-inefficiency is also a potential source of bias which would tend to overstate the within-firm share of the change in productivity. At the end of the day, however, little evidence is found for the dynamic selection effect, which should in turn reassure us about the use of decomposition methods.

Section 2 describes the ready-mix concrete industry, the data used, and the measurement issues associated with studying productivity, spatially defined markets, and competition indexes. Section 3 captures the correlation between productivity and competition with a reduced-form instrumental variables approach. In section 4 and 5 the theoretical foundations for the two effects conflated in that correlation are explored, and section 6 expounds on and implements two strategies for separating them econometrically. Section 7 concludes.

## 2 Data and Measurement

### 2.1 The Ready-Mix Concrete Industry

This paper uses US Census of Manufactures data for the ready-mix concrete industry (SIC 3273) for years 1982, 1987, and 1992. Ready-mix concrete is a mixture of cement, water, gravel, and a handful of chemical additives. Stockpiles of these materials are stored at the plant, mixed on demand, and loaded in liquid form into a ready-mix concrete truck for delivery at the construction site, where the concrete is poured.

The liquid mixture begins to set as soon as it is loaded into the ready-mix concrete truck;

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<sup>3</sup>Syverson (2004) is built on a variant of the dynamic selection story and finds an average productivity effect as well, however notes (see footnote 6) that this effect would be conflated with X-inefficiency, and that it is beyond the scope of that paper to disentangle the two effects.

besides the potential for wasted materials, there are costs associated with removing hardened concrete from the inside of the drums of ready-mix concrete trucks. These two factors both contribute to the high transportation costs which render this industry markedly local in scope. Geographic market definition is discussed below, however it is this uniquely local character which makes ready-mix concrete such an attractive industry for study; in order to measure the effect of competition on productivity, one requires variation in competitive structure. This is difficult to obtain for most manufacturing industries, which compete in an increasingly integrated world market.

A second important feature of the industry is the homogeneity of the output. Though the composition of the chemical additives may differ from firm to firm, this is thought to generate very little product differentiation. For this reason, in the years 1982, 1987, and 1992 the Products Supplement to the Census of Manufactures includes output data in cubic yards, which obviates many of the concerns that would accompany the use of deflated revenue in estimating productivity. Using physical output to measure productivity is especially apposite to this application because productivity residuals based on revenue measures will be reflect market-level and idiosyncratic demand shocks through firms' mark-ups, generating a spurious correlation between productivity and competition.<sup>4</sup>

The Census of Manufactures offers extensive data on inputs of production which are used to estimate productivity residuals, as discussed below. For more extensive discussion of the data and the ready-mix concrete industry, the reader is referred to Syverson (2008).

## 2.2 Sample Inclusion

There are over five thousand ready-mix concrete establishments observed by the Census of Manufactures in each year of my sample. Unfortunately, roughly one-third of these establishments are "administrative records" establishments; that is, small enough to be exempt from completing census forms. Data for these is a combination of administrative records from other agencies and imputation, and is therefore unusable for calculating productivity residuals.

A small handful of establishments are extensively diversified and operate in multiple SIC

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<sup>4</sup>This is less of an issue to the extent that one finds a positive correlation between productivity and competition; mark-ups in the measurement error of productivity would be *negatively* correlated with competition and therefore merely attenuate the result.

codes. Here they are excluded if less than fifty percent of their total sales is composed of ready-mix concrete. For diversified establishments which survive this exclusion, inputs devoted to ready-mix concrete are approximated by multiplying the fraction of sales from ready-mix concrete by the conflated input variable. Finally, the establishment-level price of a cubic yard of concrete is calculated by dividing revenues by quantity, and a small number of firms with extremal values are excluded from the sample.

It is important to note that while these establishments are excluded for regressions that depend on estimates of the productivity residuals, they are not excluded in the calculation of market-level variables— in particular the competition indexes discussed below in section 2.4.

## 2.3 Market Definition

This paper employs the Component Economic Area (CEA) market definition to study ready-mix concrete markets. CEAs are a complete and mutually exclusive categorization of the nation's over three thousand counties into 348 economic markets<sup>5</sup>. In contrast with the sometimes arbitrary size and shapes of counties (see Figure 1), the typical CEA is defined first by the identification of an economic node, and then the assignment of non-nodal counties to economic nodes by newspaper readership and traffic commuting patterns (see Figure 2). Johnson and Kort (2004) offers more discussion of the assignment of counties to CEAs, and Syverson (2004), which pioneered the use of CEAs in the study of ready-mix concrete, offers still more motivation for their use.

## 2.4 Measuring Competition

In a Markov-perfect industry dynamics model with full information (e.g., Ericson and Pakes (1995)), the competitive structure of the market enters the payoff and value functions of the firm through a high-dimensional state variable which includes the type of every active firm in the market. As the explicit inclusion of such a variable is infeasible for empirical work, two indexes are constructed which capture the salient features of the state of the market.

On the extensive margin, the size of the market is captured by the number of ready-mix

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<sup>5</sup>The number of CEAs was revised to 344 in 2004, however this paper employs the pre-2004 CEA definitions.

concrete firms per square mile. Informally, the more ready-mix concrete firms there are in a fixed geographic space, the more substitutable they are, and therefore the more intense the competition between them.

The second measure is meant to capture the intensive margin. The Herfindal-Hirschman Index is constructed from the revenue of active firms. Though this variable will be negatively correlated with the number of firms, it also captures the allocation of demand between firms, and therefore reflects the dispersion of firm types<sup>6</sup>

Both of these measures can be sensibly computed using either establishments or firms as the unit of observation. This paper presents results for both. Summary statistics for these competition indexes can be found in Table 1. As noted above, the calculation of the competition indexes includes the administrative record and diversified firms discussed in section 2.2.

## 2.5 Productivity Measurement

Establishment-level productivity, denoted by  $\omega_{it}$ , is measured as the additive residual from a Cobb-Douglas gross output production function in log form. That is,

$$\omega_{it} = y_{it} - \alpha_{lt}l_{it} - \alpha_{k^{(s)}t}k_{it}^{(s)} - \alpha_{k^{(e)}t}k_{it}^{(e)} - \alpha_{mt}m_{it} - \alpha_{et}e_{it} \quad (1)$$

—where  $y_{it}$  is output,  $l_{it}$  is labor,  $k_{it}^{(s)}$  is capital in structures,  $k_{it}^{(e)}$  is equipment capital,  $m_{it}$  is materials, and  $e_{it}$  is energy. Inputs and output are in logs. Input elasticities  $\alpha_t$  are estimated using industry level cost shares, which are calculated from the NBER productivity database (therefore indirectly, from the Census of Manufacturers).<sup>7</sup> Equipment and structure capital shares are constructed using reported stocks multiplied by rental rates for the two-digit industry from the BLS.<sup>8</sup>

In what follows, these productivity residuals will be the dependent variables in a series of regressions designed to look for- and to explain- the correlation between productivity and

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<sup>6</sup>Here firm type is meant to be interpreted very loosely. One firm may be dominant because it has idiosyncratically low costs; alternatively, it may have strong idiosyncratic demand, e.g. informal ties with contractors.

<sup>7</sup>This contains an implicit assumption of constant returns to scale. Syverson (2004) tests this assumption for the ready-mix concrete industry, and finds the results supportive.

<sup>8</sup>For a discussion of the use of index methods for estimating TFP with CMF data, see Syverson (2004).

competition. Two assumptions employed in the derivation of these residuals are suspect: first, constant returns to scale is assumed and has been tested in Syverson (2004).<sup>9</sup> Second, the hypothesis of X-inefficiency may be conflated with optimization failure. As discussed below, this paper remains agnostic as to the particulars, but models of X-inefficiency have been developed which are not inconsistent with optimal input choice. Still, one way to deal with this would be to wrap the entire selection correction procedure described below into a one-stage structural production function estimator based on Akerberg, Caves, and Frazer (2006)<sup>10</sup>. This paper obtains the productivity residuals in a first stage for the sake of expositional clarity.

### 3 The Productivity Effect of Competition

Taking a reduced-form approach to measuring the relationship between competition and productivity, the following regression is standard:

$$\omega_{it} = \beta_0 + \beta_c c_{m(i)t} + \epsilon_{it} \quad (2)$$

This regression is constitutive of the literature on competition and productivity, and carries hefty baggage: The first challenge is to obtain sufficient variation in competitive structure. One solution, now largely outmoded, is to run cross-industry regressions. This paper avoids the problems associated with cross-industry regressions by focusing on an industry with many local markets. Second, to the extent that productivity is estimated using deflated revenue as output, the error introduced will be correlated with the competition index via mark-ups. Foster, Haltiwanger, and Syverson (2008) identify a set of industries (including ready-mix concrete) for which both physical and revenue output data are available, and explore the relationship. As in their work, this problem is obviated by the availability of physical output

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<sup>9</sup>In the next draft of this paper, the assumption is tested by regressing  $\omega_{it}$  on the predicted level of output and  $c_{it}$ , both instrumented by the set of demand shifters. Results for this robustness check are still pending disclosure review with the US Census Bureau.

<sup>10</sup>This exercise would require additional timing assumptions on the choice of materials in order to avoid the collinearity problems described in Bond and Sderbom (2005). For instance, one might assume that materials are chosen at some point in time just prior to  $t$ , following Akerberg, Caves, and Frazer's (2006) assumptions on the choice of labor. This is not implausible; one can think of material usage as being dictated by contracts which are agreed upon prior to production. However, one additional advantage of the fully structural approach would be the incorporation of an unobservable (to the firm) idiosyncratic productivity shock.



data for ready-mix concrete.<sup>11</sup>

OLS results for (2) are presented in Table 2. For all four competition indexes there is a positive and statistically significant correlation between competition and productivity. The regressions using count indexes are run in log-log form, and therefore the coefficients  $\beta_{OLS}$  can be interpreted as elasticities of output with respect to competition<sup>12</sup>. The HHI indexes are scaled between zero and one and unlogged; the coefficient is therefore interpreted as the efficiency difference between two extrema: complete dispersion and absolute monopoly.

An obvious concern with these results is the endogeneity of competition. The presence of high-type firms will likely discourage entry, and therefore generate a non-causal correlation between concentration and productivity which biases the estimates.<sup>13</sup> One strategy for dealing with this problem is to identify an exogenous regulatory shock to the level of competition. In the trade literature, liberalization of trade regulations provides extensive data on this front; Olley and Pakes (1996) use the forced breakup of a monopsonistic downstream firm. There are limitations to this approach. On the one hand, they are often one-shot or at best finitely staged events. Moreover, because they are typically common shocks, they are identified only as time fixed effects, and therefore conflated with other sources of variation. To the extent that the shocks are not common, the identifying comparison is made either across industry or across geographic regions. An alternative approach, pioneered by Syverson (2004), builds on the insight of Sutton (1991) that competition in the long run is dictated by market fundamentals. A market-level demand shifter is an eligible instrument generating exogenous variation in competitive structure. Higher demand encourages entry, and more entry implies lower transportation costs and increased substitutability.

