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Klaus Gugler, Michael Weichselbaumer
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Centre for Economic Policy Research
77 Bastwick Street, London EC1V 3PZ, UK
Tel: (44 20) 7183 8801
www.cepr.org

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Abstract

In this paper, we analyze mergers in bidding markets. We utilize data from procurement auctions in the Austrian construction sector and estimate models of first-price sealed-bid auctions. Based on estimated cost and markups, we run merger simulations and disentangle the market power effects from potential cost efficiencies. We analyze static and dynamic models of first price auctions, and compare the outcomes of the merger simulations with the actual effects of observed mergers. Our results show that market power and efficiency effects are present post merger, leading to increased markups, but leaving the winning bid essentially unaffected by the merger. We find a good correspondence of predicted and actual effects for full mergers, but not for majority acquisitions.

JEL Classification: D44, L10 and L13
Keywords: construction procurement, evaluation of mergers, first-price auctions, independent private values and merger simulation

Klaus Gugler klaus.gugler@univie.ac.at
WU Vienna University of Economics and Business

Michael Weichselbaumer michael.weichselbaumer@wu.ac.at
WU Vienna University of Economics and Business

Christine Zulehner zulehner@safe.uni-frankfurt.de
Goethe University Frankfurt, Austrian Institute of Economic Research and CEPR

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1 Introduction

Merger analysis — the study of the determinants and effects of mergers on the merging firms and on the markets they operate — aims to assess market power and cost efficiencies. Some ground-breaking research on merger analysis has already connected theoretical models with strategies for empirical identification. As a result, merger simulations are now standard to assess the effects of a merger.[1] Despite these major advances, there is no universal model for merger analysis. Industry characteristics remain important to decide on the appropriate model application, although, in practice, a model of Bertrand competition with differentiated goods is most often used. In addition, the intricacies of estimation lead to controversial debates of empirical results of merger simulation studies and the use of a treatment effects approach has been proposed.[2]

Empirical analysis of merger simulation involving bidding markets has so far received less attention. The advanced level of auction theory[3] and its empirical modelling, though, provide fertile ground for the application to merger analysis.[4] With this paper, we plan to address the following topics: First, we simulate mergers in an auction model relying on the theoretical and empirical auction literature. Based on estimated costs and markups, we identify the effects of a proposed merger, i.e., market power and cost efficiency effects. We evaluate the mergers in our data on construction procurement auctions in Austria with respect to the non-merger benchmark as implied by the merger simulation model. Second, we estimate a static and a dynamic first-price auction model and compare them. Bidders may consider the strategic consequences of their backlog and price into their bids also the lost option value of winning today versus winning in the next auction (Jofre-Bonet and Pesendorfer, 2003). If we ignore this effect, estimated cost and thus estimated markups may yield a biased assessment of mergers. Third, we evaluate the merger simulation model in comparison to the actual outcome of the mergers observed in our data, with respect to bidding behavior and cost efficiencies. To the best of our knowledge, this is the first paper that evaluates mergers actually undertaken in auction markets and compares

[1] Merger simulation as a tool for competition policy was introduced by Hausman et al. (1994) and Werden and Froeb (1994). For an introduction to merger simulation see Davis and Garcés (2009).

[2] See the discussion of treatment effects approach versus merger simulation in Nevo and Whinston (2010).

[3] The vast auction literature is summarized by Klemperer (2004).

[4] Among notable exceptions that combined auctions to merger analysis, in particular with respect to theoretical considerations, are Klemperer (2005) and Werden and Froeb (2005). Hypothetical mergers in auctions are analyzed in Li and Zhang (2015).

them to simulated effects.

The basic model to derive marginal costs directly from observed bids and for the simulation of mergers is the standard approach of analyzing first-price auctions (Guerre et al., 2000).[5] In addition, we implement a dynamic auction model following Jofre-Bonet and Pesendorfer (2003). Based on the estimates of marginal costs, we can evaluate the effect of the merger and observe the outcome for cost efficiencies. The crucial maintained assumption of this method is — as in any merger simulation — that the theoretical model describes the agents' economic behavior well enough.[6] For our empirical analysis, we follow Athey et al. (2011) and Gugler et al. (2015), and impose a specific distribution on the bids to recover the distribution of bidders' costs using the first order condition for optimal bidding behavior. First order conditions are derived from standard profit maximization under the rules of first-price sealed bid auctions, i.e. that (in our case) the lowest bidder wins the contract. The estimated distribution of bids includes auction characteristics, firm characteristics as well as the level of competition to which firms are assumed to respond optimally.

By obtaining structural estimates of marginal costs we can disentangle the efficiency effect from the market power effect due to the merger. Decreases in marginal costs from before to after the merger should be attributable to the efficiency effect, any increase in the markup should be — ceteris paribus (i.e. holding costs constant) — attributable to the market power effect. In auction markets, the market power effect is composed of two effects. First, there is the effect due to the reduction of the number of competitors. This leads to less aggressive bidding and therefore higher markups.[7] Second, the type of the merging firms and therefore asymmetries matter (Cantillon, 2008). If, for example, the merger includes the most efficient and the second most efficient bidders, the new entity still wins for sure, even though its bid is shaded more after the merger than before. We first disentangle these two market power effects in our merger simulation model. Then, we calculate cost efficiencies and the overall effect. Finally, we compare predicted to actual merger outcomes.

Several interesting aspects can be addressed with our framework and data. We rely not only

[5] For a survey on nonparametric identification and estimation of auction models see Athey and Haile (2005). For surveys of empirical studies of auctions see Hendricks and Paarsch (1995) or Laffont (1997).

[6] Experimental evidence, especially when experienced bidders are participating in first-price auctions, shows that the equilibrium outcome is reached rapidly (Dyer et al., 1989). Bajari and Hortaçsu (2005), for example, provide evidence from experimental data that assesses the reasonableness of structural estimates.

[7] Of course, under the assumption that entry of other firms is not immediate.

on a single or a hypothetical merger, but investigate numerous actual mergers that have been completed in our sample period. The data contain many bids submitted by companies both before and after the merger providing enough information for the simulation of the mergers and the evaluation of the simulation model. The merger simulation looks at the market power and efficiency effects using the actual bids; the ex-post evaluation of the simulation model looks at ex-post bids compared to predicted based on ex-ante data.[8] Some studies on model evaluation exist (see Peters (2006), Houde (2012), Weinberg and Hosken (2013), Björnerstedt and Verboven (2012)). These studies find that merger simulation results deviate at least in specific but important aspects from actual effects, like the distribution of effects across acquirer and target or the simulated reaction of competitors. The main explanations given for these deviations are possibly wrong assumptions about demand, pre-merger competition intensity and efficiency effects. None of the studies so far, however, has considered bidding markets, despite their relevance and the rich theory that has been developed. Our results show that market power and efficiency effects are present post merger, leading to increased markups, but leaving the winning bid essentially unaffected by the merger. We also find that the predicted and actual effects for full mergers correspond well. This is, however, not true for majority acquisitions, which might be caused by problems of post merger integration.

The paper is structured as follows. The next section gives a literature survey on the price effects of merger studies where we focus on mergers in bidding markets. Section 3 provides the industry background of the Austrian construction sector, explains the rules of the procurement process, and describes the auctions and mergers in our sample covering the period 2006 to 2009. Section 4 sets up our first-price sealed bid auction model and hypothesizes on the expected effects of mergers in such a market. Section 5 presents the estimation results and the counterfactual analysis. Here, we simulate both components of the market power effect — the one due to asymmetry increasing mergers and the usual market power effect due to a reduction of the number of actual bidders. Section 6 provides the ex-post analysis of the actual mergers in the sample period, and compares the results to the predicted effects. Section 7 concludes.

[8] Ex-post evaluation of the simulation model is what Nevo and Whinston (2010) call "retrospective merger study".

2 Related literature

Merger simulation as a tool for competition policy was introduced by Hausman et al. (1994) and Werden and Froeb (1994). Subsequent research has looked at a variety of issues like alternative demand models, e.g. Nevo (2000), Epstein and Rubinfeld (2001) or Ivaldi and Verboven (2005). Some of this work has explicitly compared different demand models and showed how different functional forms may result in relevant differences in the prediction of prices; see Froeb et al. (2003), Huang et al. (2008) and Slade (2009).

Ex-post merger analysis moved in parallel with merger simulation, and often aimed at evaluating the relevance or effectiveness of competition policy towards mergers. Important work focused on mergers in major industries, such as airline markets (Borenstein, 1990; Kim and Singal, 1993), banking (Focarelli and Panetta, 2003) and gasoline (Hastings, 2004; Hastings and Gilbert, 2005; Hosken et al., 2011; Houde, 2012). Ashenfelter and Hosken (2008) take advantage of scanner data to assess mergers in five different branded goods industries. They find moderate but significant price effects in the range of 3-7% after the merger. A number of studies show that anti-competitive effects of increases in prices outweigh efficiencies: for instance, difference-in-difference analysis of journal pricing by McCabe (2002) or IV estimation of hospital pricing by Dafny (2009). These views are largely consistent with the findings of Weinberg (2008), who provides a survey of the literature on the price effects of horizontal mergers. Accordingly, many studies find increased market power and reductions in consumer welfare due to mergers. Weinberg (2008) also notes, however, that most of the studies are constrained by a relatively narrow time window around mergers and mergers are not picked at random, with a preference given to those where the anti-competitive effects are expected to be significant. Moreover, there is also a number of empirical studies that concluded that the efficiency effect can outweigh the increase in market power: Focarelli and Panetta (2003) analyze mergers in the banking industry in Italy and find that the short-term rise in prices (interest rates) was followed by a reduction in the longer run. Connor et al. (1998) look at the consolidation in the US hospital industry and show that average costs and prices rose less for hospitals that were involved in a merger. Tremblay and Tremblay (1988) argue that increases in concentration in the beer production industry led to higher efficiency because of the transfer of assets to more efficient managers. Mazzeo et al. (2013) study post-merger product repositioning and find that it could potentially lead to in-

creases in consumer welfare if more products are introduced. Ashenfelter et al. (2015) find for the Miller/Coors beer merger that the average predicted increase in concentration (measured by the delta in the Herfindahl index) would have led to a price increase of 2%, but that this was more than offset by increased efficiencies (measured by the reduction in shipping distances), eventually resulting in price decreases in the average market of 1.8%. Miller and Weinberg (2015) re-evaluate the Miller/Coors merger by additionally and explicitly estimating demand and supply functions. While merger-specific marginal cost reductions roughly counter-balance changes in unilateral pricing incentives, consumer surplus decreases due to increased tacit collusion (with Anheuser-Busch Inbev). The merger, however, increases total surplus, despite higher retail prices, due to the magnitude of marginal cost reductions. Results overall show that the effects vary strongly by industry and by the structure of competition that is modelled.

