Markups and Public Procurement: Evidence from the Czech Construction Sector, 2006-2021

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Abstract

I document the evolution of market power using firm-level data from the Czech construction sector since 2006. Contrary to the global trend of rising markups, I find that aggregate markups have decreased, declining from 40% above marginal cost in 2006 to 30% in 2021, driven primarily by firms in the upper tail of the markup distribution. By linking this data with government tenders, I examine the relationship between markups and public procurement. I find that markups are significantly higher when controlling for unobserved productivity; government contractors have price-to-marginal-cost ratios that are 0.3 higher than those of private-sector firms; and firm-level markups increase by 12% upon a firm's entry into public procurement.

Keywords Firm Behavior: Empirical Analysis; Production, Cost, Capital, Total Factor Productivity; National Government Expenditures and Related Policies: Procurement; Pricing and Market Structure; Industry Studies: Construction

JEL D22, D24, H57, L11, L74

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1 Introduction

In this paper, I investigate the relationship between markups and public procurement in the Czech construction sector over the period 2006–2021. By linking firm-level financial data with public procurement records, I explore how firms' entry into public procurement markets affects their pricing power, measured through markups. The primary focus is on understanding whether firms that win government contracts exhibit higher markups compared to those operating solely in the private sector, and how these markups evolve over time.

My research shows that, contrary to the global trend of rising markups, the average markup in the Czech construction sector has declined over the period studied. However, firms engaged in public procurement tend to maintain significantly higher markups than their private-sector counterparts. Specifically, I find that markups increase by approximately 12% after firms enter the public procurement market. This suggests that public procurement may provide opportunities for firms to exert greater pricing power, potentially due to reduced competition or other factors such as discretion and favoritism.

These findings contribute to ongoing discussions on the efficiency of public procurement systems and the extent to which they foster or inhibit competition. They also highlight the broader implications of public procurement on market power, particularly in contexts where government contracts constitute a significant portion of economic activity. This paper builds upon existing literature by providing empirical evidence of markup dynamics in public procurement, filling a gap in the understanding of how firms' market power evolves when they engage with the public sector.

1.1 Public Procurement

Public procurement accounts for approximately 12% of GDP across OECD countries, playing a critical role in government expenditure and economic activity (OECD, 2021). Ensuring efficiency in procurement is essential to prevent waste and maximize taxpayer value. Despite its significance, persistent inefficiencies arise due to issues like discretion, political favoritism, and limited competition—topics widely explored in the literature.

One major challenge in public procurement is balancing discretion with the risk of rent-seeking. Discretion allows procurement officials to tailor decisions to specific needs but also creates opportunities for corruption. In the Czech Republic, Palguta and Pertold (2017) document that officials often manipulate procurement thresholds, adjusting contract values to avoid competitive bidding. This practice bypasses open tenders and reduces transparency. Similarly, Decarolis et al. (2020) find that discretionary procedures in Italian government contracts, especially those with fewer bidders, increase the likelihood of corruption, frequently benefiting politically connected firms. Both studies suggest that while discretion can enhance efficiency, it requires robust oversight to avoid exploitation for personal or political gain. Political favoritism further contributes to inefficiency. Firms with political connections often secure contracts at inflated prices without delivering better outcomes. Baránek and Titl (2024) show that, in the Czech Republic, politically connected firms win contracts priced 6% higher than competitively awarded ones, with no corresponding improvement in quality. This misallocation of resources echoes findings in Italy, where Bandiera et al. (2009) report that public bodies with weaker governance consistently overpay for comparable goods, exacerbating procurement inefficiencies. A lack of competition, particularly single-bid contracts, also undermines procurement effectiveness. In the Czech Republic, Titl (2023) shows that about 23% of public contracts are awarded through single-bid procedures, which drive up prices. A 2012 reform aimed at reducing single-bidding resulted in a 10% drop in procurement costs, underscoring the advantages of fostering competition. In the U.S., Kang and Miller (2022) find that single-bid contracts are prevalent in federal procurement, and that unchecked discretion can stifle competition, leading to higher prices.

Overall, these findings highlight that while flexibility and discretion are important for procurement, they must be paired with strong oversight and governance to prevent corruption and ensure cost-effective, competitive outcomes.

1.2 Markups

The study of markups, defined as the ratio of price to marginal cost

$$\mu \equiv \frac{P}{c},$$

is crucial for understanding market power in both theoretical and empirical economics. Recent research has focused on how markups reflect competitive dynamics within industries, influencing welfare, pricing strategies, and policy interventions. Syverson (2024) emphasizes the dual role of markups: they signal the presence of market power and quantify its extent. Markups go beyond price-setting; they encapsulate key features of imperfect competition, allowing researchers to measure how far a firm deviates from competitive pricing. Syverson also highlights the deadweight loss associated with markups; firms with market power, unable or unwilling to engage in perfect price discrimination, often forgo socially beneficial transactions to protect inframarginal profits.

De Loecker et al. (2020) show a significant increase in U.S. markups since 1980, rising from 21% above marginal cost to 61% by 2016. This growth is concentrated among the largest firms, which have expanded their share of economic activity, indicating a growing concentration of market power. Hall (2018) corroborates this trend, further strengthening evidence of rising markups. Additionally, Autor et al. (2020) explore how increased market power has affected labor markets, particularly with the emergence of "superstar firms"—large, highly productive companies dominating their industries. These firms capture a disproportionate share of profits while employing fewer workers, contributing to the decline in labor's share of income. Autor argues that this concentration exacerbates income inequality as capital captures a larger portion of economic gains. The causes of rising markups are debated. Some researchers link this trend to weakened antitrust enforcement, which allows firms to consolidate power.

In contrast, Miller (2024) attributes the rise to technological advancements. His review suggests that productivity gains, reductions in marginal costs, and product quality improvements have enabled firms to increase markups without necessarily harming consumer welfare. This aligns with the view that technological progress boosts firm efficiency, allowing them to command higher prices through improved cost structures. However, the welfare implications of rising markups remain complex. Berry et al. (2019) caution that while higher markups may reflect efficiency gains, they could also indicate reduced competition, especially in industries with high entry barriers, where dominant firms extract excessive rents. This highlights the need to consider industry-specific factors when interpreting markup trends and assessing policy implications. Alternatively, Shapiro and Yurukoglu (2024) argue that rising markups do not necessarily signal weakened competition. In many sectors, they reflect competitive dynamics, where the most efficient firms grow larger and capture market share by offering superior products at lower costs. While some industries may experience a decline in competition, others might become more competitive due to technological progress and efficiency gains.

