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Markups and Public Procurement

Bachelor's thesis

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Declaration of Authorship

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Abstract

This thesis analyses the relationship between engagement in public procurement and markups charged by firms. While controlling for aggregate trends and individual firm characteristics, the effect is estimated in a multivariate regression framework as the percentage markup premium associated with engagement in public procurement. This approach contributes to the existing literature on public procurement, in that, rather than only making comparisons between different tenders, it benchmarks the competitiveness of public procurement against the competitiveness in markets serving private clients while not having to rely on data on expert cost estimates.

JEL Classification	D22, D24, F23, L11, H57
Keywords	Firm Behavior: Empirical Analysis, Industrial Organization, Markups, Public Procurement
Title	Markups and Public Procurement

Abstrakt

Tato práce analyzuje vztah mezi zapojením do veřejných zakázek a přirážkami účtovanými firmami. Tento vliv je při kontrole celkových trendů a individuálních charakteristik firem odhadován v rámci vícerozměrné regrese jako procentní prémie přirážky spojená se zapojením do veřejných zakázek. Tento přístup přispívá k existující literatuře týkající se veřejných zakázek tím, že namísto pouhého srovnávání různých nabídek porovnává konkurenceschopnost veřejných zakázek s konkurenceschopností na trzích sloužících soukromým klientům, přičemž se nemusí spoléhat na údaje o odborných odhadech nákladů.

Klasifikace JEL	D22, D24, F23, L11, H57
Klíčová slova	Chování firem: Empirická analýza, Organizace průmyslu, Obchodní přirážky, Veřejné zakázky
Název práce	Obchodní přirážky a veřejné zakázky

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Chapter 1

Introduction

Do firms engaged in public procurement charge higher markups? Measuring the extent to which firms exercise market power, raising price above the marginal cost of production, is a central topic in industrial organization. In private markets, low markups, i.e. prices close to marginal costs, are commonly taken as a signal that a market is subject to intensive price competition.

Many economic transactions, however, do not take place in purely private markets. Public procurement, the process by which governments and public sector organizations purchase goods, services, and construction projects from private firms, accounts for about 12% of GDP and roughly 25% of general government spending in OECD countries with contracts either directly awarded to particular firms or, frequently, decided through tenders. As public procurement accounts for a substantial portion of the taxpayers' money, governments are expected to carry it out efficiently and with high standards of conduct to ensure high service delivery and safeguard the public interest. Nevertheless, it remains the government activity most vulnerable to waste, fraud, and corruption due to the size of the financial flows involved (OECD 2023).

How competitive is public procurement? Previous studies mainly relied upon expert cost estimates to answer this question. This thesis takes a different approach in that it employs a recently developed method to measure firm markups (ratios of prices over marginal costs) to compare markups charged by firms that engage in public procurement to firms that do not but that operate in the same industries and are similar also in other respects.

An estimate of the markup for each producer at a given point in time is obtained as the wedge between a variable input's expenditure share in revenue directly observed in the data and that input's output elasticity. The former is observed directly in the standard production data. The latter is obtained by estimating the associated production function, controlling for the simultaneity and selection bias, and relying on a control function approach, paired with a law of motion for productivity, to estimate the output elasticity of the variable input. The framework relies on the cost minimization assumption and does not require any assumptions on demand and how firms compete. For each firm, two measures of participation in public procurement are computed. The first measure is a binary variable indicating whether a firm received money from a public contract in the last three years. The second measure is continuous and records the corresponding share of the firm's revenues represented by public contracts. Multivariate regression analysis is then used to study the relationship between engagement in public procurement and markups charged by firms, controlling for firm characteristics such as industry, sector, size, and technological change.

To the best of the author's knowledge, no study to date compares markups of firms that are and those that are not engaged in public procurement, and such, the thesis represents an important contribution to the literature.

It contributes to previous literature on public procurement in at least two ways. Firstly, rather than only comparing different tenders, it benchmarks the competitiveness of public procurement against the competitiveness in markets serving private clients. Secondly, it does not rely on expert cost estimates data, an approach that is common in the literature but has been criticized. By using a novel approach, the results expand the public procurement efficiency research area (Baranek & Titl 2020).

Additionally, since public procurement constitutes a large share of total GDP for most countries, the findings contribute to the literature on factors driving changes in aggregate markups (De Loecker *et al.* 2020). Last but not least, by transparently measuring public procurement efficiency, a significant cost item within governmental budgets, the empirical analysis presents value to evidence-based policymaking.

The findings suggest that firms active in public procurement charge statistically significant and economically important markup premia compared to their private sector-oriented counterparts. First, the cross-sectional results establish that government contractors have, on average, higher markups. Further, when the firm-specific unobserved attributes are taken into account, a within-firm fixed effects estimation confirms that this relationship holds, establishing that firms increase their markups after they become engaged in public procurement.

The remainder of the work is structured as follows:

- Chapter 2 begins with a simple theoretical conceptualization of market power and its measurment,
- Chapter 3 follows by placing the thesis in the context of the literature,
- Chapter 4 provides background and institutional information relevant to public procurement in the Czech Republic,
- Chapter 5 describes the data and methodology used in the analysis,
- in Chapter 6, the main results are discussed,
- and Chapter 7 concludes.