We do not know of studies on actual mergers in bidding markets. There is, however, a literature on simulated merger effects in bidding markets. Froeb and Shor (2005) is a concise survey of the auction literature on the effects of collusion and mergers. The standard way to model the effect of a merger in such a market is to assume that the private value of the merged firm is the maximum of its coalition member values. This implies that the merged firm wins all auctions that any of its pre-merger component pieces would have won. This characterization has been used by antitrust enforcement agencies to model unilateral effects of mergers and in the existing literature on mergers in auction markets (see e.g. Li and Zhang (2015), Cantillon (2008), Waehrer and Perry (2003), Brannman and Froeb (2000), Dalkir et al. (2000), or Waehrer (1999)). It is relatively easy to quantify the effects of a merger in second price sealed bid auctions, since bidders bid their true valuations: A merger pushes down the price to the third highest bid when the merging bidders would have finished first and second. For all other bidder pairs, the merger has no effect. In first price sealed bid auctions, however, the relationship between observed bids and underlying values is more complex, because bidders no longer have an incentive to bid their true values. Instead, they balance the benefits of a higher bid (a higher probability of winning) against its costs (lower profit if they win). The amount of bid shading depends upon each bidder's beliefs of the likely bids of other participants. Froeb and Shor (2005) say therefore that "mergers in first-price auctions affect prices in subtle and complex ways".[9]

[9] A second dimension of auction modeling is the distinction between common and private value auctions with different antitrust implications. Mergers in private value auctions follow an intuition similar to that of traditional markets: They are likely to be anticompetitive in the absence of offsetting efficiency gains. For common value

In a recent paper, Li and Zhang (2015) estimate the effect of a hypothetical merger in US timber auction markets. Their counterfactual analyses apply a parametric estimation of entry and value distributions to two types of mergers. First, a merger of the two lowest-ranked bidders; and second, a merger of the winner and the second-ranked bidder. Bidder asymmetry enters the model in one firm–contract specific variable, which is the distance to the timber tract that is to be contracted by the winner of the auction. After the merger, the combined entity obtains two draws from the value distribution — one based on the shorter, one based on the longer distance to tract — and can use the higher valuation as the basis for the bid. In their affiliated values specification, a merger of the bidders ranked one and two leads on average to a decrease of 4.2% of revenues for the seller. The merger of the two lowest-ranked bidders leads to an increase of 2.4% of revenues. For the IPV framework, their simulation predicts a reduction of mean seller revenue of almost 8% on average when rank one and two merge, and an increase of seller revenue of 3.3% when the low-rank firms merge. Their approach gives results for the two extreme cases and abstracts from the empirical question whether the merging bidders actually have permanently lowest or highest valuations, or have some distribution over their observed ranks.

There is a small but growing literature comparing simulated with actual price effects of mergers, and if there are any, working out the reasons for differences between the two. This is potentially important for competition authorities since they have to take merger decisions ex ante. Peters (2006) looks at the simulated and actual price increases of merging firms in several airline mergers and finds that standard simulation methods, which measure the effect of the change in ownership on unilateral pricing incentives, do not generally provide an accurate forecast. While unambiguously finding increases in prices post merger, the unexplained component of the price change is largely accounted for by supply-side effects, i.e., changes in marginal cost. Peters (2006) concludes, however, that the efficiencies necessary to generate his estimated price effects would be implausibly high and inconsistent with anecdotal evidence. A more plausible interpretation would be that some degree of tacit collusion existed prior to merger. Weinberg and Hosken (2013) also find mixed evidence on the quality of pre-merger simulations with respect to post-merger effects. In particular, their simulated price effects reverse the rank order of the estimated price effects. The "syrup merger" reduced the number of firms from three to two,

auctions — because of "winner's curse" arguments, the very existence of anticompetitive effects is not assured.

but had no significant actual price effects contrary to predictions; the "oil merger" had actually much larger price effects, despite large estimated elasticities. Weinberg and Hosken (2013) conclude that — since demand changes and efficiency effects would have to be implausibly large to explain their findings — it must be the assumed functional form of demand and the estimation strategy.

Houde (2012), in contrast, finds that his retrospective analysis to a large extent confirms the merger simulation results. The Sunoco/Ultramar merger caused a significant price increase of up to 1/2 cents per liter in the neighborhood of Sunoco stations, which corresponds to a 10% increase in retail margins, mostly due to unilateral effects. However, there are at least two caveats. First, the observed merger effect does not diminish in distance as fast as the model predicts. This is explained in part by the competitors' simulated reactions, which are too small. Second, efficiency effects may be larger than the ones that were estimated. Björnerstedt and Verboven (2012) analyze a large merger in the Swedish market for analgesics (painkillers) and find that the predicted and the actual price effects are of similar magnitude (30-40%). A closer look at a wider range of merger predictions, however, leads them to more nuanced conclusions. First, both merging firms raised their prices by a similar percentage, while the simulation model predicted a larger price increase for the smaller firm (which was the acquirer). Second, while the model predicted only very small price increases of the outsiders, two of them sizably increased prices after the merger.

Thus, the evidence on the correspondence between simulated and actual merger effects is mixed. While two of the four studies (Houde (2012), and Björnerstedt and Verboven (2012)) find corresponding average price effects between simulated and actual effects, the other two studies (Peters (2006) and Weinberg and Hosken (2013)) do not find that. All studies find that merger simulation results deviate at least in specific but important aspects from actual effects, like the distribution of effects across acquirer and target or the simulated reaction of competitors. The main explanations for these deviations are possibly wrong assumptions about demand, pre-merger competition intensity and efficiency effects.

Summarizing, there is a sizeable literature on the effects of mergers on prices in a variety of markets, the preponderance of which finds price increases due to the merger, i.e. the market power effect outweighing the efficiency effect. There are also studies, however, that concluded

that the efficiency effect outweighs the increase in market power. In auction markets, the market power effect, however, is not only due to a reduction of the number of competitors; the type of merging firms and therefore asymmetries also matter (Cantillon, 2008; Li and Zhang, 2015). All studies looking at a comparison of actual and predicted merger effects find that merger simulation results deviate at least in specific but important aspects from actual effects.

3 Industry background and data

This section provides information on the organization of procurement auctions in Austria and the data we use. In addition, we describe the mergers that took place in the years 2006-2009, the time span of our sample, provide summary statistics and a descriptive analysis of the mergers. Additional information on the industry and data is available in Gugler et al. (2015).

3.1 Organization of procurement auctions

Austrian public institutions are subject to the Federal Public Procurement Law (PPL, "Bundesvergabegesetz"). The PPL sets out the legislative framework for public procurement. Procurement includes services like cleaning, facilities like computing or furniture, and construction such as rails, roads, schools and other public buildings, etc. Our data are exclusively on procurement from the construction sector. The steps in a procurement procedure are as follows. A cost prediction by the procuring institution decides if the project receives an EU-wide announcement. As of 2006, the cut-off was 5.278 million Euros. Project announcement takes place in the corresponding official publication medium. The procuring institution makes the documents available to the bidders. At the end of the submission period, the sealed offers are opened and announced to the bidders. The bidder offering the lowest price wins the auction. All public procurement contracts are subject to the PPL.[10] Firms can participate in the procurement procedure if they fulfill general, non-discriminatory standards of qualification. The most specific criteria are supporting documents a procuring institution could demand about the availability of certain necessary machinery or qualified personnel.

[10] For small contracts, a procuring institution can nominate a firm directly, without conducting an auction. The limit for direct nomination vary in the sample period: 20,000 Euros for 01/2006, 40,000 Euros for 02/2006-4/2009, 100,000 Euros for 05/2009-12/2009. Our data do also contain projects below these limits, which are therefore voluntarily procured via auctions.

A reserve price in the sense of a predetermined value above which the auction would be withdrawn does not exist. The procuring institution has the possibility, though, to withdraw the auction if it can proof in court that the bid of the winner is "contra bonos mores" ("against good morals"). The procuring institution would have the burden of proof to show that the winning bid is far higher than its own cost estimate, which must be based on standard principles of the profession.

3.2 Data and mergers

For the empirical analysis, we combine several sources of data to complement the main data on procurement auctions in the construction sector.[11] An Austrian industrial construction company provided data including own and competitors' bids, bidders' and auction characteristics. These data cover all auctions in both building and heavy construction during the period 2006-2009 where this company took part either as the parent company itself or through a subsidiary. According to the company, the database covers more than 80% of all auctions which must be conducted according to the Austrian Public Procurement Law. Within our sample period, the data reflect on average 14% of Austria's total construction sector. Additional data is obtained from matching the bidding firms to Bureau van Dyck's Amadeus database, which contains nearly the population of companies in Austria. Matches are possible by company names and postal codes. Almost all bids were made by firms that are well known in Austria and matching is not a major concern.