Estimating Markups Two primary methods are commonly used to estimate markups: the demand-based and production-based approaches. The demand-based approach estimates markups by analyzing a firm's residual demand curve, using demand elasticities to infer market power. This method is prevalent in industrial organization (IO), where firms' pricing decisions reflect their ability to raise prices above marginal cost. In perfectly competitive markets, firms have little influence over prices, but as competition diminishes, firms can increase markups. While this approach is central to studies of imperfect competition and monopoly pricing, it requires extensive data and relies on assumptions about consumer preferences and market conditions. It is especially sensitive to the specification of demand systems and the availability of price and quantity data.

A significant drawback of the demand-based method is the need for detailed instruments to identify shifts in demand. In markets with differentiated products, the heterogeneity of consumer preferences complicates estimation. De Loecker and Syverson (2021) discuss how these assumptions can affect the accuracy of demand-based estimates. While useful, this method may be impractical in industries where demand data are scarce, necessitating alternative approaches.

De Loecker and Warzynski (2012) introduced a flexible production-based method for estimating firm-level markups directly from production data. By combining input-output elasticities with input revenue shares, this approach captures market power in both product and factor markets. It overcomes many limitations of demand-based models by relying on more readily available production data. However, the De Loecker and Warzynski (DLW) method has its own limitations. One critique is its assumption of Hicks-neutral productivity, where productivity shifts equally across all inputs. Raval (2023) shows that this assumption, combined with labor market frictions like hiring costs or monopsony power, can introduce bias by treating inputs such as labor and materials similarly. Additionally, Bond et al. (2021) highlight that the DLW approach suffers from "omitted price bias" when using revenue data rather than actual output quantities, as revenue-based estimates fail to capture firm-specific price variations. Despite these criticisms, De Ridder et al. (2024) demonstrate that revenue-based markups still reveal important trends over time and between firms, making the DLW approach valuable for studying market power patterns, even if precise markup levels require careful interpretation.

The production-based approach has been widely applied both within and outside IO. It has played a crucial role in documenting the rise of markups and contributed to discussions on market power and industry concentration in the U.S. and globally (De Loecker et al., 2020). Although this method faces challenges, particularly in measuring output elasticities, it has renewed interest in how productivity data can inform debates on market power. Beyond IO, this approach has connected productivity data to global discussions on declining labor shares, the effects of globalization, and labor market issues such as monopsony power (Autor et al., 2020), making it a valuable tool in competition policy discussions.

The DLW method relies on a first-order condition for the cost minimization of a variable input in production. This method requires the output elasticity of the variable input and its revenue share. A key assumption is that, in each period, producers minimize costs by choosing inputs optimally, free from frictions. The following markup formula arises from production and cost data:

$$\mu_{it} = \theta_{it}^{V} \frac{P_{it} Q_{it}}{P_{it}^{V} X_{it}^{V}}, \tag{1}$$

where θ_{it}^{V} represents the output elasticity of input X^{V}, which is generally specific to the producer and time period.

The flexibility of this approach stems from its independence from assumptions about market conduct or a particular demand system. Multiple first-order conditions—one for each variable input—allow for the estimation of markups with different inputs. Regardless of the input used, two key components are needed: the revenue share and the output elasticity. De Loecker and Warzynski (2012) assume that firms are price-takers in input markets, which does not preclude input providers from charging markups, potentially leading to double marginalization. The derived formula highlights that marginal cost is inferred from a single variable input, without assuming substitution elasticities among inputs or returns to scale.

An essential component of this method is the output elasticity θ_{it}^{V}, estimated using the control function approach pioneered by Olley and Pakes (1996), modified by Levinsohn and Petrin (2003), and consolidated by Ackerberg et al. (2015). This method links the production function to the economic model describing firm behavior and the competitive environment in which firms operate.

1.3 Markups and Public Procurement

I use the empirical framework of De Loecker and Warzynski (2012) to analyze how markups differ between government contractors and private-sector firms. Additionally, I examine the impact of public procurement entry on firm markups. To explore this, I correlate markups with a firm's public procurement status and evaluate whether they change upon entering public procurement, controlling for input usage. The empirical model is detailed in Appendix A. It is important to note that I do not take a specific stance on any particular economic model when interpreting the estimated markup parameters. However, I reference various mechanisms to interpret the findings.

Much of the existing literature on public procurement has focused on comparisons between tenders, with little attention paid to comparisons between public procurement and private markets. Economic models in industrial organization, which consider heterogeneous producers and firm-specific markups, suggest that more productive firms set higher markups, as these firms can afford to pay the costs associated with public procurement entry. Therefore, it is expected that government contractors will have higher markups. This relationship, which stems from supply-side heterogeneity (productivity), is predicted by many models. Another strand of trade literature investigates the role of quality differences between firms. If government contractors produce higher-quality goods using higher-quality inputs, they can charge higher markups. These mechanisms suggest that, in the cross section, government contractors should have higher markups. However, the dynamics of markups over time as firms enter public procurement markets—compared to firms already engaged in public procurement or those in the private sector—remain unclear. This paper examines both the validity of economic models that link public procurement to markups and provides new evidence on the dynamics between markups and public procurement status.

Given the above, I expect higher markups for government contractors. However, these differences are influenced by both supply- and demand-side factors that affect costs and prices. The procedure of De Loecker and Warzynski (2012) provides estimates of both markups and productivity, enabling further decomposition of the markup differences between private-sector firms and government contractors. By controlling for differences in marginal costs (i.e., productivity), I assess whether government contractors still maintain higher markups. This allows me to isolate the productivity component and explore other factors affecting prices, such as corruption, favoritism, discretion, inefficiencies, and single-bidding practices, as highlighted in the public procurement literature.

2 Data

Public procurement contracts in the Czech Republic are awarded under nationwide regulations, which require procurers to publish contract details in an online system. The dataset covers contracts awarded by central, regional, and municipal governments, as well as government-owned enterprises, spanning the period from 2005 to 2021. Since the majority of these contracts pertain to construction projects, I utilize a dataset that includes all firms active in the Czech construction sector between 2006 and 2021. This dataset, obtained through Charles University's licensed access to the MagnusWeb firm-level database (Dun & Bradstreet Czech Republic, a.s.), provides full company accounts for an unbalanced panel of 1,297 firms. The sample is restricted to firms with financial data for at least two consecutive periods, and the top and bottom one percentile of firms are trimmed based on their sales-to-cost of goods sold ratio to improve robustness in markup estimation. By linking firm-level data with public procurement records, I can track each firm's involvement in public procurement. At any given time, I can determine whether a firm is active exclusively in the private sector, has entered public procurement, has exited it, or remains an ongoing government contractor.