Chapter 2

Theory

The Cournot model with linear demand is utilized in this chapter to illustrate how markups are determined and capture the intuition that more intense competition leads to lower markups.

In the model, firms compete in quantities, taking into account the strategic interactions among them. The inverse market demand curve describes the relationship between how much money consumers are willing to pay per unit of the good (P) and the aggregate quantity (Q) of the good consumed.

Consider a game where N firms with homogenous marginal costs $MC = c$ face linear inverse demand $P(Q) = a - bQ$, with $Q = \Sigma_{i=1}^{N} q_i$. Quantities q_i constitute the action set, and the payoff functions are $\pi_i(q_i) = P(Q)q_i - cq_i$. The firm optimisation problem is then

$$\arg\max_{Q} \pi(Q) = P(Q)q_i - cq_i,$$

and from the first-order condition

$$\pi'(q_i^*) = P(Q) + \frac{\partial P(Q)}{\partial q_i} q_i^* - c = a - bQ - bq_i^* - c = 0,$$

the best response functions are

$$q_i^* = \frac{a-c}{2b} - \frac{\sum_{j \neq i} q_j}{2}.$$

Using symmetricity: $q_i = q$ for all i

$$q = \frac{a-c}{2b} - \frac{(N-1)q}{2} \quad \Rightarrow \quad q^* = \frac{a-c}{(N+1)b},$$

allows for expressing the equilibrium

$$Q^* = N\frac{a-c}{(N+1)b} \quad \Rightarrow \quad p^* = a - bQ^* = \frac{a+Nc}{N+1}$$

Prices thus remain substantially above marginal cost so long as the number of firms is not large. The corresponding markup is

$$\mu^* = \frac{p^*}{c} = \frac{a+Nc}{(N+1)c}$$

Evaluating for monopoly ($N = 1$):

$$\mu^* = \frac{a+c}{2c} = 1 + \frac{a-c}{2c},$$

while for perfect competition:

$$N \to \infty \quad \Rightarrow \quad \mu^* = 1,$$

shows the intuitive implication that the degree of departure from competitive pricing may be directly linked to the industry's structure.

While not the only model of imperfect competition, a number of its predictions are borne out by empirical evidence: markups are typically greater than 1, converge to 1 for perfect competition, and are inversely proportional to the elasticity of demand for a monopoly.

However, with different types of competition, the same market structure can lead to very different conduct. Concentration can be a misleading indicator if, for example, firms compete in prices, some firms move before others, or entry costs are endogenous. For this reason, markups — provided they can be calculated — are widely perceived as better measures of market power than market concentration.

Chapter 3

Literature review

3.1 Market power

The extent to which market outcomes reflect the exercise of market power is a long-standing and central problem in industrial organization (Einav & Levin 2010). Market power, using the definition given in Landes & Posner (1981), is the ability of a firm to influence the price at which it sells a product or service by manipulating either the supply or demand of the product or service to increase economic profit. In other words, a firm has market power if it charges prices above marginal costs (faces a demand curve that is not perfectly elastic). Commonly referenced sources of market power include, among others, a small number of firms due to high fixed costs or administrative barriers to entry, product differentiation, branding, location, patents, or network effects.

Pepall (2014) highlight that early industrial economics, working in the Structure-Conduct-Performance framework, examined firms' decisions given the industrial structure. In contrast, more modern analysis recognizes that firms' strategic behavior will be a major determinant of market structure. Despite this change in perspective, the authors emphasize that contemporary industrial economics must still address the issue of market structure or how the industry's producers are organized. They also highlight that when measuring market structure and power, researchers are very often interested in summarizing the extent to which an industry departs from the competitive ideal in a single number or index. The issue then becomes how to construct such a summary.

Using measures of a market's structure such as the concentration ratio (share of the largest firms in the total sales in a market) or the Hirschman-Herfindahl Index (sum of squared revenue shares of all firms) has the advantage in that sales data are all that is needed to compute them. However, they encounter problems such as the difficulty of accurately defining the relevant market. It is also important to highlight that a particular structure does not necessarily imply a particular outcome (e.g. price). Explicit measures of market power, such as markups, address the extent to which the market outcome deviates from the competitive ideal by comparing price and marginal cost.

By estimating the markups from Czech firm-level data, the thesis adds to the literature on measuring market power by broadening the scope of conducted empirical analyses. The results can also be valuable when seen in the context of studies that document increases in concentration measures, such as Autor *et al.* (2020) in the US, as well as Bajgar *et al.* (2023) in Europe.

3.2 Estimating markups

The markup, as used here, is defined as the price-to-marginal cost ratio, i. e. $\mu \equiv \frac{P}{c}$. It is typically obtained based either on straightforward operations with accounting variables or on estimation frameworks.