This paper employs a number of instruments to capture the level of demand for ready-mix concrete: construction employment (SIC 15), the total number of residential building permits issued, single-family building permits, five or more family building permits, and local

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<sup>11</sup>In the next draft of this paper, results will be also available for all of the estimation results with productivity calculated using revenue output, rather than physical output. It is interesting to know whether, as a simple model would predict, the use of revenue measures attenuates the results, and whether the methods can be applied to industries where physical output data is unavailable. These results are pending disclosure review at the US Census Bureau.

<sup>12</sup>It is important to remember that the percentage change interpretation of elasticities is based on consideration of small changes, and therefore breaks down here for some common and interesting cases, e.g. the addition of a second competitor in a low-demand CEA— a 100% increase in the number of competitors.

<sup>13</sup>Nickell (1996) notes that this source of endogeneity, like that stemming from the use of revenue-based productivity measures, works in the "right direction" in that it attenuates any positive correlation between productivity and competition.

government highway and road expenditure.<sup>14</sup> Summary statistics are presented in Table 1. In the regressions which follow, however, the instruments are divided by area, in square miles, to approximate the density of demand and then logged.

More firms in a finite geographic space implies more substitutability, and therefore relevance to our indexes of competition. Exogeneity is maintained by arguing that ready-mix concrete typically comprises a small portion of a construction budget, and therefore the decision whether to build is unlikely to reflect variation in mark-ups stemming from competitive structure. Using these demand shifters to instrument for the endogenous index  $c_{m(i)t}$ , the following regression is run:

$$\omega_{it} = \beta_1 + \beta_{IV}c_{m(i)t} + \epsilon_{it} \quad (3)$$

Results for the baseline IV model under a variety of specifications are presented in Table 3. For all specifications, a strong and robust effect of competition is found on productivity. For comparison, the standard of deviation of  $\omega_{it}$  over the period of the sample is found to be 0.2768. The first-stage F-statistics are presented at the bottom of the table, and suggest some concern for the strength of the instruments at predicting the endogenous regressor for those specifications using HHI. The results are rather stronger than those obtained by OLS in Table 2, which seems to support Nickell’s (1996) argument that the endogeneity bias will attenuate, rather than exaggerate, the positive correlation.

The results are reported for both lagged and contemporary instruments, for comparison with the selection correction model presented in section 6, where the importance of the distinction will be apparent. Though strong, the results have no structural interpretation. They conflate the direct effect of X-inefficiency with the bias induced by dynamic selection. The next two sections expand on the theory behind these two stories, with the ultimate goal of disambiguating them empirically.

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<sup>14</sup>Construction employment is calculated directly from the LBD. The last four instruments are taken from the USA Counties data available online from the US Census Bureau.

## 4 X-Inefficiency

The term X-inefficiency was coined by Leibenstein (1966) and born to immediate controversy. The concept was originally posed as a counterpoint contemporary optimal choice theory, which sparked a heated debate and some very colorfully titled papers (Stigler (1976), Leibenstein (1978)). Despite the controversy, two salient points were made: first, that there is an empirical correlation between competition and productivity; second, that if productive efficiencies of competition such as X-inefficiency do exist, they are potentially more significant in welfare terms than the more familiar allocative inefficiencies from market power. Figure 3 illustrates this comparison; the welfare loss of an increase from  $p$  to  $p'$  is represented by the colored deadweight loss triangle, and the welfare gain of a decrease in costs from  $c$  to  $c'$  is represented by the much larger rectangle. The intuition is simple and hearkens to Harberger (1954): productive efficiencies are bigger because they are compiled on infra-marginal sales, whereas allocative efficiencies are compiled on the margin.

Here the term X-inefficiency is used with important caveats. The "X-" has been nuanced by the development of models of asymmetric information that reconcile suboptimal outcomes with optimal choice theory. Because of this, the "inefficiency" as well is subject to caveat: opening up the black box also implies the possibility of costs which are not represented in Figure 3. A more complete model is necessary to make decisive arguments about welfare. The theoretical literature on X-inefficiency is small but varied; though it is beyond the scope of this paper to commit to one or another, a handful of such models are described by way of example.

One explanation advocated by Nalebuff and Stiglitz (1983) and Mookherjee (1983) for the empirical evidence of X-inefficiency is grounded in informational externalities of competition. The presence of competitors in the same market allows firms to statistically separate randomness in market-level demand from unobservable effort exerted by managers; in the limit, firms attain the first-best equilibrium outcome. An alternate explanation is that firms are especially motivated to improve efficiency by the threat of bankruptcy. By forcing all firms to operate at a thinner price-cost margin, competition motivates all firms to expend more resources on improving productivity (e.g., by providing stronger incentives for managers). As Schmidt's (1997) paper notes, however, the effect depends strongly on parametric assumptions. More recently, Raith (2003) offers an explanation that hinges on market dynamics. He identifies two competing effects; a business stealing effect which increases returns to im-

proving productivity when competition is more intense, and a scope effect, which decreases the returns to improving productivity when competing firms have low prices. He shows that while these effects cancel out in a static model, endogenous exit makes the prediction unambiguous: the business stealing effect dominates, and firms have more incentive to improve productivity in more competitive markets.

The set of explanations described here is both rich and incomplete; moreover, it is likely that at this level of analysis, the particular industry and institutional context is likely to play an important role. Rather than advocating a particular explanation, the argument here will remain agnostic, characterizing by X-inefficiency any story such that, at equilibrium, the production function can be represented as if the competitive structure of the market were an input of production:

$$y_{it} = f(x_{it}, c_{m(i)t}) + \phi_{it} \quad (4)$$

The generality here highlights the common and essential feature of stories of X-inefficiency which will be econometrically identified: the direct, causal effect of competition on productivity. If one could take a firm out of a less competitive market and put it into a more competitive one, X-inefficiency implies that the firm would experience an increase in productivity.

## 5 Dynamic Selection

The dynamic selection effect is a story that has gained traction in the international trade literature and owes its intellectual heritage to Melitz's (2003) innovative extensions to the general industry dynamics model of Hopenhayn (1992). In contrast to the direct productivity effect that drives X-inefficiency, dynamic selection is a story about the selection of the set of firms that are observed in equilibrium. Unprofitable firms exit, spurring entry of new firms. If the break-even threshold is stricter in more competitive markets, it will be the case that the set of firms which survive this stricter survival rule will be, on average, more productive.

Three essential features drive models which explain dynamic selection: Idiosyncratic types, an unlimited pool of ex-ante identical entrants, and endogenous exit. Particularly apposite to ready-mix construction, Syverson (2004) presents a two-stage entry game in which entrants

pay a fixed cost to learn their marginal costs, exit if the costs are too high, and then compete for the business of consumers arranged on a circle with transportation costs. Though the model does not capture the repeated play of other industry dynamics approaches, the payoff is the explicitly spatial character of stage-game competition. As demand density on the circle increases, more firms enter, and the exit cutoff becomes stricter, in turn lowering average observed marginal cost. Melitz and Ottaviano (2008), exemplary of the trade literature approach, employs parametric assumptions and structural assumptions on demand and the form of competition in exchange for closed-form analytic comparative statics. As in Hopenhayn (1992), firm types evolve according to a Markov process, and firms exit should the expected discounted value of future profits ever become negative. That exit threshold is shown to be stricter in larger markets. Finally, Backus (2011) generalizes the Hopenhayn (1992) approach to derive comparative statics without parametric restrictions or assumptions on the form of competition. In comparison with Melitz and Ottaviano (2008), the trade-off is closed-form solutions for generality.

None of these models treat competition as exogenous. While in principle one could parameterize the degree of substitutability of firms' products, the prediction would have limited empirical content for lack of natural experiments. Instead, competition is related to a plausibly exogenous shock to market size (e.g., a demand shifter). Figure 4 depicts in broad strokes the logic of the argument. Panel (a) illustrates the value function<sup>15</sup>. In Syverson (2004), the value function is simply second stage profits. In Melitz and Ottaviano (2008) and Backus (2011) it represents the expected discounted value of all future profits. The exit strategy is manifested by a kink; sufficiently low types have negative expected value to participating in the market, and therefore exit to obtain zero. The role of entry is more subtle; equilibrium entry requires that the expected value of entry, which is obtained by integrating the value function over the distribution of entrants' types, is equal to the cost of entry. Assuming for convenience that the type space is bounded  $[0, 1]$  and the distribution of entrants uniform with full support, this can be measured as the area under the value function.

An increase in market size has two countervailing effects. First, there is a direct and positive effect on all types' profits, which is represented in panel (b). However, the value function cannot be strictly higher for every type, because this would violate the equilibrium entry

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<sup>15</sup>Here it is assumed that the payoff is increasing in type, consistent with the productivity interpretation. In terms of cost, as in Syverson's (2004) model, the graph would be reflected across the y axis.

condition that the expected value of entry equal the cost of entry. Therefore the value function shifts back in, as in panel (c). The comparative static of interest, however, hinges on the subtle detail that at the new equilibrium, the x-intercept of the value function moves to the right, which is interpreted as a stricter selection rule. All of the models discussed above impose special structure to obtain this counter-clockwise rotation of the value function. In Syverson (2004), it stems from the fact that greater entry on a circle of finite size implies greater substitutability of firms, reallocating profits from lower to higher types. In Melitz and Ottaviano (2008) this is accomplished by parametric restrictions on demand and competition. Backus (2011), in contrast, achieves this by considering the broad set of stage games for which competition reallocates profits from low to high-type firms.<sup>16</sup>

The key to the dynamic selection story is this idea that competition reallocates profits from low-type firms to high-type firms, an idea which manifests itself in a variety of different assumptions in each of these models<sup>17</sup>. This reallocation drives the result that in more competitive markets, the exit rule is stricter. Where the exit rule is stricter, the set of surviving firms is on average more productive, without any direct causal effect of competition on productivity.

## 6 Methodology and Estimation

The object of the structural part of this paper is to separate the two classes of stories for why more competitive markets harbor more efficient firms: static and dynamic. The first strategy, described in section 6.1, is based on cross-sectional comparisons of markets in long-run equilibrium, and the different effects that X-inefficiency and dynamic selection have on the ergodic distribution of types. The second strategy, which is the focus of section 6.2, nests both effects in a single econometric model and is able to measure their relative contributions to the conflated effect,  $\beta_{IV}$  from section 3. Results for both models strongly favor the X-inefficiency story.