For our sample of firms we have bidder characteristics such as number of employees, sales and assets. In addition, we measure transportation costs by the distance of a firm to a construction site. Based on the construction sites' and bidders' postal codes, we used Microsoft's Bing Maps to calculate the driving distances for all bidders to the project sites corresponding to the auctions.[12] Backlog used by a firm at a point in time is calculated as in Jofre-Bonet and Pesendorfer (2003). Every project is added to the backlog when a firm wins it. Projects are assumed to be worked off linearly over their construction period, which releases capacity. Every firm's backlog obtained

[11] The construction sector accounts for 7% of Austria's GDP on average between 2006 and 2009 (in Germany this share is 4.2%, in the USA 4.4%; OECD STAN data set).

[12] For firms with multiple plants, we use the distance between the headquarter and the construction site. Plant locations are not available; different locations of a firm, though, are often operated as subsidiaries and distances then can be calculated.

is standardized by subtracting its mean and dividing by its standard deviation.[13] See Table 1 for the exact variable descriptions.

Table 1: Variable descriptions

Variable	Description
Log(number of bidders)	Log of number of bidders in the auction.
Backlog	Backlog variable, standardized by firm mean and standard deviation.
Backlog sum	Sum of backlog of the other bidders in the auction.
New orders	Gross inflow of new contracts, countrywide, per month (mill. 2006 Euros).
Engineer estimate	Engineer cost estimate for the construction project.
Log(employees)	Log of the number of employees of a bidder.
KM	Travel distance in kilometers from a bidder's location to the project site.
KM average	Average of all other, competing bidders' distances between their location and the project site.
KM sum	Sum of all other, competing bidders' distances between their location and the project site.
Same postal code	Dummy for bidder where location has the same postal code as project site.
Same district	Dummy for bidder which resides in the district of the project site.
Same state	Dummy for bidder which resides in the state of the project site.
Heavy construction	Dummy for auctions in heavy construction sector.
General contractor	Dummy for bidders serving as "general contractors".
Open format	Dummy for auctions following the "open procedure".

Auction characteristics are the technical cost estimate, the subsector (building, heavy construction) and variables describing the auction procedure. We further know the identity of the actually participating bidders and calculate cumulative auction level characteristics such as the sum of distances or the sum of backlogs.

Over the sample period, our data contain 17 transactions where both the acquirer and the target have records as bidders in the procurement auctions. To identify the transactions, we have used three sources: Thomson Reuters' SDC Platinum Database, the case list of the DG Competition (ec.europa.eu/competition) and the case list of the Austrian Competition Authority (www.bwb.gv.at). Thus, we are confident that we capture all M&A-activity in the sector. The acquirers are major players in the construction sector. They submit about a third of the 30,000 bids in our sample. The targets submit 250 bids. Ten of the 17 transactions are full acquisitions, five are acquisitions of majority interest and two are acquisitions of partial interest.

Table 2 shows an overview of the mergers. Eight horizontal mergers (five full mergers and

[13] We use planned construction duration, instead of actual, and estimate construction duration, when it is not available, by a log-log regression of size on contract duration.

three acquisitions of majority interest), i.e., mergers where both acquirer and target bid at least once in the same auction before the merger, fall within our sample period. Other mergers or takeovers concern firms which do not directly compete in the auctions before the merger. In several cases, the target retains bidding as an entity under its old name. Partial acquisitions are not considered further in the analysis.

Table 2: List of mergers

Trans-action	Date	Acquirer Bids		Target Bids		Joint Bids		Type
		before	after	before	after	before	after	
1	2006-02-01	3	190	2	32	0	1	full
2	2006-07-02	534	2999	18	38	18	6	full
3	2006-07-12	0	0	0	1	0	0	full
4	2007-04-18	1189	2344	19	0	19	0	full
5	2007-09-21	798	1077	1	3	1	0	full
6	2007-10-12	1	0	0	0	0	0	full
7	2008-02-15	123	159	3	2	0	0	full
8	2008-05-20	9	1	1	0	0	0	full
9	2008-11-07	1819	723	10	2	5	0	full
10	2008-12-06	186	96	101	24	26	1	full
11	2007-01-05	899	2634	0	0	0	0	majority
12	2007-02-01	58	224	3	7	0	0	majority
13	2008-07-15	2281	1252	1	0	1	0	majority
14	2008-09-15	2422	1111	8	0	8	0	majority
15	2008-11-07	1819	723	3	1	2	0	majority
16	2008-02-09	496	448	0	1	0	0	partial
17	2008-04-08	537	407	0	0	0	0	partial

Note: Date corresponds to date when transaction is effective.

3.3 Sample and summary statistics

Table 3 describes our sample of auctions and firms. For the econometric model, we lose observations, mainly when there is no engineer estimate in our data. Some observations are not useful because firms have gone bankrupt or have been dissolved, and there are firms that we cannot match to the BvD database. The final sample for the estimations consists of 2,069 auctions and 971 firms. The firms matched to external information account for 94.3% of our bids. The population of Austrian construction firms, as reported by the Austrian Central Bureau of Statistics, consists of 4,796 firms on average for 2006-2009 (building: 3,958, heavy: 838). Therefore, about one third of all construction firms submitted bids in the procurement auctions.

In Table 4, we show summary statistics of our sample. On average 7.6 firms take part

Table 3: Description of the sample

Sample	Observations
Auctions	3,974
minus engineer estimate n.a.	2,249
minus outliers	2,069
Firms	1,655
minus bankrupt, disolved	1,556
minus non-matched BvD data	1,342
minus non-matched BvD variables	971

Note: The top-panel shows the number of auctions in the sample and the reason why it is reduced in each line, together with the corresponding new number of observations. Below that, the second panel reports the number of firms that submitted bids. The 971 firms matched account for 94.3% of bids in the econometric model of 2,069 auctions.

in Austrian procurement auctions in the construction sector. While the number of Austrian construction firms of almost 5,000 firms on average also suggests a highly competitive market environment, there are a few large construction companies, too,[14] and there is differentiation both in the product and the spatial dimension. The firms in our sample, with a few exceptions, are mostly medium sized companies with around 50 employees.

In Table 5, we show summary statistics for the acquiring firms, the target firms and the non-merging firms. We observe that acquiring firms are larger than target firms, submit more bids, have a larger backlog and are on average less close to the construction site.

4 Merger simulation in auctions

Our empirical setting focuses on procurement auctions, where demand comes from the government. We are aware of the possibility to model the government as an additional player to represent decision-making on the demand side. For simplicity, we will neglect this and treat the government's demand decisions as unaffected by potential changes in price setting after the merger. We are also aware that we treat firms' decision to merge exogenously. This choice, however, might be influenced by past, current or anticipated future market conditions unobserved to the researcher (Nevo and Whinston, 2010). In the description of our empirical model, we closely follow Gugler et al. (2015).

[14]The largest four firms have approximately 40% market share within our sample of procurement auctions.

Table 4: Summary statistics

		All auctions	
		mean	s.d.
Firms	Number of firms	971	
	Employees	186.3	1,796.7
	Total Assets (mill.)	27.8	251.0
Auctions	Number of auctions	2,069	
	Winning bid (mill.)	2.32	7.34
	Engineer estimate (mill.)	2.43	6.48
	Order flows (mill.)	1,721.3	181.1
	Heavy construction	0.345	0.475
	General contractor	0.084	0.278
	Open format	0.831	0.375
	Actual bidders	7.62	3.17
Bids	Number of bids	14,866	
	Bid (mill.)	2.16	5.47
	Backlog	0.08	0.83
	Distance (km)	130.5	121.7
	Same postal code	0.041	0.197
	Same district	0.143	0.348
	Same state	0.508	0.495

Notes: Monetary values in 2006 Euros.

Table 5: Characteristics of acquiring, target and non-merging firms

		Acquirers		Targets		Non-merging firms	
		mean	s.d.	mean	s.d.	mean	s.d.
Firms	Number of firms	8		10		953	
	Employees	2,298.9	2,840.9	199.1		168.5	1,786.5
	Total Assets (mill.)	402.9	463.0	18.6	22.9	24.5	247.5
Bids	Number of bids	4,704		118		10,044	
	Bid (mill.)	2.61	6.61	3.81	6.73	1.93	4.81
	Backlog	0.18	0.79	-0.06	0.77	0.04	0.84
	Distance (km)	223.7	121.2	91.8	71.9	87.3	95.0
	Same postal code	0.011	0.101	0.127	0.335	0.055	0.225
	Same district	0.028	0.158	0.178	0.384	0.197	0.395
	Same state	0.160	0.356	0.695	0.453	0.669	0.466

Notes: Monetary values in 2006 Euros.

4.1 Bidding behavior

In our model, the bidding process follows a standard first-price sealed bid auction.[15] Each contract is an auction independent from decisions on the other contracts. In particular, we start

[15] For an introduction to first-price sealed bid auction models, see, for example, Krishna (2009).

with the case where firms do not consider the influence of their backlog on the behavior in the next auction. The set of bidders is $\mathcal{N} = 1, ..., N$. Bidders are risk-neutral and their identities are known.[16] Each bidder i obtains an independent cost draw c_i from a distribution F_i with continuous density f_i and support $[\underline{c}, \overline{c}] \subset R_+$. The bidder with the lowest bid wins the contract and receives this bid, given that the bid is not higher than r, which is the secret reserve price of the seller.[17] The bidding strategy $b_i = b_i(c_i; \mathcal{N})$ of bidder i gives the optimal bid as a function of the cost draw c_i and the set of competing bidders.