Table 1: **Firms and Public Procurement in Czech Construction**

Year	**No. firms**	**No. Firms Active in Public Procurement**
2006	227	86
2007	290	97
2008	348	112
2009	412	131
2010	497	138
2011	506	130
2012	457	152
2013	235	97
2014	243	96
2015	245	118
2016	338	174
2017	660	376
2018	708	388
2019	764	408
2020	769	426
2021	562	298

3 Results

In this section, I apply the De Loecker and Warzynski (2012) framework to estimate markups for Czech manufacturing firms, testing whether government contractors, on average, exhibit different markups compared to private-sector firms. Additionally, I leverage the substantial entry into public procurement markets within my dataset to analyze how markups evolve as firms enter and exit these markets. To the best of my knowledge, this is the first study to provide robust econometric evidence of this relationship.

To estimate markups in the context of public procurement, I incorporate a firm's procurement status, as well as any other factor influencing optimal input demand, into the control function. Specifically, I include a firm's public procurement status in all input demand equations (as an element of z_{it}) and allow it to directly influence the law of motion for productivity. After estimating the output elasticity of the variable inputs, I compute the implied markups using the first-order conditions (FOCs) derived in Equation 1.

The analysis begins by documenting the main patterns of markups in the Czech construction sector. I focus on these estimates to highlight several key findings. First, I examine the relationship between markups and public procurement status both cross-sectionally and over time. Second, I explore how markups relate to other economic variables. Finally, I discuss the broader implications of my results on aggregate markup trends.

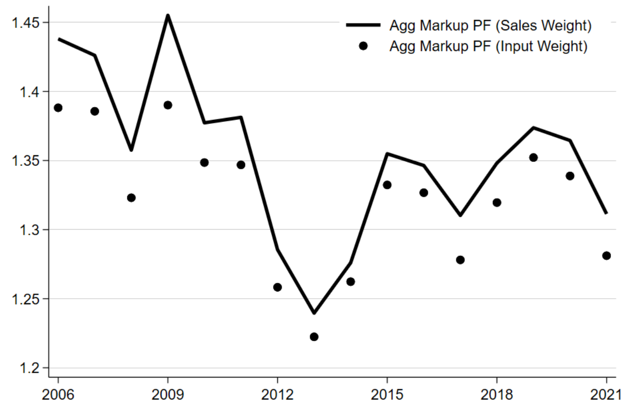
3.1 The Evolution of Markups in Czech Construction

Aggregate Markup The markup measure in Equation 1 is the product of the output elasticity, θ, and the inverse of the variable input's revenue share, $\frac{PQ}{P^V V}$. The revenue share is directly observed in firms' income statements, while I estimate the output elasticities. These elasticities are both firm- and time-specific, reflecting technological differences across firms and changes over time. The average markup is calculated as:

$$\mu_t = \sum_i m_{it}\mu_{it},$$

where m_{it} represents the weight of each firm. I use the share of sales as the weight and also compare it with total costs as the input weight. The gap between sales-weighted and input-weighted aggregate markups is notable. Figure 1 illustrates the evolution of average markups in the construction sector over time. Early in the sample period, markups remained stable around 1.45, declined to 1.25 during 2012–2014, and then increased slightly above 1.35 by the 2020s. In 2006, the average markup stood at 44% above marginal cost, compared to 31% in 2021.

Figure 1: Average Markups. Estimated output elasticities $\hat{\theta}_{it}^{V}$ are time- and firm-specific.

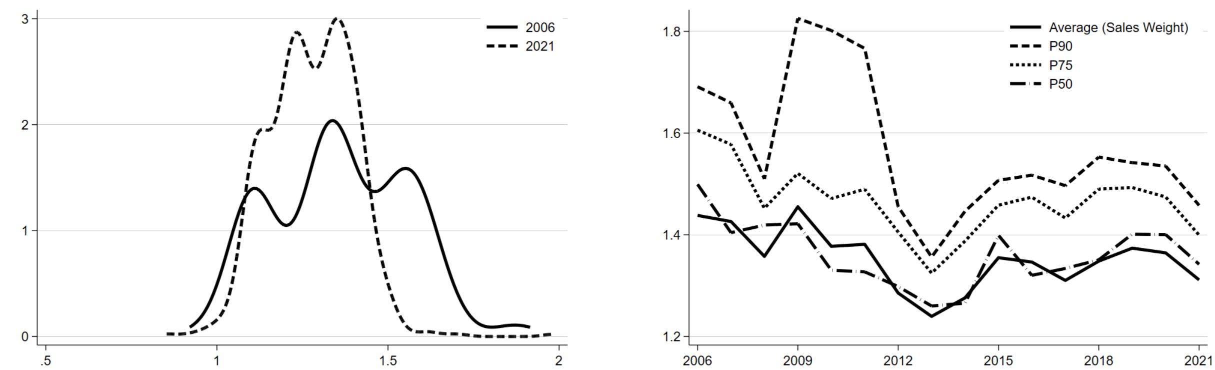


The Distribution of Markups Averages alone do not fully capture the changes in the distribution of markups. The strength of the De Loecker and Warzynski (2012) method lies in its ability to estimate firm-specific markups, allowing for an analysis of the entire distribution. One key finding is that the overall decline in markups is driven by a small number of firms, with the majority experiencing only a modest decrease. To illustrate the shifts in the distribution, I plot the kernel density of unweighted markups for 2006 and 2021 in Figure 2a. The variance of markups has narrowed over time, with a notable thinning and shortening of the upper tail. This reduction in the upper tail largely accounts for the decline in the average markup. Appendix B provides the data underlying Figure 1.

Since the kernel density does not account for firm weights, I also plot the moments of the sales-weighted markup distribution over time in Figure 2b. Firms are ranked by markup, with percentiles weighted by each firm's market share, making the percentiles comparable to the share-weighted average. The ranking is updated annually, so the top firms may vary from year to year.

The decline in average markups is driven by firms in the upper half of the markup distribution. The median (P50) and lower percentiles remain mostly stable. The sharpest drop occurs at the 90th percentile, particularly before 2012, where markups fall from 1.8 to 1.4. This indicates that the overall reduction in average markup is primarily due to a few firms experiencing significantly lower markups than in earlier periods. This finding aligns with Titl (2023), who shows that the 2012

Figure 2: The Distribution of Markups $\hat{\mu}_{it}$



(a) Kernel Density (unweighted)

(b) Percentiles (revenue-weighted)

Czech public procurement reform, which eliminated single-bid contracts, led to a 10% reduction in prices relative to estimated costs for these contracts.