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<sup>16</sup>Formally, this is accomplished by assuming that the reduced-form stage game profit function has increasing differences between completely ordered measures of types and the demand shift parameter.

<sup>17</sup>Boone (2008) argues that the reallocation of profits from low types to high types is not merely correlated with competition, but essential to it. He proposes relative profits of high types to low types as a measure of competition, and shows in a number of examples that it performs better than some other measures at predicting welfare gains.

## 6.1 The Quantile Approach

The identification strategy in this section hinges on the distinct predictions of the X-inefficiency and the dynamic selection story for the ergodic distribution of types. Combes, Duranton, Gobillon, Puga, and Roux (2010) develop a related strategy for distinguishing economies of agglomeration from dynamic selection in cross-industry data on French establishments. The key insight of their paper is that within-firm effects (for them, agglomeration, here X-inefficiency) will shift the entire distribution, while the dynamic selection story hinges on a shifting left-truncation, thereby contracting and distorting the distribution.

### 6.1.1 X-Inefficiency vs. Dynamic Selection

A visual motivation for the distinction is presented in Figure 5: Panel (a) illustrates a constant additive shift of the entire distribution; an implication of the linear baseline model for X-inefficiency. Panel (b) illustrates a shift only of the truncation point; the left side moves substantially, but the right tail is fixed and the distribution contracts. The interpretation of this truncation shift as the dynamic selection effect hinges on the assumption that optimal exit strategy is characterized by a simple threshold rule for idiosyncratic type, a common implication of industry dynamics that follow Hopenhayn (1992).<sup>18</sup>

The prediction of the top panel depends heavily on the assumption that the effect of X-inefficiency does not depend on  $\phi_{it}$ , an assumption inconsistent with, for instance, Schmidt's (1997) story of bankruptcy aversion. The prediction of the lower panel, however, is not driven by parametrics: it implies that if the dynamic selection story is dominant, most of the productivity gains from competition should be evident in the left side of the distribution.

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<sup>18</sup>The argument made by figure 2 is impressionistic, and the figures depict a normal distribution. A more complete model would require substantial additional assumptions, parametric and otherwise, to capture the dynamic implications of a linear shift or a shift in the truncation point, however the intuition here is clear: mechanisms that work via shifts affect the entire distribution, while mechanisms that operate on the truncation point will affect primarily the left tail. An fully specified example of an industry dynamics model which generates these results is offered by Combes, Duranton, Gobillon, Puga, and Roux (2010).

### 6.1.2 Estimation

The empirical strategy adopted here is to regress deciles of the CEA-level distribution of observed  $\omega_{it}$  on the competition index  $c_{m(i)t}$ , instrumented for by the set of demand shifters:

$$\rho_{mt}^{(k)} = \beta_d^{(k)} c_{mt} + \nu_{mt} \quad (5)$$

– where  $\rho^{(k)}$  is the  $k^{\text{th}}$  decile (so that  $k \in 1, \dots, 9$ ) of the distribution of  $\omega_{it}$  in market  $m$ , and the unit of observation is the market.

The implication of figure 2 from section 6.1.1 is clear:  $\beta_d^{(k)}$  should be decreasing in  $k$ . The prediction of the X-inefficiency story is dependent on the parametric assumption of a constant effect, therefore the main interest is to ask whether the movement of  $\beta_c^{(k)}$  in  $k$  is consistent with the truncation shift.

### 6.1.3 Results

Though the argument has been somewhat informal, the results offered in Table 4 and depicted graphically in Figures 6-9 are stark. Contrary to the prediction of the dynamic selection story,  $\beta_d^{(k)}$  seems to be constant or increasing in  $k$ ; sharply increasing at the far right tail.<sup>19</sup>

The above is not a formal statistical test, but offers strong evidence against the null that dynamic selection is the primary story. To develop this identification strategy more rigorously would require extensive assumptions, parametric and otherwise. The next section offers a rigorous, structural identification strategy without such assumptions and, further, can measure the relative contribution of both stories to the observed correlation.

## 6.2 The Selection Correction Approach

Reconsider briefly the reduced-form IV regression run in section 3, where the competition index  $c_{m(i)t}$  is instrumented for using the set of demand shifters:

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<sup>19</sup>Because HHI is a measure of concentration rather than competition, both the prediction and the results are of opposite sign.



$$\omega_{it} = \beta_1 + \beta_{IV}c_{m(i)t} + \epsilon_{it}$$

The elasticity coefficient  $\beta_{IV}$  was interpreted as the reduced-form correlation coefficient of productivity and competition. However, by imposing additive separability of X-inefficiency and idiosyncratic productivity as well as linearity of the effect of competition<sup>20</sup> one can go further:

$$\omega_{it} = \beta_X c_{m(i)t} + \phi_{it} \tag{6}$$

The coefficient  $\beta_X$  is interpreted as a structural primitive describing X-inefficiency, and the divergence between the true  $\beta_{IV}$  and the correlation coefficient estimated in section 3 stems from selection bias induced by dynamic selection. The error term,  $\phi_{it}$ , has a structural interpretation as well, as establishment-level idiosyncratic productivity.

With parametric restrictions, one could proceed with a selection correction in the spirit of Heckman (1979). Alternatively, with data on the selection-relevant observables for non-selected firms, a nonparametric selection-correction would be viable. An aversion to parametric restrictions and a lack of such data makes the selection problem difficult.

A way forward, borrowed from Olley and Pakes (1996), is to give up one year of data and impose a stricter selection rule: that the firm was observed at time  $t - 1$ . If the bias induced can be written in terms of time  $t$  and  $t - 1$  observables, a control function can be used to solve the endogeneity problem. In the next two sections, just such a control function is derived from a model of the decision problem of the firm.

### 6.2.1 The Firm's Decision Problem

In order to capture the bias explicitly, a fuller model of the firm's exit choice is presented. It is a finite-firm model with multidimensional states in the spirit of Ericson and Pakes (1995) as extended by Doraszelski and Satterthwaite (2010).

Stage-game profits are given by  $R(\phi_{it}, x_{it}, S_{m(i)t}, d_{m(i)t})$ , where  $\phi_{it}$  represents, as before, the idiosyncratic establishment-level productivity shock,  $x_{it}$  is a vector of firm-specific state

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<sup>20</sup>Linearity is assumed for comparison with  $\beta_{IV}$ . The relationship between  $c_{m(i)t}$  and  $\omega_{it}$  is nonparametrically identified.

variables (e.g., capital, age, and idiosyncratic establishment-level demand), the state of the market  $S_{m(i)t}$  includes all firms' types, and  $d_{m(i)t}$  is a vector of exogenous demand shifters. The first assumption is the timing of play:

$$\phi \text{ evolves} \rightarrow \text{stage game} \rightarrow \text{entry and exit} \quad (\text{A1})$$

The conclusions here are robust to entry before exit and vice versa, as well as to the inclusion of choice variables which affect the firm specific state in  $x_{it}$ . What is important about (A1) is that the stage game is played at the new productivity level and before the exit decision, which implies that in the data-generating process, observables are generated even for exiting firms. At the time of the exit choice, the firm is assumed to condition on the following information set:

$$\mathcal{I}_{it} \equiv \langle \phi_{it}, x_{it}, S_{m(i)t}, d_{m(i)t} \rangle \quad (\text{A2})$$

Firms' decisions may affect both their own states and the state of the market. However,  $\phi_{it}$  is assumed to evolve according to an exogenous Markov process. Formally,

$$p(\phi_{it} | \mathcal{I}_{it-1}) = p(\phi_{it} | \phi_{it-1}) \quad (\text{A3})$$

Additional assumptions are required to guarantee existence of equilibrium with a nonempty set of active firms in this market, however that is beyond the scope of this paper. The interested reader is referred to Doraszelski and Satterthwaite (2010). These assumptions are made for the purposes of identification, as discussed below, where one can also find a discussion of the implications of weakening or reversing them.

### 6.2.2 Identification

Recall (6), which formally nests the X-inefficiency hypothesis:

$$\omega_{it} = \beta_X c_{m(i)t} + \phi_{it}$$

The stricter selection rule allows one to condition both on the information set of the firm at time  $t - 1$  as well as survival from  $t - 1$ . Let  $\phi_{it}^*$  be the minimum  $\phi$  required to sustain

nonnegative expected discounted profits; then, survival from  $t - 1$  implies  $\phi_{it-1} \geq \phi_{m(i)t-1}^*$ . In order to derive the selection correction in terms of observables, one takes the expectation of both sides of (6) conditional on  $\langle \mathcal{I}_{it-1}, \phi_{it-1} \geq \phi_{m(i)t-1}^* \rangle$ :

$$\begin{aligned} \mathbb{E}[\phi_{it} | \mathcal{I}_{it-1}, \phi_{it-1} > \phi_{m(i)t-1}^*] &= \beta_0 + \beta_X \mathbb{E}[c_{m(i)t} | \mathcal{I}_{it-1}, \phi_{it-1} > \phi_{m(i)t-1}^*] \\ &\quad + \mathbb{E}[\phi_{it} | \mathcal{I}_{it-1}, \phi_{it} > \phi_{m(i)t}^*] \end{aligned} \quad (7)$$

Focusing on the last term, which represents selection bias, note that (A1) and (A2) imply that  $\phi_{it-1} > \phi_{m(i)t-1}^*$  is fully determined by  $\mathcal{I}_{it-1}$ . Therefore,

$$\mathbb{E}[\phi_{it} | \mathcal{I}_{it-1}, \phi_{it} > \phi_{m(i)t}^*] = \mathbb{E}[\phi_{it} | \mathcal{I}_{it-1}] \quad (8)$$

Moreover, the exogeneity of the Markov process (A3) implies that the only relevant information in  $\mathcal{I}_{it-1}$  for the expected value of  $\phi_{it}$  is  $\phi_{it-1}$

$$\begin{aligned} \mathbb{E}[\phi_{it} | \mathcal{I}_{it-1}] &= \mathbb{E}[\phi_{it} | \phi_{it-1}] \\ &= \psi(\phi_{it-1}) \end{aligned}$$

– where  $\psi$  is some unknown function. Though  $\phi_{it-1}$  is not directly observable, the model implies  $\phi_{it-1} = \omega_{it-1} - \beta_X c_{m(i)t-1}$ . As the arguments of the selection bias can be rewritten in terms of observables, a control function can account for the bias:

$$\omega_{it} = \beta_2 + \beta_X c_{m(i)t} + \psi(\omega_{it-1} - \beta_X c_{m(i)t-1}) + \varepsilon_{it}$$

The function  $\psi$  is estimated by sieve, which allows for flexible parametric form that is increasing in complexity and nonparametric in the limit (see Chen (2007)). That  $\psi$  is treated flexibly is important because its is unknown without substantial further structure and solving a dynamic programming problem. Since  $\psi(\cdot)$  captures the bias conditional on prior type and survival, the remaining error  $\varepsilon_{it}$  is mean-zero conditional on  $\mathcal{I}_{it-1}$  by construction. Consistent with (A2), lagged demand shifters are used to instrument for  $c_{m(i)t}$ . Alternatively, one could modify (A2) to give firms foresight, in which case contemporary instruments would be appropriate.