Following Guerre et al. (2000), we write bidder i's expected profit as

$$\pi_i(c_i; \mathcal{N}) = max_{b \leq r}(b_i - c_i) \prod_{j \in \mathcal{N} \setminus i} (1 - G_j(b; \mathcal{N})), \tag{1}$$

where $G_j(b; \mathcal{N}) = F_j(b_j^{-1}(b; \mathcal{N}))$, i.e., the probability of j to bid less than b, and $b_j^{-1}(b; \mathcal{N}) = c_j$. We focus on Bayesian Nash equilibria in pure bidding strategies. The first order condition for bidder i is then

$$\frac{1}{b_i - c_i} = \sum_{j \in \mathcal{N} \setminus i} \frac{g_j(b_i; \mathcal{N})}{(1 - G_j(b_i; \mathcal{N}))}, \tag{2}$$

which provides the basis for estimating bidders' cost distributions. An explicit solution to (2) does not exist, but, together with the boundary conditions that $b_i(\overline{c}; \mathcal{N}) = \overline{c}$ for all i, the equation uniquely characterizes optimal bidding strategies. Maskin and Riley (2000) show that in equilibrium, the bidders use a markup strategy and bid their values plus a shading factor that depends on the equilibrium behavior of opponents.[18]

4.2 Empirical approach

Applying the approach of Guerre et al. (2000), we first estimate the distribution of bids and derive then an estimate for the distribution of bidders' costs. Based on the estimated cost, we

[16] It is a useful simplifying assumption in the empirical auction literature to assume common knowledge of the set of actual bidders. Our personal conversations with firms active in procurement construction suggest that it is suitable for our environment to assume that competitors are known before submitting a bid.

[17] Our data do not contain rejected bids and we cannot estimate the distribution of secret reserve prices.

[18] The conditions for a unique equilibrium are provided in Maskin and Riley (2003) and Lebrun (2006). Note that we do not observe auctions with only one single bidder.

calculate markups. Costs and markups are our measures of interest to evaluate the effects of the mergers in our data.

Similar to Athey et al. (2011) and as in Gugler et al. (2015), we use a parametric approach to estimate the distribution of bids. We specify a Weibull distribution that depends on bidder characteristics, $\mathcal{X}$, auction characteristics, $\mathcal{Z}$, and on the set of bidders, $\mathcal{N}$ (see Table 1 for the list of variables):

$$G_i(b_i|\mathcal{X},\mathcal{Z},\mathcal{N}) = 1 - \exp\left\{ - \left(\frac{b_i}{\lambda_i(\mathcal{X},\mathcal{Z},\mathcal{N})} \right)^{\rho_i(\mathcal{X},\mathcal{Z},\mathcal{N})} \right\}. \tag{3}$$

The covariates affect the scale parameter $\lambda_i(\mathcal{X},\mathcal{Z},\mathcal{N})$ and the shape parameter $\rho_i(\mathcal{X},\mathcal{Z},\mathcal{N})$ linearly, i.e., $\lambda_i(\mathcal{X},\mathcal{Z},\mathcal{N}) = \lambda_0 + \lambda_{\mathcal{X}}\mathcal{X} + \lambda_{\mathcal{Z}}\mathcal{Z} + \lambda_{\mathcal{N}}\mathcal{N}$ and $\rho_i(\mathcal{X},\mathcal{Z},\mathcal{N}) = \rho_0 + \rho_{\mathcal{X}}\mathcal{X} + \rho_{\mathcal{Z}}\mathcal{Z} + \rho_{\mathcal{N}}\mathcal{N}$. We estimate (3) with maximum likelihood estimation. Given that the equilibrium is unique or bidders choose the same equilibrium, estimates of G_j and the corresponding density function g_j, denoted by $\hat{G}_j$ and $\hat{g}_j$, permit straightforward calculation of the individual costs:[19]

$$\hat{c}_i = \phi_i(b_i;\mathcal{X},\mathcal{Z},\mathcal{N}) = b_i - \frac{1}{\sum_{j\in\mathcal{N}\setminus i} \frac{\hat{g}_j(b_i|\mathcal{X},\mathcal{Z},\mathcal{N})}{1-\hat{G}_j(b_i|\mathcal{X},\mathcal{Z},\mathcal{N})}}. \tag{4}$$

With the pseudo sample of bidders' costs, $\hat{c}_i$, we are able to calculate the distribution of bidders' costs as

$$\hat{F}_i(\hat{c}|\mathcal{X},\mathcal{Z}) = \hat{G}_i(\phi_i^{-1}(\hat{c}_i;\mathcal{X},\mathcal{Z},\mathcal{N})|\mathcal{X},\mathcal{Z},\mathcal{N}), \tag{5}$$

where we again specify the scale and the shape parameter to depend linearly on the parameters and estimate the model with maximum likelihood.

4.3 Dynamic model

In the dynamic model, we closely follow Jofre-Bonet and Pesendorfer (2003) and, in the application to the current data, Gugler et al. (2015).[20] A static model neglects the lost option value of

[19] If one observes all bids and bidder identities, Li and Zhang (2015), Campo et al. (2003), and Laffont and Vuong (1996) show that the asymmetric independent private values model is identified.

[20] Balat (2012) adds endogenous entry and unobserved heterogeneity to the dynamic first-price auction model.

winning a current auction versus winning future auctions and markups can be underestimated. Jofre-Bonet and Pesendorfer (2003) estimate a dynamic game with sequential equilibria based on symmetric Markovian strategies.

The state transition function is denoted by ω and deterministically captures the effect of winning a contract on the backlog. Our definition of ω is identical to the definition in Jofre-Bonet and Pesendorfer (2003). We denote $\mathcal{Q} = (\mathcal{X}, \mathcal{Z}\prime, \mathcal{N})$, where $\mathcal{Z}\prime = \mathcal{Z} \setminus (s_i, s_{-i})$, s_i the backlog of bidder i and s_{-i} the backlog of all other bidders. The hazard function of bids submitted by bidder i is defined as

$$\hat{h}(.|\mathcal{Q}, s_i, s_{-i}) = \frac{\hat{g}(.|\mathcal{Q}, s_i, s_{-i})}{1 - \hat{G}(.|\mathcal{Q}, s_i, s_{-i})}, \tag{6}$$

with $\hat{G}$ and $\hat{g}$ the estimated distribution function and the estimated density function. Using (6), the main equation resulting from the model of Jofre-Bonet and Pesendorfer (2003) is the first order condition that gives an estimate of private costs:

$$\begin{aligned}\hat{c}_i = \phi(b|\mathcal{Q}, s_i, s_{-i}, h, V) = b - \frac{1}{\sum_{j \in \mathcal{N} \setminus i} \hat{h}(b|\mathcal{Q}, s_j, s_{-j})} \\ -\beta \sum_{j \in \mathcal{N} \setminus i} \frac{\hat{h}(b|\mathcal{Q}, s_j, s_{-j})}{\sum_{l \in \mathcal{N} \setminus i} \hat{h}(b|\mathcal{Q}, s_l, s_{-l})} [V_i(\omega(\mathcal{Q}, s, i)) - V_i(\omega(\mathcal{Q}, s, j))],\end{aligned} \tag{7}$$

where β is the discount factor. To calculate equation (7), we estimate the value function V based on a numerical approach to the explicit expression for the value function derived in Jofre-Bonet and Pesendorfer (2003). To calculate the numerical solution, we draw a random sample of 50 states and 200 contracts. For every bidder on the grid of states we approximate other states by a quadratic polynomial, estimated by a robust regression with firm fixed effects.

4.4 Expected effects of a merger

As pointed out in the literature survey above, we expect that whenever the market power effect outweighs the efficiency effect, prices (bids) would increase. In auction markets, however, the market power effect is not only due to a reduction of the number of competitors, but the type of merging firms and therefore asymmetries also matter (see Cantillon (2008), and Li and Zhang

(2015)). If more efficient firms merge, they retain a high probability of winning (in the extreme case of a merger of the first-ranked and second-ranked firm, the new entity wins for sure), even though the merging firm shades bids more after the merger than before the merger. The incentive to shade bids more after the merger emerges because the optimal bid is equal to the expected cost of the competitors conditional on the competitors' costs being less than the bid. If there are fewer bidders in an auction and/or the remaining competitors are weaker, the markup goes up, because the expected conditional cost of competitors increases after the absorption of one of the competitors. This implies that bidders' expected rents go up in equilibrium and this gives the first hypothesis:

Hypothesis 1: The markup of merging firms goes up post merger, ceteris paribus (holding costs constant); i.e., there is a market power effect.

Costs of the combined entity can decrease after the merger, and this efficiency effect would drive the bids down after the merger. In general, both market power and efficiency effects can be present at the same merger, thus our second hypothesis is:

Hypothesis 2: The marginal costs of merging firms go down post merger, i.e., there is an efficiency effect due to the merger.

Prices (here: bids) rise when the market power effect outweighs the efficiency effect. Ex ante, we do not know which effect dominates, and this is what is tested below.[21]

5 Estimation results and counterfactual analysis

In this section, we describe our estimation results for the bid and the cost distribution and then for the counterfactual analysis. We obtain marginal cost distributions from the static and the dynamic models and use both for the counterfactual analysis.

[21] The main underlying assumption for hypothesis one is that a decrease in the number of bidders and/or remaining weaker bidders yield higher procurement prices. These are standard competition arguments, but need not always be true. In a model with common values, informational asymmetries, such as the "winners' curse", may offset the above arguments. For example, Somaini (2011) and Hong and Shum (2002) provide evidence of interdependent valuations in the construction industry. Even in an independent private values model as we apply here, bidder asymmetries or costly bidding may lead to the effect that more bidders could lead to reduced price competition. Cantillon (2008) shows that the composition of strong versus weak bidders is the relevant factor. Li and Zheng (2009) show that it is possible that, as the number of potential competitors increases, bidding may become less aggressive.