3.2 Relating Markups and Public Procurement

Do Government Contractors Have Different Markups? Given the availability of firm-specific markups, I can directly relate a firm's markup to its public procurement status using a regression framework. I estimate the percentage difference in markups between government contractors and private-sector producers. A key advantage of using log markups is that the results remain robust even if the variable inputs used to compute markups are subject to adjustment costs. As long as government contractors are not disproportionately affected by these costs, the results hold. Additionally, I rely on logged markups because the variation in firm-level markups is substantial, and ordinary least squares (OLS) helps minimize proportional deviations rather than absolute deviations. After estimating the regression, I convert these percentage differences into absolute markup values.The specification used is:

$$\ln \mu_{it} = \delta_0 + \delta_1 pp_{it} + \mathbf{b}'_{it}\sigma + \nu_{it}, \tag{2}$$

where pp_{it} is a public procurement dummy, and δ_1 measures the percentage markup premium for government contractors.[1] The vector $\mathbf{b}_{it}$ contains all control variables, with σ as the corresponding coefficients. It is important to note that I do not interpret δ_1 as a causal parameter; instead, this

[1] I control for variable input and capital use to capture differences in size and factor intensity, as well as year-subindustry interactions to account for aggregate markup trends.

specification tests whether government contractors, on average, have different markups. To my knowledge, this relationship has not been previously documented, making these results an important contribution.

While I am not primarily interested in the coefficients of the control variables, I will revisit the correlation between markups and other economic factors later. This regression is estimated at the manufacturing level, with a full interaction of year and sub-industry dummies.[2] Once δ_1 is estimated, I compute the absolute markup difference by applying the percentage difference to the constant term, which represents the domestic average markup. I denote this difference by μ_{PP}, calculated as $\hat{\mu}_{PP} = \hat{\delta}_1 \exp(\hat{\delta}_0)$, following the parameter estimates. Table 2 presents the results.

Table 2: Markups and Public Procurement I: Cross-Section

Markup (level)	Coefficient	Std. Err.	z	[95% Conf. Interval]
Public Procurement Premium	0.327	0.018	18.08	[0.2918, 0.3628]

Note: Estimates are obtained after running equation 2. The standard error is derived from a nonlinear combination of the relevant parameter estimates, using the delta method, and is cluster robust. All regressions include variable input, capital, and full 47 year and NACE 2-digit division dummies as controls. N = 7,261. Adjusted R² = 0.758.

The percentage premium parameter estimate $\hat{\delta}_1$ is 0.149, with a highly precise standard error of 0.003. These results align with economic models where government-contracting firms, on average, charge higher markups due to greater productivity, allowing them to undercut rivals in the tender process. This prediction is supported by comparing the average markup of government contractors to private-sector firms in the cross-section. However, some models suggest that firms with identical productivity levels will charge the same markup, implying that productivity differences are the primary driver of markup variations. The estimation procedure provides both markups $\mu_{it} = \frac{P_{it}}{C_{it}}$ and productivity ω_{it}, allowing for a more nuanced analysis. When both a firm's public procurement status and productivity are included, the coefficient on public procurement (δ_1) decreases and changes sign, from 0.15 to 0.03, as expected. Controlling for productivity accounts for differences in marginal costs, meaning the coefficient on public procurement status now reflects the variation in average prices between government contractors and non-contractors. To clarify, I estimate the following:

$$(\ln P_{it} - \ln C_{it}) = \delta_0 + \delta_1 pp_{it} + \delta_2 \omega_{it} + b'_{it}\sigma + \nu_{it},$$

Here, δ_1 measures the average price difference (in percentages) if ω_{it} fully captures $\ln C_{it}$. Importantly, the public procurement effect remains significant even after controlling for productivity.

[2] I also estimated the model by year and industry; the magnitude varies as expected—see Appendix C.

In fact, the public procurement dummy explains approximately 20% of the markup difference, indicating that factors beyond productivity—such as differences in average prices—play a crucial role in explaining the markup disparity between government contractors and private-sector firms. This finding is consistent with the public procurement literature, which highlights varying levels of competitiveness between public procurement and private markets. Additionally, simple differences in demand elasticities and income across markets could also explain price variations, though data constraints prevent further discrimination between these mechanisms.

These results carry potentially significant policy implications. Models with heterogeneous firms emphasize the reallocation of market share from less efficient producers to more efficient ones, with government contractors expected to be more productive, enabling them to cover the fixed costs of entering public procurement markets. However, the findings call for a more cautious interpretation of the public procurement productivity premium and its role in aggregate productivity growth. Given that measured productivity is a residual of a sales-generating production function, it captures the unexplained portion of sales from the factors used in production and may include unobserved differences in input and output quality, as well as market power effects. These findings underscore the need to study the public procurement-productivity relationship alongside market power within an integrated framework. In the next section, I further explore the markup trajectory as a function of public procurement status.

Public Procurement Entry and Markup dynamics So far, I have estimated differences in average markups between government contractors and private-sector firms. My dataset also allows me to investigate whether markups vary significantly within the group of government contractors. In particular, I explore whether a specific pattern of markups emerges for firms entering public procurement markets, both before and after they become government contractors. These results can help test theories of self-selection into public procurement markets. I now focus on three categories of government contractors identifiable in my sample: *starters* (firms that enter public procurement), *quitters* (firms that exit public procurement), and *continuous contractors* (firms that contract with the government throughout the sample period) (see Appendix D). I estimate the following regression, comparing markups before and after public procurement entry and exit, while also estimating the markup differential for firms that consistently receive government contracts:[3]

$$\ln \mu_{it} = \gamma_0 + \gamma_1 \text{Entry}_{it} + \gamma_2 \text{Exit}_{it} + \gamma_3 \text{Always}_i + \mathbf{b}'_{it}\sigma + \nu_{it}, \tag{3}$$

[3]I exclude 152 firms that enter or exit public procurement markets more than once during the sample period.

where $\text{Entry}_{it} = 1$ if a firm becomes a government contractor and 0 otherwise, and $\text{Exit}_{it} = 1$ if a firm ceases contracting with the government. The constant term captures the average log markup for private-sector firms, including those that enter or exit public procurement markets. The primary interest lies in the coefficient γ_1, which measures the percentage markup difference for starters between the pre- and post-public procurement periods. Similarly, γ_2 measures the effect of public procurement exit on markups, while γ_3 captures the markup difference for continuous contractors, which I expect to be positive. Given the static nature of most models, there is little theoretical guidance for γ_1; hence, these results provide new empirical evidence on markup dynamics and public procurement status. I compute the implied markup-level effect of public procurement entry as:

$$\hat{\mu}_{PP}^{entry} = \hat{\gamma}_1 \exp(\hat{\gamma}_0),$$

and report the results in Table 3. I find that public procurement entry is associated with substantially higher markups, approximately 12%, after controlling for aggregate markup changes. The other coefficients align with expectations (see Appendix E). Notably, including productivity (as done earlier) reveals a significant effect for public procurement entry (t-statistic = 4.5). This indicates that price changes are linked to public procurement entry, likely influenced by factors such as competition, corruption, discretion, demand conditions (e.g., elasticities), and quality differences, as discussed previously. Table 3 presents both percentage and level estimates. My results indicate that public procurement entry is associated with a significant markup increase of approximately 12%, corresponding to a level increase between 0.23 and 0.35 (95% confidence interval, calculated using the delta method). When allowing the markup effect to vary with public procurement intensity—by interacting the public procurement dummies with the share of export sales in total sales—the coefficient on public procurement entry is larger, indicating a 14.5% increase. This allows me to trace the markup trajectory over time based on the share of public procurement sales in total sales.