Given an estimate of  $\beta_X$ , one can go a step further to capture the dynamic selection effect by a reduced-form parameter denoted  $\beta_{DS}$ , which will offer a useful point of comparison. First, net out  $\hat{\beta}_X c_{m(i)t}$  from  $\omega_{it}$  to obtain  $\hat{\phi}_{it}$ . Then run the following regression, instrumenting for  $c_{m(i)t}$  using the set of demand shifters:

$$\hat{\phi}_{it} = \beta_3 + \beta_{DS} c_{m(i)t} + \xi_{it} \quad (9)$$

The null of X-inefficiency only implies that  $\beta_{DS} = 0$ . The story captured by  $\beta_{DS}$  is the selection effect. The limited modeling assumptions imposed by this paper offer no structural interpretation, however  $\beta_{DS}$  can be thought of as the reduced-form average dynamic selection effect weighted by the sample of markets observed, which can be compared in magnitude to  $\beta_X$ . In this sense, the model nests both X-inefficiency and dynamic selection as explanations for the correlation found in the IV regressions of section 3.

Intuitively, identification hinges on being able to write the bias introduced by selection as a function of objects which are either observed or implied by the model. By controlling for  $\phi_{it-1}$  nonparametrically, the variation which remains is innovation in productivity. Some of this innovation may be explained by exogenous shocks to competition as predicted by the set of instruments for demand, and the rest is explained by the Markov evolution (A3) of productivity types.

### 6.2.3 Results

Estimates from the selection correction model are presented in Table 5 for each of the eight specifications presented in the IV and quantile approaches. The first set of results present the nonlinear two-stage least-squares estimates of  $\beta_X$ , the primitive describing the direct effect of X-inefficiency. The second set offer a reduced-form estimate of the contribution of the dynamic selection story,  $\beta_{DS}$ . These results are condensed and presented in comparison with the IV estimates from section 3 in Table 6.

After taking out the direct causal effect, only in models (2) and (4) does one obtain a statistically significant (at the 0.05 level)  $\beta_{DS}$ . The results suggest that X-inefficiency explains the majority of the correlation identified by  $\beta_{IV}$ . To ask this question in another way, probits were run to ask how whether competition, instrumented by the set of demand shifters, predicts survival into the next period, conditional on type and other observable characteristics

of the establishment. Coefficient estimates are presented in Table 7. Confirming intuition, productivity is clearly correlated with survival; however the insignificance of the coefficient on  $c_{m(i)t}$  supports the conclusion that dynamic selection is not an economically significant story in this industry.<sup>21</sup>

## 7 Conclusion

This paper has offered evidence for a correlation between productivity and competition in ready-mix concrete. Two explanations were identified from the literature: X-inefficiency and dynamic selection, and two empirical strategies were developed and implemented to nonparametrically distinguish between them. The quantile approach yielded results directly opposite those predicted by the dynamic selection story: the biggest movements in the distribution of productivity residuals was in the right tail rather than in the left. The selection correction approach, on the other hand, was able to measure the relative contribution of the two stories, and weighed in emphatically behind X-inefficiency.

In some ways this result is unsatisfying; X-inefficiency is the less-specified of the two stories, and the conclusion here begs the question of what is driving the within-firm response to competition. Some reflections can be gleaned from the evidence compiled here. For instance, the movement of the right tail would imply that bankruptcy aversion is not the primary story in ready-mix concrete. A fuller treatment of this question is beyond the scope of this paper, but an important direction for future research. It is only with a theoretical framework to explain the direct productivity response that one can begin to assess the welfare implications of these productive efficiencies.

Leibenstein (1966) observed that if productivity and competition are correlated, then the Econ 101 story of deadweight loss triangles may not be the most compelling reason to worry about fostering robust competition. The first step towards turning that observation into policy prescription is to understand the source of the correlation, a matter on which no consensus has been reached. The evidence compiled here suggests that the way forward is to look *within* the firm at the organization of production.

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<sup>21</sup>Results in Table 7 are coefficients and not marginal effects; the emphasis here is on the insignificance, rather than the magnitude of the effect. See Collard-Wexler (2011) for extensive further work on the determinants of selection in the ready-mix concrete industry.

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Table 1: Summary Statistics by CEA

	1982	1987	1992
HHI (firms)	0.2869 (0.1947)	0.2831 (0.1898)	0.2739 (0.1817)
HHI (estab.)	0.2358 (0.1881)	0.2450 (0.1923)	0.2383 (0.1804)
no. ready-mix concrete estab.	14.9167 (14.8358)	14.9856 (15.7969)	14.6322 (15.5931)
no. ready-mix concrete firms	10.1700 (8.4732)	11.2557 (10.2049)	11.2040 (10.2581)
area	10805.9560 (33851.9390)	10805.9560 (33851.0000)	10805.9560 (33851.9390)
construction employment	2740.7902 (4197.1217)	3531.4943 (5667.1252)	3127.8764 (4748.9594)
residential building permits	2741.1925 (5597.7480)	4404.3937 (7826.0237)	3140.8736 (4482.5234)
single-family permits	1487.1523 (2703.0781)	2937.9368 (4893.4924)	2611.5862 (3863.4182)
5+ family permits	1012.2615 (2921.0631)	1209.9914 (3003.9534)	397.6552 (686.7842)
local highway and road spending	41425.4570 (61114.3630)	59956.4170 (95423.6860)	77196.7130 (124830.3000)

Table 2: OLS Results

	firm-level competition index		estab.-level competition index	
	no. firms	HHI-firms	no. estab.	HHI-estab.
const.	-1.9043*** (0.0333)	-2.1300*** (0.0094)	-1.9353*** (0.0299)	-2.1321*** (0.0090)
$\beta_{OLS}$	0.0392*** (0.0054)	-0.1002** (0.0407)	0.0362*** (0.0051)	-0.1193*** (0.0440)
N	8829	8829	8829	8829
$R^2$	0.0167	0.0021	0.0147	0.0024

Regressions of  $\omega_{it}$  on each of the four competition index variables separately.

Table 3: Instrumental Variables Results

$c_{m(i)t}$	firm-level competition index			HHI-firms			number of firms			HHI-firms			number of firms			estab.-level competition index		
	lagged	contemporary	lagged	contemporary	lagged	contemporary	lagged	contemporary	lagged	contemporary	lagged	contemporary	lagged	contemporary	lagged	contemporary	lagged	contemporary
instruments	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
const.	-1.7837*** (0.0398)	-1.7703*** (0.0429)	-1.9261*** (0.0346)	-1.7548*** (0.0776)	-1.8142*** (0.0346)	-1.8191*** (0.0364)	-1.9643*** (0.0229)	-1.9183*** (0.0375)	0.0506*** (0.0064)	0.0625*** (0.0068)	-0.9231*** (0.2002)	-2.1304*** (0.4283)	0.0479*** (0.0059)	0.0576*** (0.0061)	-0.9263*** (0.1755)	-1.6077*** (0.2760)		
$\beta_{IV}$																		
N	5771	8521	5771	8521	5771	8521	5771	8521	5771	8521	5771	8521	5771	8521	5771	8521	5771	8521
first-stage F-test	188.05	199.41	3.08	1.70	238.93	245.51	3.79	2.48										

IV regressions of  $\omega_{it}$  on competition index variables using the following instruments, either lagged or contemporary: general construction employment, residential building permits, single-family residence building permits, 5+ family residence building permits, and local government highway expenditures, all per square mile. The first-stage F-test is from a separate, CEA-level regression of the competition index on instruments.

Table 4: Decile Effects ( $\beta_d^{(k)}$ )

model	1 <sup>st</sup>	2 <sup>nd</sup>	3 <sup>rd</sup>	4 <sup>th</sup>	5 <sup>th</sup>	6 <sup>th</sup>	7 <sup>th</sup>	8 <sup>th</sup>	9 <sup>th</sup>
(1)	0.0539*** (0.0109)	0.0566*** (0.0096)	0.0543*** (0.0092)	0.0540*** (0.0076)	0.0494*** (0.0074)	0.0478*** (0.0078)	0.0473*** (0.0091)	0.0531*** (0.0107)	0.0712*** (0.0139)
(2)	0.0529*** (0.0092)	0.0622*** (0.0088)	0.0619*** (0.0085)	0.0589*** (0.0067)	0.0519*** (0.0067)	0.0444*** (0.0071)	0.0426*** (0.0076)	0.0509*** (0.0087)	0.0631*** (0.0114)
(3)	0.0353 (0.2799)	-0.4243 (0.2691)	-0.4610* (0.2524)	-0.4641* (0.2376)	-0.5836** (0.2387)	-0.5793** (0.2409)	-0.5291** (0.2685)	-0.7889** (0.3032)	-1.4635** (0.4293)
(4)	-2.1660** (0.9798)	-2.3453** (0.9584)	-2.2692*** (0.8805)	-2.3225*** (0.8757)	-2.0275*** (0.7603)	-1.7842*** (0.6855)	-1.7392*** (0.6680)	-1.8826*** (0.6800)	-2.3333*** (0.7788)
(5)	0.0525*** (0.0108)	0.0548*** (0.0093)	0.0524*** (0.0088)	0.0524*** (0.0073)	0.0482*** (0.0071)	0.0467*** (0.0075)	0.0459*** (0.0088)	0.0517*** (0.0103)	0.0698*** (0.0133)
(6)	0.0503*** (0.0091)	0.0587*** (0.0085)	0.0583*** (0.0082)	0.0563*** (0.0065)	0.0490*** (0.0064)	0.0416*** (0.0068)	0.0409*** (0.0074)	0.0484*** (0.0084)	0.0589*** (0.0109)
(7)	-0.0630 (0.2697)	-0.5096* (0.2620)	-0.5560** (0.2419)	-0.5698** (0.2330)	-0.6689*** (0.2315)	-0.6813*** (0.2391)	-0.6318** (0.2645)	-0.8702*** (0.2924)	-1.5342*** (0.4081)
(8)	-1.5186** (0.6550)	-1.5947*** (0.5919)	-1.5411*** (0.5317)	-1.5172*** (0.4992)	-1.2423*** (0.4085)	-1.0709*** (0.3758)	-1.1209*** (0.3978)	-1.3330*** (0.4319)	-1.7023 (0.4991)

Results from CEA-level instrumental variables regressions where the dependent variable is the  $n$ th decile of the distribution of  $\omega_{it}$  by CEA. The models, indexed from 1 to 8, correspond to those in Table 3: 1-4 use firm-level competition indexes, and 5-8 use establishment-level. 1-2 and 5-6 use the count index of competition, whereas 3-4 and 7-8 use HHI. Finally, odd-numbered models use lagged variables, whereas even-numbered ones use contemporary. The results of this table are depicted graphically in Figures 6-9.