5.1 Determinants of the bid distribution and bidder costs

Table 6 displays the estimation results of the determinants of the bid distribution. Column (1) shows the estimates for the scale parameter λ, and column (3) for the shape parameter ρ. The standard errors are placed in parentheses in columns (2) and (4). Consistent with a private value auction format, the estimated effect of the log of the number of bids is negative. More bidders increase the competitive intensity in the auction. We use the log of the number of bidders to account for the diminishing marginal influence of this variable on bids. Own backlog and the backlog of the other bidders measure firms' capacity constraints. The estimated coefficients of both backlog measures are positive. If their own backlog is higher, firms bid less aggressively since they have higher opportunity costs, i.e., the lost option value of winning today versus winning tomorrow increases; firms bid also less aggressively when they know that their competitors have higher backlogs and therefore higher costs. We also observe that new contracts in the construction sector overall increase firms' bids, implying that a higher level of demand in the industry leads firms to bid less aggressively.

Table 6: Determinants of the distribution of bids

	Scale, λ		Shape, $\rho \times 1000$	
	(1)	(2)	(3)	(4)
Log(Number of bidders)	-16,619.79**	(3,389.642)	0.26**	(0.087)
Backlog	2,694.62**	(710.623)	-0.03	(0.020)
Backlog of other bidders	1,206.15**	(233.723)	0.03**	(0.006)
New contracts	22.52**	(2.789)	0.00*	(0.000)
Engineer estimate	1.13**	(0.004)	0.00**	(0.000)
Log Employees	-479.82	(353.582)	0.14**	(0.010)
Distance	83.79**	(19.656)	-0.00	(0.001)
Distance squared	-0.16**	(0.036)	-0.00	(0.000)
Average distance	-88.42**	(21.708)	-0.00**	(0.000)
Distance of other bidders	37.80**	(4.193)	0.00*	(0.000)
Same postal code	-6,834.86**	(2,596.612)	-0.16*	(0.078)
Same district	2,431.45	(1,723.317)	0.06	(0.039)
Same federal state	-761.29	(2,114.833)	-0.14**	(0.052)
Heavy construction	5,574.40	(2,974.766)	-0.07	(0.041)
General constructor	41,282.32**	(10,140.962)	0.91**	(0.101)
Open format	10,127.64**	(1,243.763)	0.08	(0.052)
Constant	-16,727.04	(9,677.279)	1.91**	(0.250)
Number of Observations	14,866			

Notes: Column (1) shows the coefficients estimated for the scale parameter λ of the Weibull distribution of bids. Column (3) is for the shape parameter ρ. Standard errors are shown in parentheses next to the parameter estimates in columns (2) and (4). $*$ ($**$) stands for significance at the 5% (1%) level.

One of the main determinants of the bids is the engineer estimate, the cost estimate of the project by the engineers of the firm providing the data. In our model, it mainly describes the heterogeneity across projects. While the log of the number of employees, our firm-specific size measure, is insignificant, we observe that bidders strategically react to their own and the travel distances of their competitors. The further away their firm is from the project site, the further away competitors and the further away the average bidder in an auction, the higher the bids. Further included dummy control variables are: same postal code of firm and project site, same district and same state; open format auctions; heavy construction auctions; and bidder is a general contractor.

Using the first order conditions (4) from the static model and (7) from the dynamic model, we back out costs and estimate their determinants using a Weibull model for each. In these models, we include variables describing a firm's cost such as backlog and distance, but no strategic variables such as backlog or distance of others. The estimated cost functions are reported in Table 7. We find similar, but quantitatively somewhat different estimates for the two cost models. There is a strong positive effect of the engineer cost estimate on firms' cost, and of the backlog as well. The driving distance to the construction site increases cost at a diminishing rate. We also find that larger firms have lower costs, consistent with economies of scale. Other controls, such as same postal code of firm and project site, same district, open format auctions, and if the bidder is a general contractor, also significantly influence firms' costs.

Summarizing, our results on the determinants of the bid distribution as well as of the distribution of costs provide us with consistent results. The number of bidders, but also observed heterogeneity across bidders and auctions, significantly influence bid and cost distributions. This is important for the merger simulations that follow.

5.2 Merger experiments

The structural models allow us to analyze how mergers affect bidding. We analyze the supposed channels of merger effects by reporting two experiments. The first experiment applies to a merger of the firms ranked first and second. In our counterfactuals, we let these two firms merge in all auctions of our sample and report the mean effect. From a competition policy perspective, this is — as outlined above — the worst merger that can happen, since the market power effects

Table 7: Determinants of the distribution of costs – static and dynamic model

	Static model		Dynamic model	
	Scale, λ	Shape, ρ	Scale, λ	Shape, ρ
	(1)	(2)	(3)	(4)
Backlog	3,909.65**	-0.00	3,836.29**	0.01
	(749.956)	(0.016)	(938.456)	(0.021)
Engineer estimate	1.07**	0.00**	1.06**	0.00**
	(0.004)	(0.000)	(0.004)	(0.000)
Log Employees	-1,290.63**	0.07**	-1,578.42**	0.04**
	(381.313)	(0.009)	(414.163)	(0.011)
Distance	134.92**	0.00**	83.76**	0.00**
	(22.059)	(0.000)	(27.498)	(0.001)
Distance squared	-0.28**	-0.00**	-0.18**	-0.00**
	(0.039)	(0.000)	(0.047)	(0.000)
Same postal code	-8,660.61**	-0.09	-9,764.55**	-0.06
	(2,924.650)	(0.052)	(2,750.515)	(0.094)
Same district	5,403.23**	-0.00	4,810.16*	-0.03
	(1,662.218)	(0.038)	(2,350.422)	(0.061)
Same federal state	2,836.94	0.02	590.48	0.19**
	(2,456.951)	(0.043)	(3,046.649)	(0.060)
Heavy construction	2,501.81	-0.06*	-3,183.84	-0.16**
	(3,314.216)	(0.030)	(4,360.812)	(0.040)
General constructor	23,186.20*	0.51**	19,577.74	0.47**
	(11,112.876)	(0.072)	(10,586.431)	(0.087)
Open format	13,943.47**	0.21**	13,561.79**	0.06
	(1,235.487)	(0.036)	(1,627.416)	(0.051)
Constant	1,294.89	2.19**	7,404.43	2.26**
	(4,137.621)	(0.087)	(4,972.079)	(0.101)
Observations	14,724		14,649	

Notes: Columns (1) and (3) shows the coefficients estimated for the scale parameter λ of the Weibull distribution of costs; columns (2) and (4) for the shape parameter ρ. Standard errors are shown in parentheses below the parameter estimates. $*$ ($**$) stands for significance at the 5% (1%) level.

are largest in this setting. The calculated effects can be interpreted as the average merger effect for all firm pairs ever first or second in our sample of auctions.

Our second experiment applies to the mergers which we empirically observe in the data. A cross tabulation of the respective rank-pairs in the auctions where both acquirers and targets jointly bid before the merger shows that the average rank of the acquirer is 4.19, and the average rank of the target is 4.24. As Table 8 shows, "worst mergers" (i.e., when bidders ranked one and two merge and denoted by "1/2"-mergers) are only observed in 4% of the auctions (3 out of 72), "1/3"-mergers in 9.7% (7 out of 72), "1/4"-mergers and "2/3"-mergers in 12.5% (9 out of 72), respectively. Acquirers rank first in 10 auctions, targets rank first in 9 auctions. In the simulations for the second experiment, we take a weighted average of the average merger effects

for all firm pairs ever ranked as empirically observed in the mergers. This means, that in 3 out of 72 cases there is a merger of firms ranked one and two, in 7 out of 72 cases a merger between firms ranked one and three, and so on. As we report winning bids and winning markups, the weighted average is an average between the "1/2"-mergers and the rest. For comparison, we also provide the results for the subsample that includes all auctions in which merging parties jointly participated before they merged.

Table 8: Ranks of bids before merger

	Target				
Acquirer	1	2	3	4+	Total
1	-	2	4	4	10
2	1	-	6	7	14
3	3	3	-	6	12
4+	5	6	6	19	36
Total	9	11	16	36	72

Notes: Ranks of bids of acquirer and target when both are bidding in the same auction.

Both experiments disentangle the two market power effects (change in observed asymmetries and reduction of the number of firms) and simulated cost savings to obtain predicted bids and markups after the merger. Concerning the first market power effect (change in observed asymmetries), we assume that the number of firms does not change, i.e., that immediate entry takes place post merger. We hereby implicitly assume that the entering firm is as efficient as the average firm.[22] Concerning the second market power effect (reduction of the number of bidders), we assume that the merger reduces the number of bidders by one. Concerning the hypothetical efficiency effect, the traditional idea is that the merged firm has two cost draws and can choose the minimum. The cost draw can depend on cost determinants, as recently applied in Li and Zhang (2015), who use hauling distance as their firm-specific cost shifter. For our experiments, we predict bids and costs using the Weibull models (3) and (5). For the counterfactual analysis, we let the combined firms choose their *minimum* backlog, distance and location, the *sum* of their employees, and the *minimum* of the unobserved cost, i.e., the residual from the Weibull cost estimations.

[22] Obviously, if we would assume that the entering firm is as efficient as the second-ranked firm, this market power effect would be zero.

We then run the following counterfactuals: *Counterfactual A:* The firms ranked one and two merge, the number of firms stays the same (immediate entry). The first-ranked bidder maintains the same cost level, but can bid the second-ranked bid. This counterfactual isolates the market power effect, if the most efficient firms merge and shade their bids more.

Counterfactual B: The number of bidders decreases by one. This counterfactual isolates the market power effect, if a merger reduces the number of actual bidders.