Interpreting My Results I report two major findings: (i) in the cross-section, government contractors have higher markups than their private-sector counterparts within the same industry, and (ii) in the time series, markups increase when firms enter public procurement markets, even after controlling for aggregate demand and supply effects via year dummies. How can these results be explained? Several hypotheses can account for these findings. First, more efficient producers are likely to face more efficient competitors, charge lower prices, sell more in the private market, and outcompete rivals in public procurement tenders. Their cost advantage enables them to set

Table 3: Markups and Public Procurement II: Entry Effect

Entry Effect on Markups	Percentage ($\hat{\gamma}_1$)	Level ($\hat{\mu}_{PP}^{entry}$)
Public Procurement Premium	0.120 (0.006)	0.275 (0.022)

Note: Estimates are obtained after running equation 3. The $\hat{\mu}_{PP}^{entry}$ standard error is derived from a nonlinear combination of the relevant parameter estimates, using the delta method, and both standard errors are cluster robust. All regressions include variable input, capital and full 47 year and NACE 2-digit division dummies as controls. Firms that enter or exit public procurement markets are not included in the regression: N=5,744. Adjusted R^2 = 0.736.

higher markups under certain conditions regarding the relative efficiency of firms in both private and public procurement markets. These firms also tend to exhibit higher measured productivity. An alternative explanation is that demand elasticities differ in public procurement markets, or that government valuations of goods differ from those in the private sector. The exact mechanism underlying these results cannot be tested with the available data, as I lack firm-specific price information that could help distinguish the markup difference between cost and price effects. However, I demonstrated that even after controlling for cost differences, Czech government contractors still exhibit higher average markups, suggesting that other factors influencing prices are at play. This aligns with recent work by Titl (2023), Baránek and Titl (2024), and Szucs (2024), which highlight the role of competition, discretion, and favoritism in public procurement markets.

In conclusion, my evidence shows that markups differ for government contractors and increase significantly—both economically and statistically—when firms enter public procurement markets.

Markups and Productivity Although not the primary focus of my analysis, I extend the investigation by relating firm-level markups to productivity. The De Loecker and Warzynski (2012) framework provides estimates for both markups and productivity. Specifically, after estimating the production function coefficients, I derive productivity as follows:

$$\hat{\omega}_{it} = \hat{\phi}_{it} - f(v_{it}, k_{it}; \hat{\beta}),$$

where $f(v_{it}, k_{it}; \hat{\beta})$ represents the predicted output based on variable inputs and capital, using the estimated coefficients $\hat{\beta}$. A broad class of industrial organization models predicts that firms with lower marginal costs (i.e., higher productivity) tend to charge higher markups, all else being equal. For instance, in Cournot competition models, more productive firms capture larger market shares and, consequently, set higher markups. I estimate equation 2 again, this time replacing export status with productivity, and find a highly significant and positive coefficient of 0.89 on productivity. These results align with a wide range of theoretical models, confirming that more productive firms charge higher markups. However, I refrain from further analysis, as productivity estimates may include price or demand variation, making them imperfect measures of marginal costs. The De Loecker and Warzynski (2012) framework could be used to explore the distinct roles of productivity and markups in public procurement entry and exit behavior—an important avenue for future research, though beyond the scope of this paper. It is also important to note that the productivity estimates capture all unexplained variations in total revenue from input factors, potentially including market power effects, as emphasized in public procurement literature. [4]

Heterogeneity and Robustness I discuss several robustness checks below. First, I explore differences in markups for government contractors in the civil engineering sub-industry relative to other construction projects, as well as differences in markups for government contractors classified as sole proprietors compared to companies and cooperatives. Next, I address the role of the decreasing public procurement markup premium in driving the aggregate markup trajectory over time. Lastly, I evaluate the robustness of using deflated sales to proxy for output.

I have shown that government contractors generally have higher markups and that these increase after entering public procurement. However, government contractors operate in different markets, and my markup estimates encompass a mix of market-specific markups. To investigate whether markups differ across construction sub-industries, I leverage firm-specific public procurement project data. Specifically, I revisit the effect of public procurement entry on markups, accounting for contracting intensity, to examine the distinct effects on private-sector and public procurement markups.

In the Czech Republic, public procurement in construction includes building construction, civil engineering, and specialized activities such as electrical and plumbing installations. To determine if markups are higher for contractors involved in complex projects like road and railway construction, I introduce interaction terms for the NACE 2-digit division 42 (civil engineering) in equation 2. I estimate a point coefficient of 0.037 (standard error = 0.01), reflecting approximately a 4% higher markup for government contracts in civil engineering compared to average contracts for building construction and specialized activities. This result aligns with the "superstar firm" hypothesis (Autor et al., 2020), as civil engineering firms tend to have higher factor intensity (capital and cost of goods sold). Due to data limitations, I cannot test other hypotheses, such as differen-

[4] Both markups and productivity enter significantly in a public procurement entry and exit logit regression, controlling for aggregate effects. This suggests that both play distinct roles in shaping public procurement entry behavior.

tial quality leading to greater markups, which remains a topic for future research. I also examine whether markups differ for government contracts supplied by sole proprietors compared to those supplied by companies or cooperatives. My dataset identifies 12 sole proprietors, and I find a highly significant (t-statistic = 8.09) interaction term of 0.082, suggesting a notable markup premium for sole proprietors. These findings may indicate possible discretion, as documented by Baránek and Titl (2024).

In addition, I interact the public procurement dummy with yearly indicators for 2006–2021, using 2006 as the reference year. The results show significantly lower markup premia over time, with differences in markup premia relative to 2006 growing from around -1% to more than -4% by the end of the period. These findings mirror those in Appendix C, obtained by estimating equation 2 separately for each year. This suggests that the declining public procurement markup premium has played a substantial role in the overall decline in aggregate markups.

Decomposing the Public Procurement Entry Markup Effect Thus far, I have demonstrated that markups increase when firms enter public procurement markets. However, my markup estimates reflect a combination of private-sector and public procurement market markups. While the De Loecker and Warzynski (2012) framework can estimate market-specific markups, my dataset does not include information on hours worked or employees by destination market, which limits my ability to disentangle private-sector and public procurement markups. I instead focus on the share of public procurement sales in total sales, interacting this with the public procurement entry dummy to determine if private-sector markups change upon public procurement entry.