Table 5: Instrumental Variables with Selection Correction Results

$c_{m(i)t}$	firm-level competition index				estab.-level competition index			
	number of firms		HHI-firms		number of estab.		HHI-estab.	
instruments	lagged	contemporary	lagged	contemporary	lagged	contemporary	lagged	contemporary
model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const.	-3.2914*** (0.3548)	-0.4448* (0.2575)	1.3591** (0.6670)	-0.1113 (0.3860)	0.5798 (0.4866)	-0.5795** (0.2478)	0.7297 (0.5162)	0.5465 (0.6295)
$\beta_X$	0.0424*** (0.0092)	0.0461*** (0.0079)	-0.6955*** (0.2441)	-1.1115*** (0.1755)	0.0397*** (0.0080)	0.0461*** (0.0074)	-0.7231*** (0.1958)	-1.0628*** (0.1722)
N	3600	3513	3600	3513	3600	3513	3600	3513
const.	-1.7837*** (0.0398)	-1.7703*** (0.0429)	-1.9261*** (0.0346)	-1.7548*** (0.0776)	-1.8142*** (0.0346)	-1.8191*** (0.0364)	-1.9643*** (0.0229)	-1.9183*** (0.0375)
$\beta_{DS}$	0.0082 (0.0064)	0.0163** (0.0068)	-0.2276 (0.2002)	-1.0189** (0.4283)	0.0082 (0.0059)	0.0114* (0.0061)	-0.2032 (0.1755)	-0.5449* (0.2760)
N	5771	8521	5771	8521	5771	8521	5771	8521

This panel depicts two sets of results for each model. The first obtain  $\beta_X$  from the selection correction procedure which controls nonparametrically for  $\phi_{it-1}$ . The second set of results obtain  $\beta_{DS}$  by an instrumental variables regression of the implied  $\phi_{it}$  on competition indexes.

Table 6: Comparison of Results

$c_{m(i)t}$	firm-level competition index			HHI-firms			estab.-level competition index			
	number of firms			HHI-firms			number of estab.			
instruments	lagged	contemporary	lagged	contemporary	lagged	contemporary	lagged	contemporary	lagged	contemporary
model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(7)	(8)
$\beta_{IV}$	0.0506*** (0.0064)	0.0625*** (0.0068)	-0.9231*** (0.2002)	-2.1304*** (0.4283)	0.0479*** (0.0059)	0.0576*** (0.0061)	-0.9263*** (0.1755)	-1.6077*** (0.2760)		
$\beta_X$	0.0424*** (0.0092)	0.0461*** (0.0079)	-0.6955*** (0.2441)	-1.1115*** (0.1755)	0.0397*** (0.0080)	0.0461*** (0.0074)	-0.7231*** (0.1958)	-1.0628*** (0.1722)		
$\beta_{DS}$	0.0082 (0.0064)	0.0163** (0.0068)	-0.2276 (0.2002)	-1.0189** (0.4283)	0.0082 (0.0059)	0.0114* (0.0061)	-0.2032 (0.1755)	-0.5449* (0.2760)		

Summary of results from Tables 3 and 5. This table presents for direct comparison the decomposition of the IV estimator into X-inefficiency and dynamic selection components.

Table 7: Probit Results

	firm-level competition index		estab.-level competition index	
	no. firms	HHI-firms	no. estab.	HHI-estab.
constant	0.9993*** (0.1910)	0.9900*** (0.1740)	0.9821*** (0.1858)	0.9631*** (0.1640)
$c_{m(i)t}$	0.0170 (0.0197)	-0.5981 (0.5460)	0.0143 (0.0190)	-0.6321 (0.5238)
$\omega_{it}$	0.3131*** (0.0590)	0.3069*** (0.0599)	0.3151*** (0.0590)	0.3061*** (0.0598)
K (structures)	0.0169 (0.0250)	0.0166 (0.0250)	0.0165 (0.0250)	0.0158 (0.0250)
K (equipment)	0.1179*** (0.0234)	0.1164*** (0.0235)	0.1185*** (0.0234)	0.1182*** (0.0234)
age	-0.0219*** (0.0032)	-0.0223*** (0.0032)	-0.0218*** (0.0032)	-0.0220*** (0.0032)

Results from instrumental variables probit regressions of survival dummies ( $\chi_t = 1$  iff the firm is present at time  $t + 1$ ) on firm observables. The competition index  $c_{m(i)t}$  is defined by the model. Capital is observed in two forms in the Census of Manufactures data, structures (e.g., buildings) and equipment (e.g., ready-mix concrete trucks). Age is constructed from the LBD. All instruments are contemporary.