Counterfactual C: The firms ranked one and two merge and the number of bidders decreases by one. The merging firms can choose their minimum backlog, distance and location, the sum of their employees, and the minimum of the unobserved cost. For the new predicted bids, bidders react to the changed number of bidders and to the changed cost structure. This counterfactual isolates the hypothetical efficiency effect for a "1/2"-merger and the no-entry case.

Counterfactual A': The firms ranked as observed empirically merge, the number of firms stays the same (immediate entry). This counterfactual isolates the market power effect when firms merge that are as efficient as empirically observed.

Counterfactual C' and C": The firms ranked as observed empirically (*C'*) and in the sub-sample of actual mergers (*C"*) merge and the number of bidders decreases by one. The merging firms can choose their minimum backlog, distance, and location, the sum of their employees, and the minimum of the unobserved cost. For the new predicted bids, bidders react to the changed number of bidders and to the changed cost structure. This counterfactual isolates the hypothetical efficiency effect for the average observed merger and the no-entry case.

Table 9 contains the simulated effects. The results obtained with the static model are very similar to the results obtained with the dynamic model. The results for counterfactuals *C*, *C'* and *C"* provide the overall net effect of the merger, i.e., including the two components of the market power effect and the efficiency effect.

The upper panel of Table 9 ("Experiment 1") shows very large effects for the first experiment. Due to the market power effect of combining the two most efficient firms in all auctions, the winning bid in the static and the dynamic model increases by 7.45%. This hurts the seller, while markups go up by around 4.5 percentage points in both models benefiting the merging firms. The second component of the market power effect, i.e., reducing the number of actual bidders, is comparatively small. Winning bids increase by around 1% and markups go up by

around half a percentage point. Hypothesized cost reductions yield a decrease in the winning bid by more than two percentage points. This efficiency effect increases markups further by about one percentage point in the dynamic model, but by only 0.35% in the static model. Combining market power and efficiency effects results in an average winning bid that is 6.07% (both models) higher than the observed bids. Markups of the winners are 5.34 percentage points higher in the static model and 6.22 percentage points higher in the dynamic model relative to the markups based on observed bids.

Our results for extreme "1/2"-mergers imply that hypothesized cost efficiencies would reduce the market power effects by more than two percentage points. The seller, however, would still suffer from a sizeable increase in winning bids in case of such a merger. In turn, firms profit from higher markups and decreased costs: markups increase because the two most efficient firms combine interests, the number of actual bidders goes down and the merging firms can reap part of the efficiencies generated by the merger. Of course, the scenario on efficiencies (the merged firm has two cost draws and can choose the optimum) might be overly optimistic, and while the market power effects are immediate, the efficiency effect may materialize only after some time.

The second panel of Table 9 ("Experiment 2") shows the simulation results on mergers, if one assumes that the types of mergers, i.e.,"1/2"-merger, "1/3"-merger, etc., occur as frequently as empirically observed (counterfactuals A' and C'). Since the "average" merger involves firms with an average rank of around four (see above), not surprisingly, the market power effect due to changes in observed asymmetries as well as the hypothesized efficiency effect go down dramatically as compared to scenarios A and C. The market power effect due to the creation of a more efficient firm (again assuming simultaneous entry of an entrant that is as efficient as the average firm) is now only 0.31% on winning bids and 0.21 percentage points on markups.[23] The hypothesized efficiency effect reduces average winning bids by 1.09% (0.25 = 0.31 + 1.03 - 1.09 for the static model) and increases markups by 1.05% (1.73 = 0.21 + 0.47 + 1.05 for the static model) leading to net effects of around 0.25% on winning bids and between 1.7 (static model) and 2.7 (dynamic model) percentage points on markups. Again we observe a difference between models with a larger change in markups simulated from the dynamic model. This indicates that neglecting the strategic dynamic effect may yield underestimated markups as marginal cost are

[23] The market power effect due to a reduction in the number of actual bidders is the same as for counterfactual B, i.e. 1.03% on winning bids and 0.5 percentage points on markups.

Table 9: Estimated and counterfactual winning bids and markups

	Static model Winning Bids (1)	Static model Winning Markups (2)	Dynamic model Winning Bids (3)	Dynamic model Winning Markups (4)
Observed				
All auctions	2340.9	21.82	2342.0	23.49
	(170.4)	(0.54)	(170.5)	(0.56)
Subsample	7043.1	13.54	7043.1	14.03
	(1643.2)	(2.29)	(1643.2)	(2.29)
Experiment 1: rank 1+2/all auctions				
A: rank 1+2 only (immediate entry)	2470.3	26.34	2471.5	27.92
	(176.8)	(0.53)	(176.9)	(0.55)
Difference	7.45%**	4.52**	7.45%**	4.43**
	(0.19)	(0.09)	(0.19)	(0.09)
B: -1n.	2341.8	22.29	2342.9	23.95
	(170.3)	(0.54)	(170.4)	(0.57)
Difference	1.03%**	0.47**	1.03%**	0.46**
	(0.08)	(0.03)	(0.08)	(0.02)
C: rank 1+2/-1n./Δcost	2470.7	27.17	2471.9	29.71
	(176.9)	(0.55)	(177.0)	(0.60)
Difference (total effect)	6.07%**	5.34**	6.07%**	6.22**
	(0.13)	(0.21)	(0.21)	(0.19)
Experiment 2: observed mergers/all auctions				
A': observed mergers (immediate entry)	2346.3	22.03	2347.4	23.70
	(170.7)	(0.54)	(170.7)	(0.56)
Difference	0.31%**	0.21**	0.31%**	0.21**
	(0.01)	(0.00)	(0.01)	(0.00)
C': observed mergers/-1n./Δcost	2346.3	23.55	2347.4	26.21
	(170.7)	(0.56)	(170.8)	(0.18)
Difference (total effect)	0.25%**	1.73**	0.25%**	2.72**
	(0.01)	(0.08)	(0.01)	(0.18)
Experiment 3: observed mergers/subsample				
C": subsample/-1n./Δcost	7050.0	16.60	7050.0	17.06
	(1644.3)	(2.39)	(1644.3)	(0.18)
Difference (total effect)	0.09%**	3.06**	0.09%**	3.02**
	(0.02)	(0.66)	(0.02)	(0.68)

Notes: Winning bids in thousand Euros. Markups in percent. Subsample includes all auctions in which merging parties jointly participated before they merged. Standard errors in parentheses. $*$ ($**$) stands for significance at the 5% (1%) level.

otherwise incorrectly estimated.

The lowest panel of Table 9 ("Experiment 3") provides the counterfactual results for those auctions only where both the acquirer and target bid and, therefore, take place before the

mergers. While the results are qualitatively similar to the results with the sample using all auctions, we find larger effects for the change in markups. The net effects are again that merging firms win and sellers lose, but the effect for the latter is relatively small. Both models show about 3 percentage points higher markups after the merger and winning bids that increase by about 0.1%. Compared to the results from counterfactual *C'*, simulated winning bids increase by slightly less and markups by more. This indicates that using the subsample of actual mergers achieves higher efficiency gains than the average hypothesized merger.

Before we turn to the ex-post analysis, we analyze six full mergers and four majority acquisitions[24] individually and run a counterfactual analysis for winning bids and winning markups based on the second experiment for each acquirer. We replicate the experiments from before using the sample of all auctions, but provide the overall effect in percent only. Table 10 gives the results of this analysis. For both models, the effects of mergers on winning bids fall in the narrow range between 0.15% and 0.26%. The effects on markups vary by more and lie between 0.17% and 2.60% for the static model, and are again larger for the dynamic model, ranging between 0.58% and 3.62%. Thus, while the predicted change in the winning bids is similar across models, expected increases in markups are higher for the dynamic model.

Summarizing, our simulation analysis on the effects of mergers yields smaller numbers, if one utilizes the empirical distribution of the ranks of the merging firms. Otherwise, we obtain a rather large market power effect. This is not surprising as we let firms ranked one and two merge. Using the empirical distribution, we find slightly increased winning bids and significantly larger markups. The simulation analysis at the individual merger level indicates that effects on winning bids are small and fairly similar across mergers, while effects on markups vary more and are larger for the dynamic model than for the static model.

6 Ex-post analysis

We now compare the simulation results from the structural auction model with an ex-post evaluation of the mergers in our sample.

[24] Compared to Table 2, we lose some mergers due to data availability.

Table 10: Counterfactual winning bids and markups for full mergers and majority acquisitions

		Static model Winning		Dynamic model Winning	
		Bids	Markups	Bids	Markups
Type	Merger	(1)	(2)	(3)	(4)
Acquirer and target horizontally overlap					
Full	2	0.24%**	2.60**	0.24%**	3.62**
		(0.03)	(0.43)	(0.03)	(0.57)
Full	4	0.24%**	2.11**	0.24%**	2.83**
		(0.02)	(0.24)	(0.02)	(0.31)
Full	5	0.23%**	1.54**	0.23%**	2.53**
		(0.02)	(0.23)	(0.02)	(0.38)
Full	9	0.24%**	1.85**	0.24%**	3.08**
		(0.01)	(0.20)	(0.01)	(0.34)
Full	10	0.26%**	0.51**	0.26%**	0.68**
		(0.03)	(0.10)	(0.03)	(0.16)
Majority	13	0.25%**	1.85**	0.25%**	2.50**
		(0.01)	(0.15)	(0.01)	(0.21)
Majority	14	0.26%**	1.81**	0.26%**	2.46**
		(0.01)	(0.15)	(0.01)	(0.20)
Majority	15	0.24%**	1.85**	0.24%**	3.08**
		(0.01)	(0.20)	(0.01)	(0.34)
Acquirer and target do not horizontally overlap					
Full	7	0.21%**	0.31**	0.21%**	0.58**
		(0.04)	(0.08)	(0.04)	(0.25)
Majority	12	0.15%**	0.17	0.15%**	0.99
		(0.04)	(0.19)	(0.04)	(0.89)

Notes: Effect of the empirically observed merger in percent on the winning bids and change in markups in auctions where the acquirer won using the sample of all auctions.