For firms with a small share of sales from public procurement (e.g., less than 1%), I examine whether private-sector markups change. I find a significant coefficient of 0.117 for γ_1, corresponding to a level effect of 0.27, consistent with previous estimates. However, when adjusting for the public procurement sales share, the markup entry effect is minimal for firms selling a small proportion in public procurement markets. For firms with less than 1% of sales from public procurement, markups increase by only 0.12%, suggesting no significant change in private-sector markups.

This approach has limitations. As public procurement sales shares may increase over time, separating private and public procurement markups becomes challenging. Moreover, the assumption that inputs are used in proportion to final sales may not hold, and a more optimal weight should be considered in future research. To estimate market-specific markups by firm, one could introduce a demand system for each market alongside an assumption about the cost function. While the De Loecker and Warzynski (2012) approach avoids the need to specify these assumptions, I can still compare markups across producers and examine how markups change with public procurement entry over time, without decomposing market-specific markups within a firm.

Unobserved Prices and Revenue Data In estimating output elasticities, I implicitly treat deflated sales as a proxy for physical quantity, potentially introducing omitted variable bias, as discussed by Klette and Griliches (1996). However, in my context, I am less concerned with obtaining precise productivity estimates. As noted by De Loecker and Warzynski (2012), unobserved prices primarily affect productivity estimates. In my case, unobserved prices likely bias output elasticities downward, as increases in input usage generally drive prices down under common demand and cost specifications. This suggests that I may underestimate markups, but this bias predominantly affects level estimates rather than the relationship between markups and public procurement status. To address this issue, I correct markups using a proxy for productivity, $h(\cdot)$, controlling for price variation correlated with productivity. Although demand shocks unrelated to the non-parametric output, including the proxy $\phi_t(\cdot)$[5], may still bias the input coefficient estimates, this does not impact my primary results, as I consistently relate logarithmic markups to public procurement status. I estimate the following regression:

$$\left(\ln \theta_{it}^V - \ln \alpha_{it}^V\right) = \theta_0 + \theta_1 pp_{it} + \nu_{it},$$

where price bias is expected to affect output elasticities. When employing a more flexible production technology, such as the translog, I encounter a trade-off: allowing output elasticities to vary introduces potential bias from unobserved prices. Nevertheless, my average percentage difference in markups remains consistent, provided the difference $\ln \hat{\theta}_{it}^V - \ln \theta_{it}^V$ is not correlated with public procurement status pp_{it}. To mitigate this issue, I control for inputs in all markup regressions. Using the translog production function, I estimate:

$$\hat{\theta}_{it}^V = \theta_{it}^V + \rho(v_{it}, k_{it}),$$

where $\rho(\cdot)$ captures the potential bias stemming from unobserved firm-level price deviations. This strategy is applied consistently throughout my analysis.

[5]Refer to Appendix A for further details on this notation.

4 Conclusion

Using firm-level data on publicly traded firms in the Czech construction sector, I analyze the evolution of market power by estimating firm-specific markups and documenting their distributional characteristics. Since 2006, markups have dropped from 40% to nearly 30% in 2021, representing a 10 percentage point reduction. This decline is predominantly driven by firms with the highest initial markups. Over time, the distribution of markups has become less skewed, characterized by a thinner upper tail.

I also establish the link between markups and public procurement using a method that accommodates a wide range of price-setting models while recovering firm-specific markups. This approach eliminates the need for assumptions regarding constant returns to scale or explicit measures of the user cost of capital. Using data on Czech construction firms, I test whether (i) government contractors charge higher markups on average, and (ii) markups change when firms enter or exit public procurement markets. The Czech Republic provides a particularly interesting context, having transitioned from a centrally planned to a market economy with relatively fast GDP growth. However, institutional weaknesses, particularly corruption and inefficiencies in public procurement, have been identified as key impediments to economic progress. The results show significant and robust differences in markups between government contractors and private-sector firms. Government contractors consistently exhibit higher markups, which aligns with the observed productivity premium among these firms. However, these findings raise important questions about the nature of these revenue-based productivity differences. I also provide new econometric evidence that markups increase significantly when firms enter public procurement markets. These findings suggest that government contractors exhibit greater market power, which shifts significantly when firms enter public procurement. Furthermore, examining the heterogeneity in public procurement markup premia, I find that civil engineering projects and sole proprietors benefit from significantly higher pricing power compared to other public procurement construction projects and entities. By linking the fall in aggregate markups to the dynamics of public procurement markups, I provide empirical evidence of the factors driving the overall decline in markups. These results represent a preliminary step toward understanding the relationship between market power and public procurement. They corroborate existing evidence and offer potential explanations for the substantial gains in market power observed when firms become government contractors.

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Appendix

A The De Loecker and Warzynski Framework

Consider an economy with N firms, indexed by i. Firms are heterogeneous in terms of their productivity Ω_{it} and production technology $Q_{it}(\cdot)$. In each period t, firm i minimizes the contemporaneous cost of production given the following production function:

$$Q_{it} = Q_{it}(\Omega_{it}, V_{it}, K_{it}),$$

where V is the vector of variable inputs of production (e.g., labor, intermediate inputs, materials, etc.), K_{it} is the capital stock, and Ω_{it} represents productivity. The key assumption is that within each period, variable inputs adjust frictionlessly, while capital is subject to adjustment costs and other frictions. For simplicity, we treat the vector V as a scalar V for exposition purposes. We consider the Lagrangian objective function associated with the firm's cost minimization problem:

$$L(V_{it}, K_{it}, \lambda_{it}) = P_{V_{it}} V_{it} + r_{it} K_{it} + F_{it} - \lambda_{it} \left(Q(\cdot) - Q_{it} \right),$$

where P_V is the price of the variable input, r is the user cost of capital, F_{it} is the fixed cost, and λ_{it} is the Lagrange multiplier. The first-order condition with respect to the variable input V is given by:

$$\frac{\partial L_{it}}{\partial V_{it}} = P_V - \lambda_{it} \frac{\partial Q(\cdot)}{\partial V_{it}} = 0.$$

Multiplying all terms by $\frac{V_{it}}{Q_{it}}$ and rearranging, we obtain the expression for the output elasticity of input V:

$$\theta_{it}^V \equiv \frac{\partial Q(\cdot)}{\partial V_{it}} \cdot \frac{V_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \cdot \frac{P_V V_{it}}{Q_{it}}.$$