Figure 1: County Map of the USA

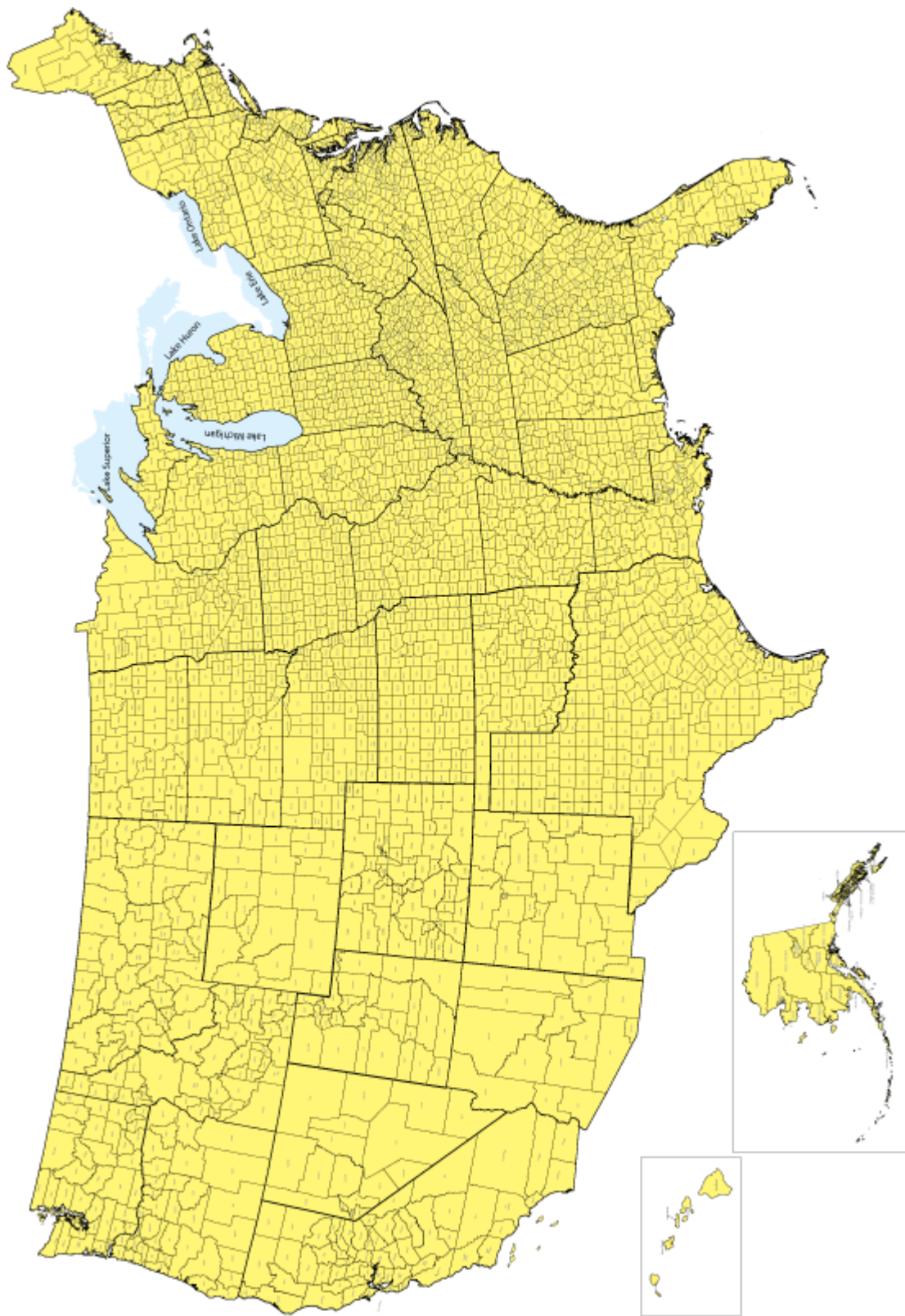




Figure 2: CEA Map of the USA

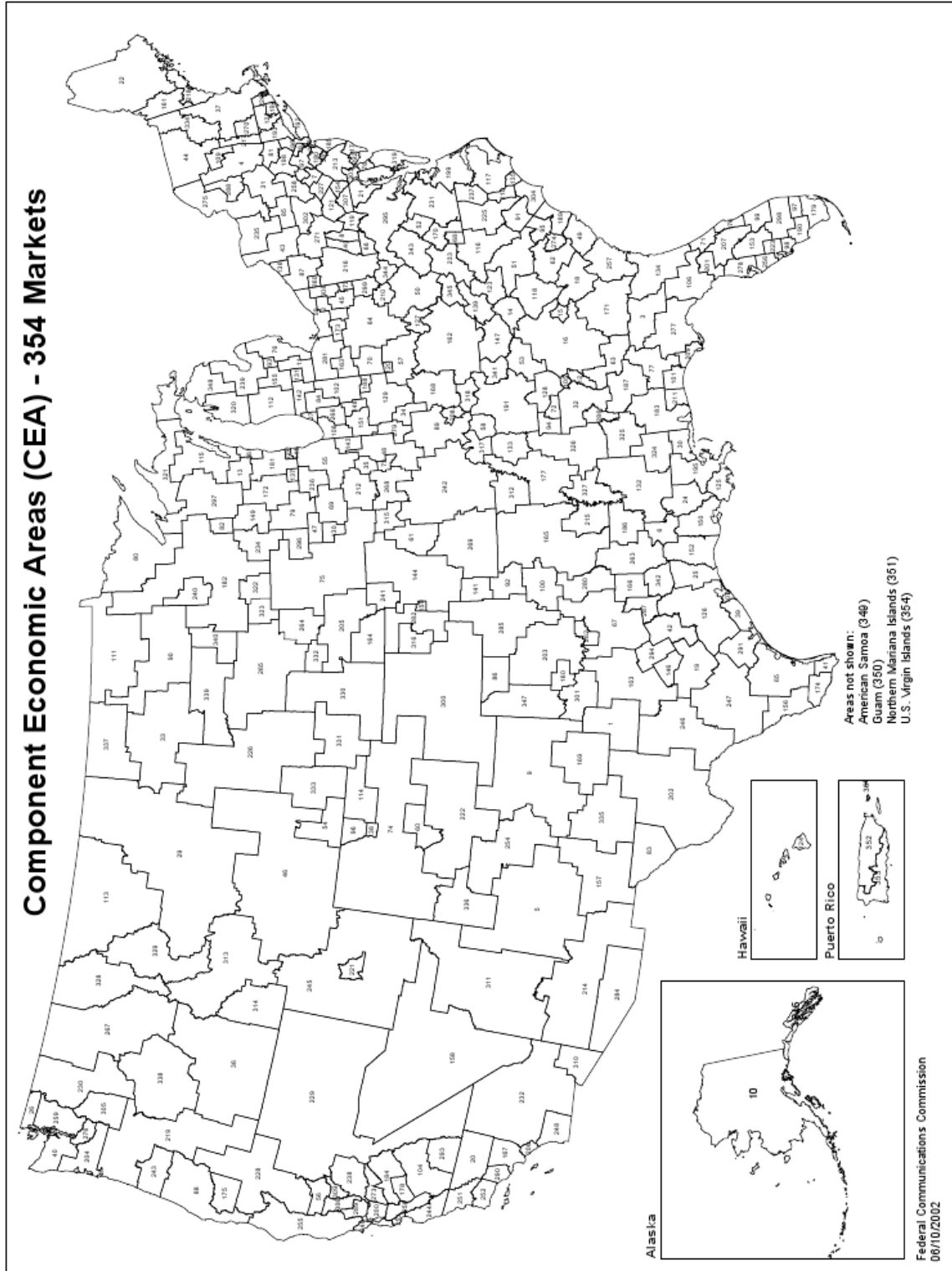
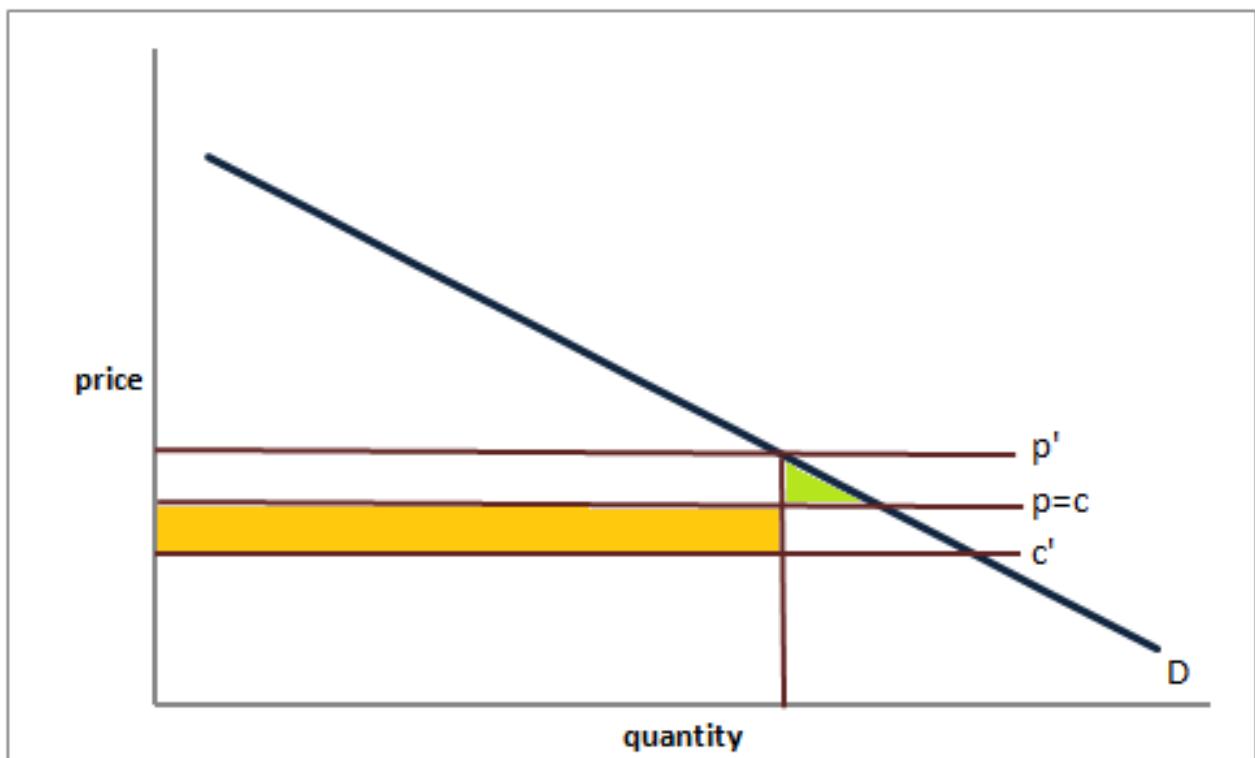


Figure 3: Allocative vs. Productive Efficiencies



Comparison of allocative and productive efficiencies from comparable changes in price and cost, respectively. Deadweight loss, the allocative inefficiency, is represented by the shaded triangle. Productive efficiencies are represented by the much larger shaded rectangle.

Figure 4: Value Function Response to Change in Market Size.

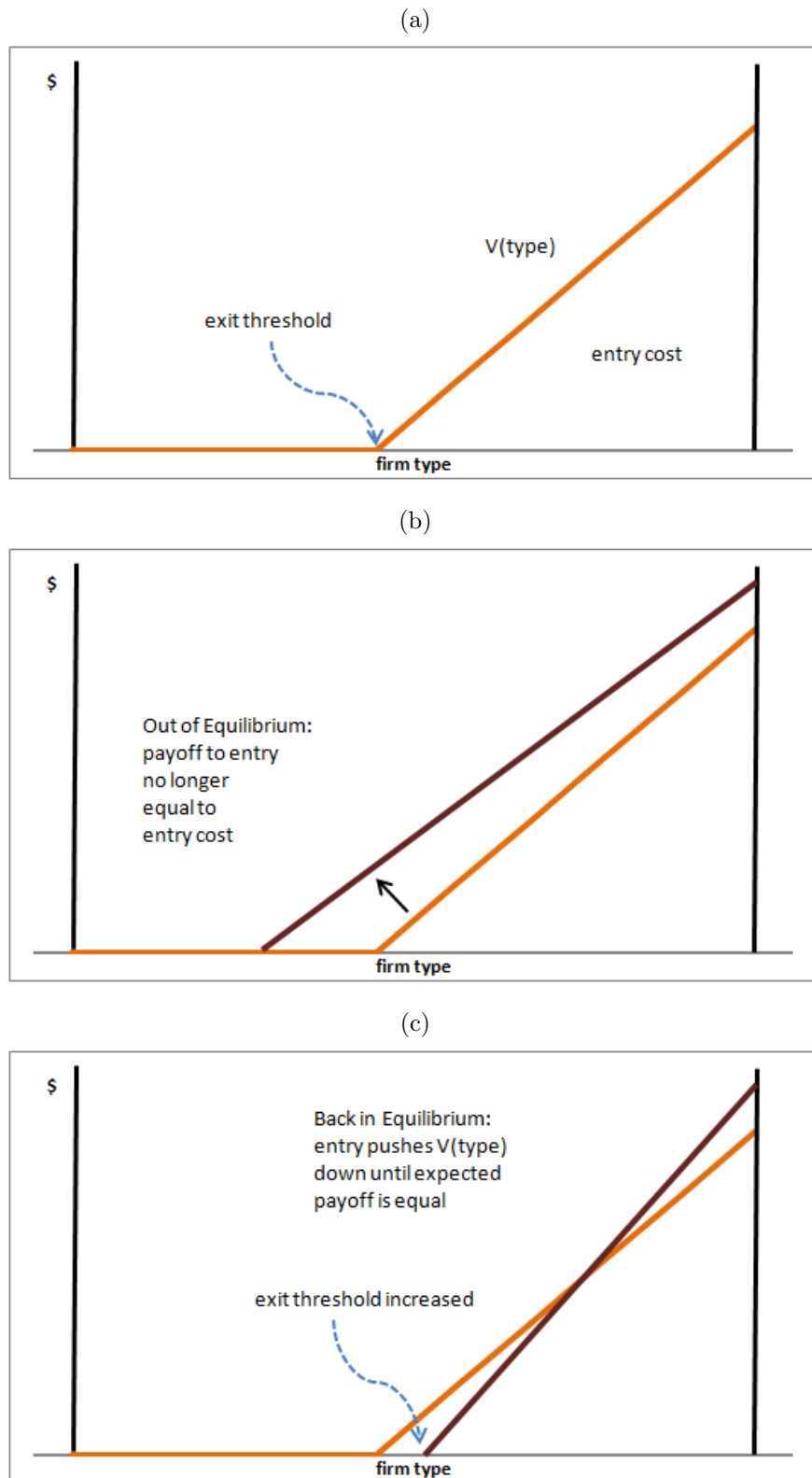
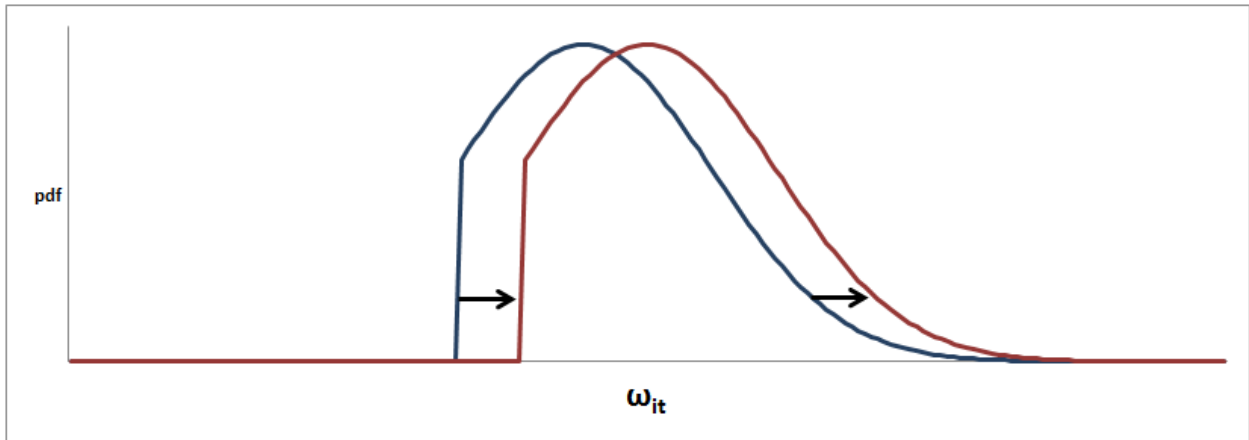


Figure 5: Predicted effect of two narratives on productivity residual distribution.