6.1 Setup

For the ex-post analysis we have to make an assumption about the auctions we consider to be treated post merger. Our data source provides a classification on the subindustry of projects, which we call "segment". The depth of the classification is comparable to 6-digit NAICS codes plus one to two extra digits. Each project falls into one of 50 different segments. Assignment to a segment is sometimes on a higher level, e.g., simply "civil engineering", which presumably corresponds to projects that cover several different lower-level segments. We assume that acquirers are only treated in those auctions which fall into the segments where its target operates, either before the merger or after the merger — if it still existed as a legal entity after the merger. We make this assumption because acquirers are usually much larger companies than targets (see

Table 5) and it is unlikely that all auctions where the acquirer bids post merger are treated auctions. The assumption we make — only segments where the target is active are treated segments — essentially implies that the horizontal overlap between acquirer and target defines treated auctions. Thus, if, for example, the acquirer is active in 30 segments of the construction sector, but the target is only active in 2 of them (say bridge building and road construction), we would say that post merger all auctions in those two segments where the acquirer or target participated are treated; however, the auctions in those two segments where they do not participate as well as the 28 other segments are not treated and may potentially serve as a control group.[25]

Measuring the merger effect relative to a firm's own history clearly would ignore changes in auction characteristics or other factors that affect all bidders. Oligopoly theory and our first price auction model also predict that all firms in the market (in our case auction) are affected by the merger. In the ex-post analysis for the evaluation of the winning bid at the auction level, we estimate the equation

$$\texttt{Winning Bid}_{jt} = \alpha_0 + \alpha_1 \texttt{Post}_t + \alpha_2 \texttt{Auction}_j + \alpha_3 \texttt{Post}_t \times \texttt{Auction}_j + \omega X_{jt}, \tag{8}$$

where the dummy variable $\texttt{Post}_t$ refers to the time period when the transaction is effective. $\texttt{Auction}_j$ is a dummy variable for the auctions which we consider treated as defined above. α_3 measures the winning bids difference in an auction post merger, compared to the other, non-treated auctions. X_{jt} is a vector of bid- and auction-specific variables that are determined before the auction takes place, and includes backlog, distance, distance squared, new contracts, engineer estimate, log employees, and number of potential bidders.

The evaluation of markups and costs includes all bids. The equation for markups is

$$\texttt{Markup}_{ijt} = \beta_0 + \beta_1 \texttt{Firm}_i + \beta_2 \texttt{Post}_t + \beta_3 \texttt{Auction}_j + \beta_4 \texttt{Firm}_i \times \texttt{Post}_t + \beta_5 \texttt{Post}_t \times \texttt{Auction}_j, \tag{9}$$

where $\texttt{Markup}_{ijt}$ is either the markup from the static or the dynamic model. $\texttt{Firm}_i$ is a dummy variable for the merging firm i. β_4 measures the difference of the bids of a merging firm from the other bidders in the auction, while β_5 captures the difference of all bids in auctions which the merger treats (in the sense above) from bids in auctions which we consider non-treated.

[25] Below we run a robustness checks on this assumption (see Table 14).

The equation for costs is

$$\texttt{Cost}_{ijt} = \gamma_0 + \gamma_1 \texttt{Firm}_i + \gamma_2 \texttt{Post}_t + \gamma_3 \texttt{Auction}_j + \gamma_4 \texttt{Firm}_i \times \texttt{Post}_t + \gamma_5 \texttt{Post}_t \times \texttt{Auction}_j + \delta X_{ijt}, \tag{10}$$

where $\texttt{Cost}_{ijt}$ is either the cost from the static or the dynamic model. The dummy variables included have the same interpretation with respect to costs as the corresponding dummies have in equation (9) for markups. Again, we include the same X-variables as in equation (8).

6.2 Results

In Table 11, we show the effect of mergers on winning bids, estimated markups, and costs. We report the coefficients separately for each of the acquisitions. We only report the estimates of the α_3-, β_5- and γ_5-coefficients. We do not report the β_4- and γ_4-coefficients, because all of them are insignificant. Insignificance of treatment within the auction on the firm level is not surprising, since treatment of the merging firm affects its immediate competitors, too. Auction level effects as reported in Table 11 are therefore most relevant.

In six of the ten analyzed mergers, the changes in winning bids are insignificant, three are significant at the 10%-level, and only one merger effect is significant (positive) at the 5%-level (majority acquisition 13). Thus, the mergers in our sample do not appear to change prices (winning bids) considerably on average, consistent with the merger simulation results depicted in Table 10. Turning to the markup effects, we find a good correspondence of simulated and actual effects for full mergers, but not for majority acquisitions. On average, we obtain estimated markups that increase post merger with a similar magnitude as the simulated markups (with the only exception being merger 5 for the dynamic model which is insignificant negative). For full mergers 2, 4, 9 and 10, the effect is in the range of 1.3 to 4.2 percentage points (static model). This is very close to the predicted markup changes of Table 10. Moreover, we find that dynamic markup increases are larger than static markup increases in most cases. Majority acquisitions with a horizontal overlap, however, display significantly negative effects on markups — in contrast to our predictions of Table 10. Mergers without horizontal overlap show no significant effects on markups. Finally, we estimate reductions in costs in five of the six full mergers, only full merger 5 displays the opposite. This corresponds again reasonably well to our predictions of Table 10. In contrast, three of the four majority acquisitions experience

Table 11: Acquirers before and after the merger

Type	Merger	Winning bid (α_3) (1)	Static markup (β_5) (2)	Dynamic markup (β_5) (3)	Static cost (γ_5) (4)	Dynamic cost (γ_5) (5)
Acquirer and target horizontally overlap						
Full	2	-53.19	1.30	1.88+	-142.14+	-127.58+
		(176.91)	(0.81)	(0.96)	(76.44)	(65.34)
Full	4	-221.56+	4.20*	5.30*	-243.93*	-233.04*
		(130.29)	(0.59)	(0.70)	(55.98)	(47.75)
Full	5	14.46	0.72	-1.18	339.97*	488.54*
		(305.07)	(1.45)	(1.78)	(136.74)	(120.96)
Full	9	-151.25	3.18*	3.65*	-61.46	-76.81
		(172.48)	(0.72)	(0.84)	(67.91)	(56.90)
Full	10	-463.06+	2.54*	3.51*	-365.29*	-337.53*
		(279.99)	(1.29)	(1.57)	(121.60)	(106.20)
Majority	13	723.37*	-2.21+	-2.08	284.08*	490.50*
		(233.55)	(1.16)	(1.42)	(109.32)	(96.06)
Majority	14	-485.57+	-4.59*	-6.25*	-98.33	-133.53
		(262.30)	(1.25)	(1.51)	(118.14)	(102.37)
Majority	15	327.22	-3.33*	-2.65+	249.31*	387.03*
		(251.77)	(1.17)	(1.42)	(110.53)	(96.15)
Acquirer and target do not horizontally overlap						
Full	7	-156.66	1.16	0.67	-256.72+	-129.54
		(322.38)	(1.50)	(1.86)	(141.01)	(125.65)
Majority	12	-467.97	2.18	3.59	567.36*	551.93*
		(523.58)	(2.50)	(3.25)	(233.90)	(218.55)

Notes: Results for the coefficients on $\texttt{Post}_t \times \texttt{Auction}_j$ in equations (8), (9) and (10). Transactions that do not appear in the Table have an insufficient number of bids — either before or after the transaction, or both — to permit evaluation. An asterisk indicates significant differences at the 5%-level, a plus the 10%-level of a two sided t-test. Winning bids and costs regressions include as control variables: backlog, distance, distance squared, new contracts, engineer estimate, log employees, and number of potential bidders. Standard errors are below the coefficients, in parentheses.

increases in costs. Overall, the results from the ex-post analysis indicate that, while markups increase after full mergers, the net effect on bids appears to be close to neutral, since costs go down. Majority acquisitions differ in that markups go down on average, since it seems that cost efficiencies could not have been realized.

What do our results imply for the accuracy of predicting merger effects using simulations from auctions models? First, our simulations correspond qualitatively and in most cases quantitatively very well to actual merger effects for full mergers. For these mergers we predict close to zero or slightly positive effects on winning bid, effects of around two to three percentage points

on markups, and sizeable efficiency effects. With the exception of one full merger, this is what we actually observe. It appears that we model market power and efficiency effects reasonably well for full mergers. In contrast, our model predictions do fairly bad in predicting the effects for majority acquisitions. Not only do we miss the direction of how markups change, we also do not accurately simulate cost efficiencies. Our conclusion from this exercise is that auction models are useful tools when analyzing the ex ante effects of full mergers, but they may miss important aspects of majority acquisitions. Especially, cost efficiencies do not appear to be realized in these acquisitions (at least not in the time span analyzed by us) in contrast to our simulations. We conjecture that determinants not included in our model — e.g., problems of post-merger integration in majority acquisitions — might be responsible for these findings.

6.3 Robustness

As mentioned above, for the ex-post analysis we have to make an assumption about the auctions we consider to be treated post merger. We assume that acquirers are only treated in those auctions which fall into the segments where its target operates, essentially implying that the horizontal overlap between acquirer and target defines treated auctions. We then took as control auctions, i.e., non-treated auctions, all other auctions. With this approach we — in all probability — circumvent the problem of potential treatment of the control group, i.e., the problem of a contaminated control group. One problem with this approach might be — despite the inclusion of pre-auction characteristics of bidders and non-outcome auction-specific covariates — that the control auctions are not good comparison units, since they may be very heterogenous and very different from the merging firms' auctions. We therefore perform two robustness checks. (1) Deletion of all auctions from the sample which take place outside the target's segments. These estimations compare auctions where the acquirer or target take part post merger with auctions in the same segments of the target where the merging firms do not take part post merger. (2) Propensity-score matching on the nearest neighbor and on four nearest neighbors, using the non-outcome auction-specific covariates (number of potential bidders, new contracts, engineer estimate, heavy, general contractor, and open). Both adaptations of the control group reduce the heterogeneity of comparison units and increase comparability to treated auctions. The results are qualitatively very similar and are displayed in Tables 12, 13 and 14 in the Appendix. We conclude that the choice of control group does not affect our main results materially.