The Lagrange multiplier λ_{it} is a direct measure of marginal cost, and we define the markup as the ratio of price to marginal cost: $\mu_{it} = \frac{P}{\lambda_{it}}$. Substituting marginal cost into the markup expression, we derive the formula for the markup:

$$\mu_{it} = \theta_{it}^V \cdot \frac{P_{it} Q_{it}}{P_V V_{it}}.$$

Consider the following general production function:

$$Q_{it} = F(V_{it}^1, V_{it}^2, \ldots, V_{it}^V, k_{it}; \beta) \exp(\omega_{it}),$$

where Q_{it} is the output of firm i at time t, V_{it}^v are the variable inputs, k_{it} is the capital stock, β represents the common technology parameters, and ω_{it} is the firm-specific productivity shock. Next, we consider the log-linear version of the production function, incorporating unobserved productivity shocks ω_{it} and measurement error ϵ_{it}:

$$y_{it} = f(v_{it}, k_{it}; \beta) + \omega_{it} + \epsilon_{it},$$

where y_{it} is the logged output, $f(x_{it}, k_{it}; \beta)$ is the production function in log form, v_{it} represents the vector of variable inputs, k_{it} is capital, and ϵ_{it} includes unanticipated production shocks and measurement error. We explicitly allow for measurement error in output and assume that ϵ_{it} is i.i.d. and uncorrelated with input choices. To obtain consistent estimates of the parameters of the production function β, and thus compute θ_{it}^V, we use the demand for variable inputs as a proxy for productivity:

$$v_{it} = v_t(k_{it}, \omega_{it}, z_{it}),$$

where z_{it} represents additional state variables that influence input demand, such as input prices or a firm's public procurement status. By inverting the input demand function $v_t(\cdot)$, we can recover an estimate of unobserved productivity ω_{it}. We start by specifying a second-order approximation translog production function, which is given by:

$$y_{it} = \beta_v v_{it} + \beta_k k_{it} + \beta_{vv} v_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{vk} v_{it} k_{it} + \omega_{it} + \epsilon_{it},$$

where y_{it} represents the log of output for firm i at time t, v_{it} and k_{it} are the logged values of variable and capital inputs, and ω_{it} denotes unobserved productivity. The term ϵ_{it} captures measurement error and unanticipated production shocks. In the first stage, we estimate expected output using the following equation:

$$y_{it} = \varphi_t(v_{it}, k_{it}, z_{it}) + \epsilon_{it},$$

where $\varphi_t(\cdot)$ captures the systematic component of output, which depends on variable inputs, capital, and additional controls (z_{it}) such as demand or market conditions that affect input demand.

These control variables help ensure that the productivity estimates are robust even in the presence of imperfect competition or heterogeneous demand across firms. The first-stage estimate of expected output, $\hat{\varphi}_{it}$, is obtained as follows:

$$\hat{\varphi}_{it} = \beta_v v_{it} + \beta_k k_{it} + \beta_{ll} v_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{vk} v_{it} k_{it} + h_t(v_{it}, k_{it}, z_{it}),$$

where $h_t(\cdot)$ accounts for variations in productivity driven by variable inputs, capital, and other firm-specific factors. The second stage relies on the law of motion for productivity, modeled as a first-order Markov process:

$$\omega_{it} = g_t(\omega_{it-1}, p_{it-1}) + \xi_{it},$$

where ξ_{it} represents the productivity innovation. To account for firm-level decisions that affect future productivity, such as public procurement status, we allow for additional lagged and observable decision variables p_{it-1} in the estimation of the productivity process. This adjustment addresses the potential issues raised regarding the limitations of assuming exogenous productivity processes. Once we have estimated $\hat{\varphi}_{it}$, we compute the firm's productivity ω_{it} for any given parameter set $\beta = (\beta_v, \beta_k, \beta_{vv}, \beta_{kk}, \beta_{vk})$ using the following expression:

$$\omega_{it}(\beta) = \hat{\varphi}_{it} - \beta_v v_{it} - \beta_k k_{it} - \beta_{vv} v_{it}^2 - \beta_{kk} k_{it}^2 - \beta_{vk} v_{it} k_{it}.$$

We then estimate the productivity innovation $\xi_{it}(\beta)$ by non-parametrically regressing $\omega_{it}(\beta)$ on its lag $\omega_{it-1}(\beta)$ and the public procurement indicator, and recovering the residuals. This process enables us to estimate all of the production function coefficients and to account for the role of productivity in the input-output relationship. To obtain the production function parameters, we form moment conditions based on the innovations to productivity. These moments rely on a timing assumption that capital decisions are made one period ahead, meaning that capital should not be correlated with the innovation to productivity. We use the following moment condition:

$$E\left[\xi_{it}(\beta)\begin{pmatrix} v_{it-1} \\ k_{it} \\ v_{it-1}^2 \\ k_{it}^2 \\ v_{it-1}k_{it} \end{pmatrix}\right] = 0,$$

where $\xi_{it}(\beta)$ represents the productivity innovation, and v_{it-1} and k_{it} are the lagged variable and capital inputs, respectively. These moment conditions allow us to identify the parameters of the production function using standard Generalized Method of Moments. The identification strategy exploits the fact that capital is predetermined, meaning that it is decided in advance and should not be correlated with the contemporaneous productivity innovation ξ_{it}. By contrast, variable inputs are assumed to respond flexibly to productivity shocks within the period, and thus the expectation of $v_{it}\xi_{it}$ is expected to be nonzero. In order for lagged variable inputs to serve as a valid instrument for current variable inputs, it is necessary to assume that input prices are serially correlated over time. Finally, we use block bootstrapping to estimate standard errors, ensuring that the error structure reflects the autocorrelation across firms and time.

Under a translog production function, the output elasticity for variable input (V) is given by:

$$\hat{\theta}_{it}^{V} = \hat{\beta}_v + 2\hat{\beta}_{vv} v_{it} + \hat{\beta}_{vk} k_{it},$$

With the estimated output elasticities in hand, we use the first-order condition on input demand and our to compute markups as follows:

$$\mu_{it} = \frac{\hat{\theta}_{it}^{V}}{\hat{\alpha}_{it}^{V}},$$

where $\hat{\theta}_{it}^{V}$ is the output elasticity of input V, and $\hat{\alpha}_{it}^{V}$ is the expenditure share of input V in firm i's total revenue. However, we do not directly observe the true expenditure share of input V_{it}, as we only observe firm-level output $\tilde{Q}_{it}$, which is measured with error. The observed output is given by:

$$\tilde{Q}_{it} = Q_{it} \exp(\epsilon_{it}),$$

where Q_{it} is the true output and ϵ_{it} represents measurement error or unanticipated shocks to output. The first stage of our procedure provides an estimate of ϵ_{it}, which we use to correct the observed expenditure share:

$$\hat{\alpha}_{it}^{V} = \frac{P_{it}^{V} V_{it}}{P_{it} \tilde{Q}_{it}} \exp(\hat{\epsilon}_{it}),$$

This correction eliminates any variation in expenditure shares not related to variables that affect input demand, including input prices, productivity, technology parameters, and market characteristics, such as the elasticity of demand and income levels.