(a) X-Inefficiency



(b) Dynamic Selection

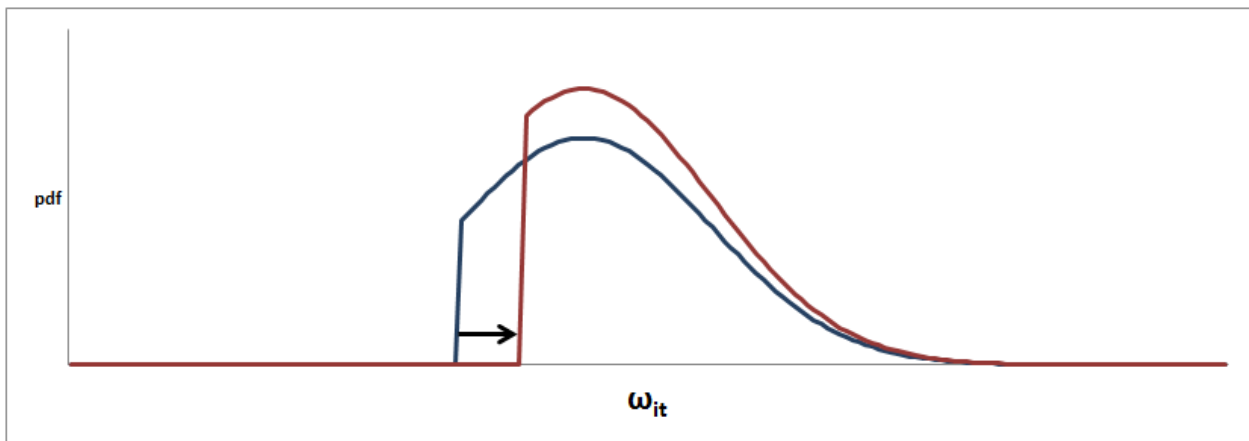
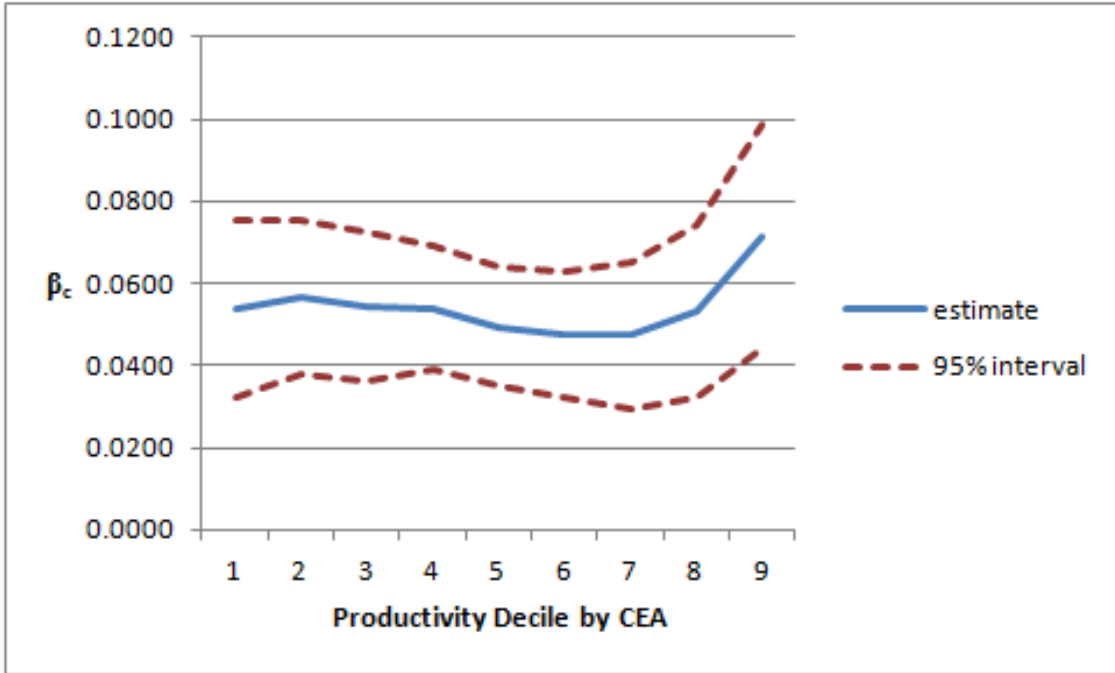


Figure 6: Effect of the number of ready-mix concrete firms on deciles of the productivity residual distribution by CEA. Corresponds to models (1) and (2).

(a) instruments: lagged



(b) instruments: contemporary

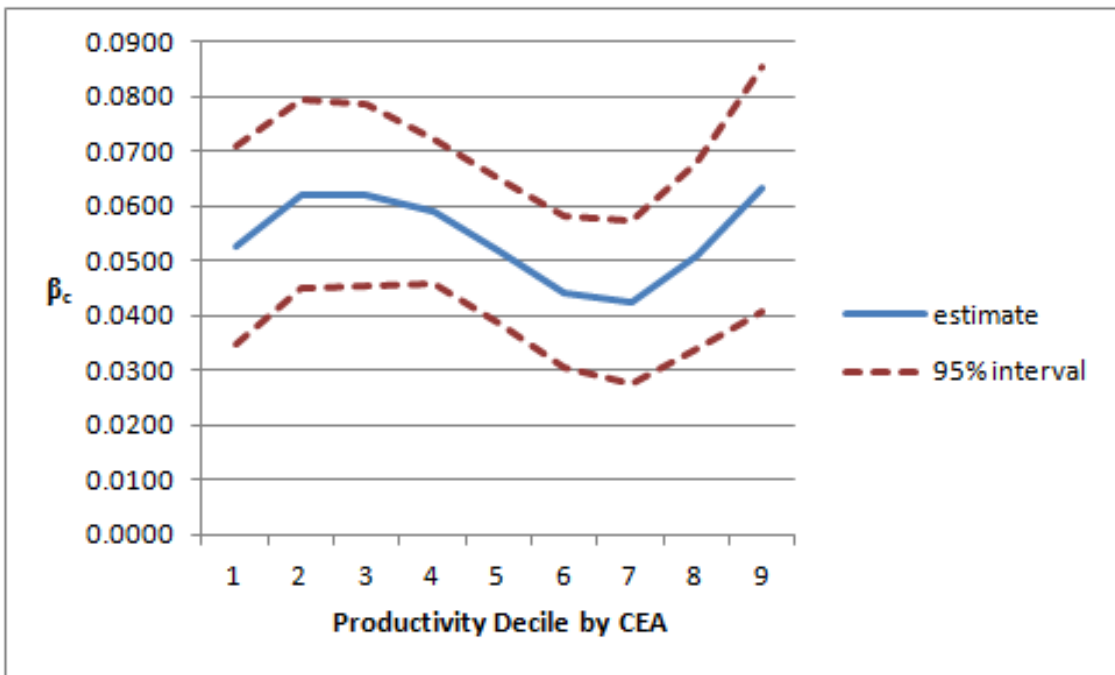
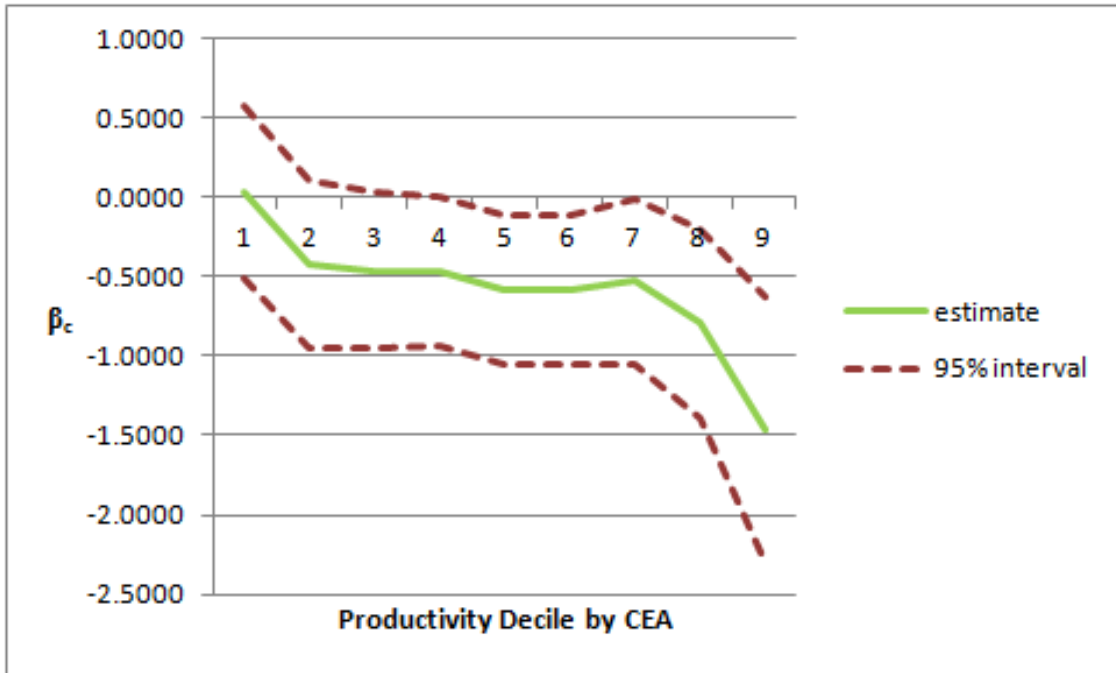


Figure 7: Effect of HHI (calculated using firms) on deciles of the productivity residual distribution by CEA. Corresponds to models (3) and (4).