7 Conclusions

In this paper, we analyze mergers in bidding markets and consider ex-ante as well as ex-post predictions. With data from procurement auctions in the Austrian construction sector, we estimate models of first-price sealed-bid auctions. Based on estimated cost and markups, we run merger simulations and disentangle the market power effects from potential cost efficiencies. As pointed out by the theoretical literature on mergers in bidding markets, there are two market power effects. One is due to mergers that increase asymmetry (the creation of a more efficient firm allows more shading despite of still a high probability of winning). The other is the usual market power effect due to a reduction of the number of actual bidders. In our counterfactual analysis, we simulate both effects. We also compare static and dynamic models of first price auctions, and the outcomes of merger simulations with the effects of actual mergers.

Our first result is that the simulation results, as expected, depend on the assumed type of merger, i.e., the assumed ranks of the merging firms in the auctions. If the first-ranked firm merges with the second-ranked firm, the market power effect due to a change in asymmetry is very large, because the merged entity can essentially bid as high as the second-ranked firm and still wins the auction for sure. This dwarfs the market power effect due to a reduction of actual bidders. Because we witness real-world mergers in our sample period, we use information on the ranks of firms in the simulations. Empirically, the average rank of the acquirer and the target is around four. Utilizing this information we get a much smaller but more plausible (asymmetry) market power effect. Our second result is that we do not find large differences in the predictions of the static and the dynamic models when looking at winning bids. The estimated effects of mergers on markups based on the dynamic model appear to be larger (by around one percentage point) than those based on the static model.

Finally, we find that markups increase and bidders' cost go down post merger. This is true for full mergers and the pattern emerges both in the simulated counterfactuals and for the actually observed full mergers ex post. In both cases, the net effect on bids is close to neutral. This implies that consumer surplus does not increase and producer surplus goes up. Therefore, overall welfare increases for the full mergers in our sample. There is, however, a caveat. While we conclude that auction models are useful when analyzing the ex ante effects of full mergers, they seem to miss important aspects of majority acquisitions. Especially, cost efficiencies do not

appear to have realized in these acquisitions, in contrast to our simulation results. Determinants of merger effects which we do not model, e.g. problems of post-merger integration in majority acquisitions, might be responsible for these findings.

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A Additional results for ex-post analysis

Table 12: Ex-post analysis after nearest neighbor matching

Type	Merger	Winning bid (α_3)	Static markup (β_5)	Dynamic markup (β_5)	Static cost (γ_5)	Dynamic cost (γ_5)
Acquirer and target horizontally overlap						
Full	2	-114.62	4.31*	3.56*	-331.45*	-281.79*
		(129.53)	(1.09)	(1.25)	(71.66)	(68.67)
Full	4	-379.91*	5.27*	5.55*	-422.08*	-322.75*
		(142.70)	(0.88)	(0.99)	(68.98)	(62.10)
Full	5	75.64	0.46	-0.20	349.91	472.72*
		(430.96)	(1.38)	(2.15)	(215.27)	(164.85)
Full	9	-124.68	1.81+	2.33*	-62.46	-86.67+
		(104.51)	(1.03)	(1.13)	(55.53)	(50.38)
Full	10	-428.87	5.79*	8.76*	-435.42	-485.63*
		(587.41)	(1.75)	(2.09)	(268.44)	(235.02)
Majority	13	459.94	0.47	-1.22	-70.29	203.31
		(788.28)	(1.60)	(2.03)	(319.82)	(260.25)
Majority	14	-0.08	-9.47*	-10.36*	316.47*	258.28*
		(256.77)	(1.62)	(2.04)	(132.81)	(123.21)
Majority	15	295.29	-4.25*	-3.87*	135.42	325.42+
		(568.12)	(1.42)	(1.85)	(269.87)	(181.76)
Acquirer and target do not horizontally overlap						
Full	7	-1174.09	7.55*	8.55*	-1725.12*	-1206.68*
		(838.36)	(2.22)	(2.60)	(383.55)	(330.34)
Majority	12	-853.78	-1.18	4.32	-148.25	-162.43
		(790.89)	(3.64)	(4.44)	(456.53)	(432.94)

Notes: Results for the coefficients on $\texttt{Post}_t \times \texttt{Auction}_j$ in equations (8), (9) and (10). Control observations are obtained by matching the nearest neighbor of the auction where the acquirer/target participates, based on auction characteristics (number of potential bidders, new contracts, engineer estimate, heavy, general contractor, and open) and with exact before/after matching. Transactions that do not appear in the Table have an insufficient number of bids — either before or after the transaction, or both — to permit evaluation. An asterisk indicates significant differences at the 5%-level, a plus the 10%-level of a two sided t-test.

Table 13: Ex-post analysis after matching four nearest neighbors

Type	Merger	Winning bid (α_3)	Static markup (β_5)	Dynamic markup (β_5)	Static cost (γ_5)	Dynamic cost (γ_5)
Acquirer and target horizontally overlap						
Full	2	-70.85	1.64+	1.95+	-122.07*	-125.61*
		(107.38)	(0.87)	(1.01)	(56.68)	(55.15)
Full	4	-320.95*	5.98*	6.81*	-351.49*	-292.79*
		(117.42)	(0.72)	(0.83)	(59.13)	(50.88)
Full	5	51.27	-0.39	-1.90	283.23+	306.98*
		(300.53)	(1.36)	(1.93)	(154.38)	(130.31)
Full	9	-139.08	3.38*	3.83*	-47.41	-43.55
		(112.70)	(0.85)	(0.93)	(52.05)	(48.97)
Full	10	-497.35	2.42+	4.58*	-425.23*	-424.55*
		(383.05)	(1.46)	(1.80)	(196.72)	(147.38)
Majority	13	797.11	0.22	0.24	294.46	406.41*
		(496.96)	(1.17)	(1.55)	(209.42)	(171.68)
Majority	14	-740.80+	-6.36*	-7.88*	-260.91	-314.45*
		(395.96)	(1.21)	(1.58)	(158.64)	(137.27)
Majority	15	280.17	-3.71*	-2.62+	174.49	276.19*
		(371.17)	(1.10)	(1.46)	(174.58)	(123.51)
Acquirer and target do not horizontally overlap						
Full	7	-843.03+	2.56	2.00	-887.64*	-614.48*
		(482.72)	(1.71)	(2.10)	(229.10)	(197.22)
Majority	12	-1131.27	-0.17	3.98	132.45	49.71
		(979.47)	(2.59)	(3.35)	(505.21)	(396.83)

Notes: Results for the coefficients on $\texttt{Post}_t \times \texttt{Auction}_j$ in equations (8), (9) and (10). Control observations are obtained by matching the four nearest neighbors of the auction where the acquirer/target participates, based on auction characteristics (number of potential bidders, new contracts, engineer estimate, heavy, general contractor, and open) and with exact before/after matching. Transactions that do not appear in the Table have an insufficient number of bids — either before or after the transaction, or both — to permit evaluation. An asterisk indicates significant differences at the 5%-level, a plus the 10%-level of a two sided t-test.

Table 14: Merger evaluation with industry restriction

Type	Merger	Winning bid (α_3)	Static markup (β_5)	Dynamic markup (β_5)	Static cost (γ_5)	Dynamic cost (γ_5)
Acquirer and target horizontally overlap						
Full	2	-275.64	3.79	3.44	-405.48*	-341.09*
		(319.89)	(2.41)	(2.66)	(153.14)	(139.75)
Full	4	-169.32	7.91*	7.73*	-226.73*	-234.85*
		(185.05)	(1.34)	(1.47)	(86.27)	(78.88)
Full	5	-356.31	7.46*	7.89*	1236.11*	475.77
		(954.07)	(2.03)	(2.66)	(463.10)	(375.60)
Full	9	-187.12	1.62+	1.85+	-92.20	-26.43
		(128.78)	(0.95)	(1.04)	(56.71)	(49.54)
Full	10	-491.04+	2.38+	3.19*	-390.51*	-362.78*
		(278.69)	(1.29)	(1.57)	(121.97)	(106.03)
Majority	13	-201.41	-4.96+	-5.93+	321.62	425.74
		(1282.25)	(2.73)	(3.55)	(619.02)	(499.55)
Majority	14	-459.09	5.64+	-3.47	-235.49	-193.79
		(643.33)	(3.25)	(4.24)	(306.78)	(279.59)
Majority	15	-205.30	-3.29+	-4.27+	-151.83	187.99
		(862.11)	(1.93)	(2.57)	(412.99)	(330.50)
Acquirer and target do not horizontally overlap						
Full	7	-144.55	2.01	1.58	-264.12+	-173.26
		(350.77)	(1.49)	(1.85)	(153.65)	(130.41)
Majority	12	-841.57*	1.81	3.96	162.62	163.19
		(314.79)	(2.65)	(3.28)	(156.27)	(150.38)

Notes: Results for the coefficients on $\texttt{Post}_t \times \texttt{Auction}_j$ in equations (8), (9) and (10). Control group contains only auctions which are in the same segment as the target of each transaction. Transactions that do not appear in the Table have an insufficient number of bids — either before or after the transaction, or both — to permit evaluation. An asterisk indicates significant differences at the 5%-level, a plus the 10%-level of a two sided t-test.