B Unweighted Markup Distribution

Table 4: Summary Statistics by Year

Year	p10	p25	p50	p75	p90	Mean	SD	N
2006	1.09	1.19	1.35	1.51	1.60	1.36	0.20	227
2007	1.04	1.10	1.35	1.50	1.58	1.32	0.20	290
2008	1.06	1.11	1.27	1.42	1.49	1.27	0.17	348
2009	1.05	1.10	1.28	1.42	1.49	1.27	0.18	412
2010	1.03	1.09	1.25	1.37	1.45	1.25	0.18	497
2011	1.04	1.10	1.28	1.40	1.49	1.27	0.19	506
2012	1.02	1.11	1.24	1.36	1.44	1.24	0.17	457
2013	1.04	1.12	1.20	1.30	1.35	1.21	0.13	235
2014	1.03	1.13	1.23	1.35	1.42	1.23	0.14	243
2015	1.09	1.20	1.29	1.42	1.47	1.31	0.19	245
2016	1.08	1.19	1.31	1.44	1.50	1.31	0.17	338
2017	1.13	1.23	1.30	1.42	1.48	1.32	0.16	660
2018	1.13	1.23	1.32	1.46	1.53	1.34	0.17	708
2019	1.15	1.26	1.33	1.45	1.51	1.35	0.16	764
2020	1.12	1.23	1.31	1.43	1.50	1.33	0.16	769
2021	1.11	1.19	1.28	1.37	1.42	1.28	0.14	562

Table 5: Summary Statistics by NACE 2-digit division

NACE 2	p10	p25	p50	p75	p90	Mean	SD	N
41: Construction of Buildings	1.24	1.28	1.39	1.46	1.53	1.38	0.14	3950
42: Civil Engineering	1.14	1.21	1.29	1.36	1.46	1.30	0.14	681
43: Specialised Activities	1.03	1.07	1.14	1.25	1.32	1.17	0.14	2630

Table 6: Summary Statistics by Public Procurement

Public Procurement	p10	p25	p50	p75	p90	Mean	SD	N
0: Private-sector firms	1.04	1.10	1.21	1.29	1.35	1.21	0.15	4034
1: Government-contractors	1.25	1.31	1.42	1.48	1.54	1.41	0.13	3227

C Cross Sectional Results by Year and NACE 2-digit divison

Table 7: **Percentage Public Procurement Markup Premia by Year**

Year	N	Adjusted R^2	δ_1
2006	227	0.876	0.181 (0.008)
2007	290	0.917	0.161 (0.007)
2008	348	0.865	0.166 (0.007)
2009	412	0.821	0.160 (0.008)
2010	497	0.756	0.169 (0.008)
2011	506	0.754	0.188 (0.009)
2012	457	0.761	0.168 (0.007)
2013	235	0.730	0.151 (0.010)
2014	243	0.835	0.146 (0.007)
2015	245	0.657	0.156 (0.013)
2016	338	0.764	0.136 (0.007)
2017	660	0.673	0.149 (0.006)
2018	708	0.718	0.138 (0.005)
2019	764	0.643	0.135 (0.005)
2020	769	0.712	0.134 (0.005)
2021	562	0.614	0.136 (0.006)

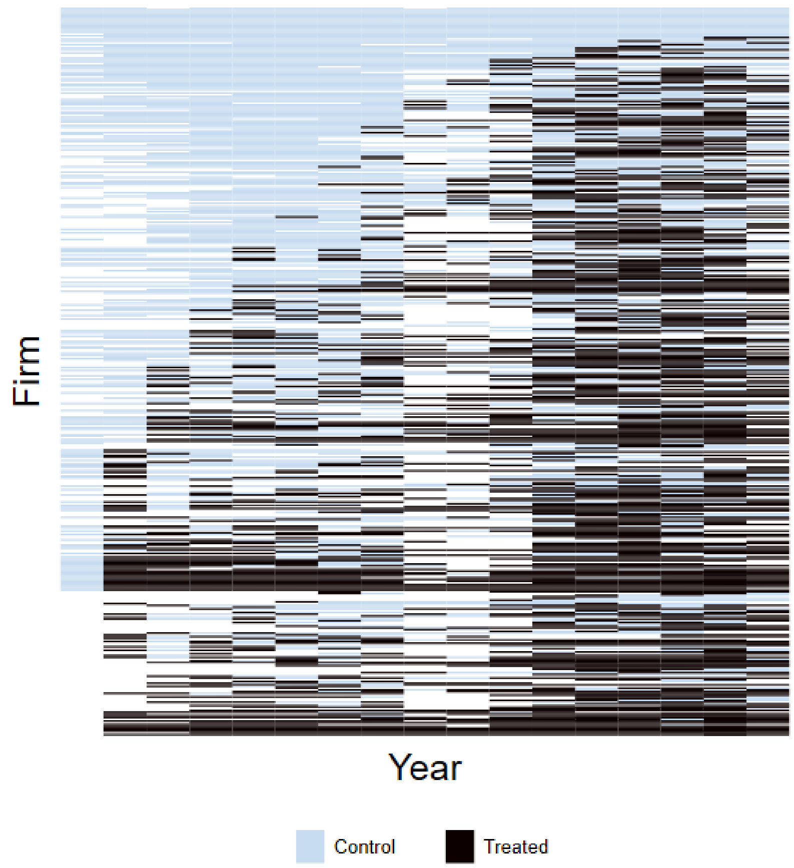
Note: Estimates are obtained after running equation 2 by year. Cluster robust standard errors in parentheses.

Table 8: **Percentage Public Procurement Markup Premia by NACE 2-digit**

	41	42	43
	Construction of Buildings	Civil Engineering	Specialised Activities
δ_1	0.144	0.154	0.158
	(0.004)	(0.008)	(0.006)
N	3950	681	2630
Adjusted R^2	0.620	0.723	0.601

Note: Estimates are obtained after running equation 2 by sub-industry. Cluster robust standard errors in parentheses

D Panel Data Structure



Note: This figure shows all 342 unique public procurement histories for the 7,261 firms with estimated markups in the sample. Black: Government Contractors, Blue: Firms inactive in Public Procurement, White: Missing.

E Time Series Result: Parameter Estimates

γ_0 (Constant)	γ_1 (Entry)	γ_2 (Exit)	γ_3 (Always)
0.831	0.120	-0.038	0.153
(0.054)	(0.006)	(0.009)	(0.005)

Estimates are obtained after running equation 3.
Cluster robust standard errors in parentheses.
N = 5744. Adjusted R^2 = 0.736.