(a) instruments: lagged



(b) instruments: contemporary

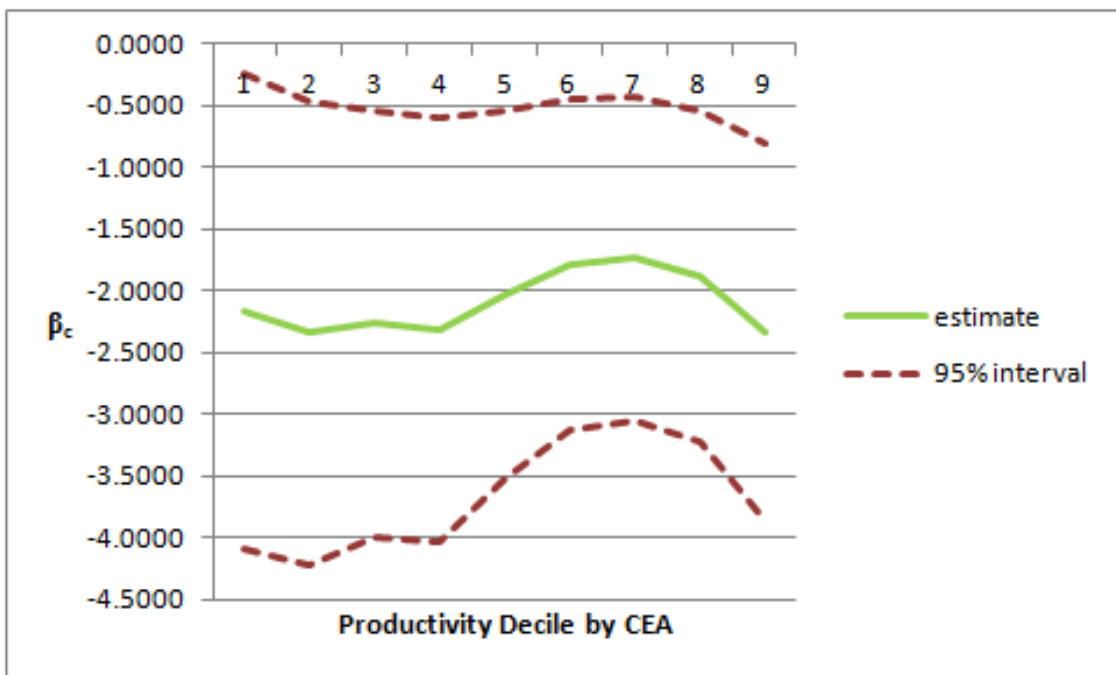
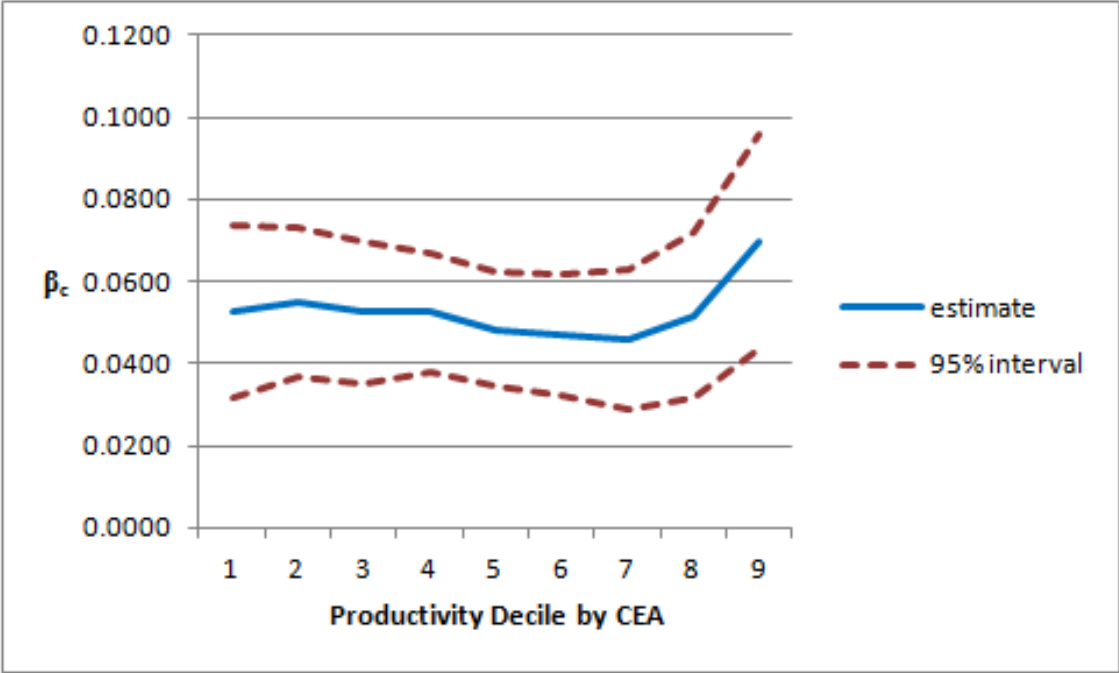


Figure 8: Effect of the number of ready-mix concrete establishments on deciles of the productivity residual distribution by CEA. Corresponds to models (5) and (6).

(a) instruments: lagged



(b) instruments: contemporary

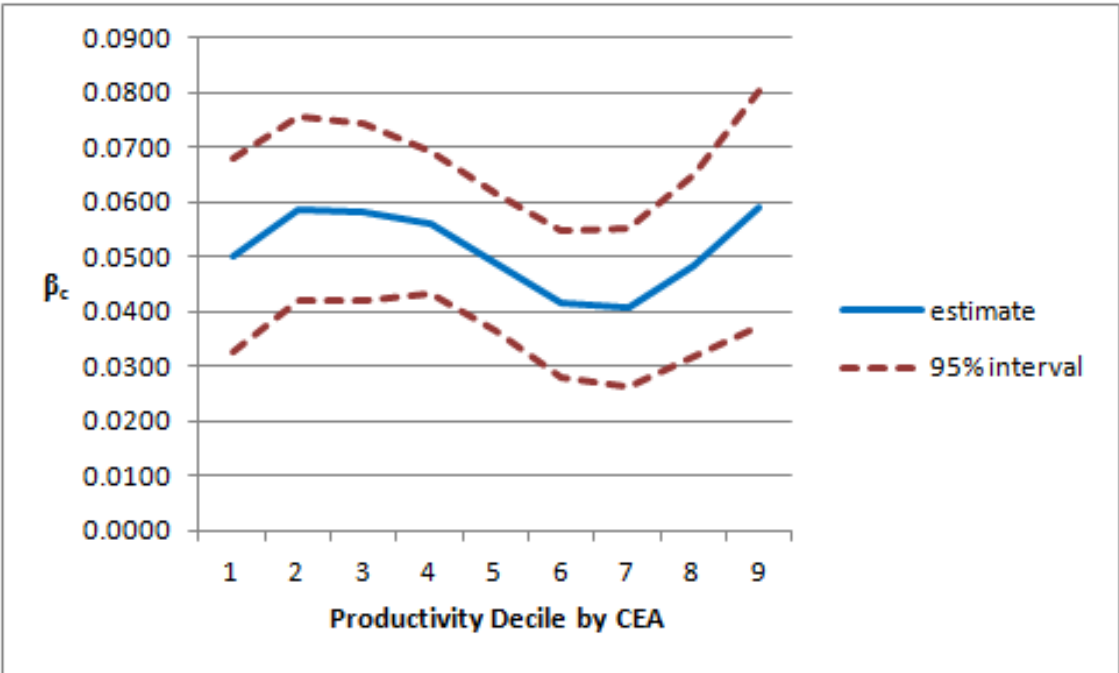
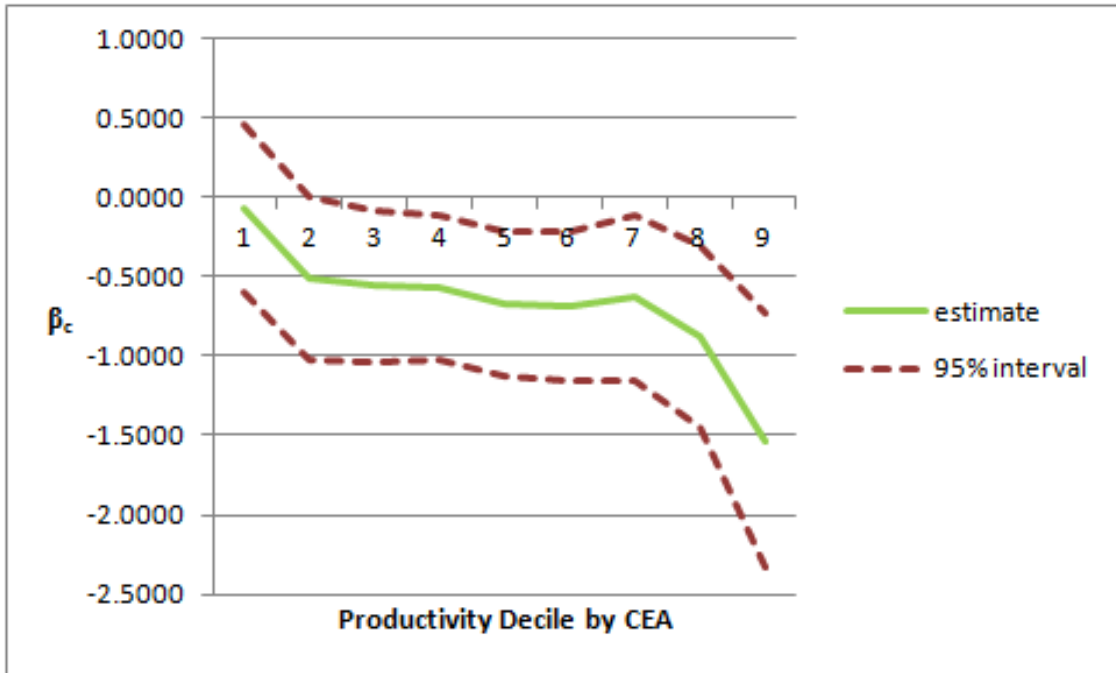


Figure 9: Effect of HHI (calculated using establishments) on deciles of the productivity residual distribution by CEA. Corresponds to models (7) and (8).

(a) instruments: lagged



(b) instruments: contemporary