3.2.1 The accounting approach

Multiplying both the numerator and the denominator of the ratio above by total output (Q) yields $\mu = \frac{PQ}{cQ}$, and the accounting technique then hinges on directly observing the item cQ in the data. Under this setup, the markup equals the profit rate, as in, for example, Karabarbounis & Neiman (2019). The discussion around accounting frameworks, dating back to Bresnahan (1989), relates to this method. While straightforward to implement, it comes with undesirable assumptions. The first is the equality of marginal and average production costs, which requires that there are no economies of scale, i.e. no fixed costs. Second, it implicitly assumes all important production factors to be perfect substitutes in production. Finally, the cost measure (cQ) does not equal marginal cost if it includes cost items that do not fluctuate with output.

3.2.2 The demand approach

The traditional approach to markup estimation comes from the New Empirical IO literature (see Bresnahan (1989)) and relies on the specification of a demand system that delivers price elasticities of demand. Pakes (2021) provides an overview of techniques created in this context to recover the estimates of the marginal cost of production and related markups. These approaches provided a toolkit to combine demand and supply in an equilibrium analysis of imperfectly competitive markets.

As Einav & Levin (2010) explain: In equilibrium, each firm sets its price to equal marginal cost plus a markup that depends on the semi-elasticity of its demand curve, taking the prices of competing products as given. The authors then explain that these equilibrium conditions allow a researcher who has obtained estimates of consumer demand and firm costs to compute equilibrium prices, or to test hypotheses about non-cooperative pricing behavior, perhaps against alternative behavioral assumptions such as collusive pricing.

The techniques used in this context relied on market-level data, for instance, Rosse (1970). Some more recent implementations have used consumer-level data, e.g. Berry *et al.* (2004). According to De Loecker & Syverson (2021), the main issue with this method, apart from that it restricts attention to a particular model of conduct from which the first-order condition price equations are derived, is this requirement of information on product-level prices and quantities for all relevant products in a market, often unavailable to researchers.

3.2.3 The production approach

An alternative and complementary approach to markup estimation was proposed by De Loecker & Warzynski (2012). Building on Hall (1988), who proposed a model utilizing industry-level production data based on the fundamental insight that markups may be approximated using the information on the total value of output and revenue share of a variable input, the authors introduced a general framework for estimating firm-level markups by relying on cost minimization of a variable input of production.

The methodology links the markup μ_{it}, the output elasticity of the variable input θ_{it}^V and its revenue share $\frac{P_{it}Q_{it}}{P_{it}^V V_{it}}$ by the following expression:

$$\mu_{it} = \theta_{it}^V \frac{P_{it}Q_{it}}{P_{it}^V V_{it}},$$

Highlighted in De Loecker & Syverson (2021), the fundamental assumption behind this approach is that, in a given period, producers minimize cost by optimally choosing those inputs that are free from frictions, the statically chosen factors (as opposed to the dynamically chosen factors, which face adjustment costs and other frictions). The authors further emphasize the flexibility of the approach in that the markup expression is derived without specifying conduct in the product market or a particular demand system. They also note that, under the production approach, the marginal cost of production is derived from a single variable input without imposing any particular substitution elasticity with respect to other inputs (variable or fixed) or returns to scale and contrast it to the accounting approach introduced above: Only in the case of constant returns to scale and either a single variable input or only variable inputs in the production function (thus excluding fixed costs), will the accounting-based markup be correct.

Implementing the production approach requires the revenue share and the output elasticity of the variable input. While the former is often easy to calculate from the data, an estimate of the latter is needed. In order to obtain this parameter, De Loecker & Warzynski (2012) rely on the insights and practices of the production function estimation literature.

3.2.4 Production function estimation

Several critical econometric difficulties present themselves in estimating production functions, i.e. the relationship $f(\cdot)$ between the inputs $\mathbf{X}$ and the output Q where productivity Ω is the output unexplained by observable inputs:

$$Q = f(\Omega, \mathbf{X}).$$

First, measurement issues arise in this process as most datasets do not record physical quantities and firm-level prices. Still, in contrast to the productivity residual, the output elasticities can be identified by relating (deflated) output sales to input expenditures (De Loecker & Eeckhout 2018). Second, in violation of the ordinary least squares, input choices (the explanatory variables) and productivity levels (the error term) are likely to be correlated. As De Loecker & Syverson (2021) explain, ideal instruments to deal with the simultaneity bias, input prices, are often either unavailable to the econometrician, or their variation across producers is unlikely to satisfy the exclusion restriction. The authors then mention two primary approaches used in the literature: factor shares and production function estimation. The former relies on the condition for static cost minimization: an input's output elasticity equals the product of that input's cost share and the scale elasticity. While straightforward to implement, due to the assumptions it imposes, the latter, production function estimation, has seen more uptake. Reviewed in Ackerberg *et al.* (2007) and Ackerberg *et al.* (2015), the control function and the dynamic panel data methods are the main approaches used in this context.

The control function approach proposed by Olley & Pakes (1996), modified by Levinsohn & Petrin (2003) and further developed in Ackerberg *et al.* (2015) is the most widely used in production function estimation. The method utilizes a two-stage generalized method of moments procedure with bootstrapped standard errors, accounting for unobserved productivity as a function of apparent firm-level decisions. The first stage removes measurement error and transitory productivity shocks from the firm output, and the second stage imposes structure on the productivity process to identify the production function. Additionally, Wooldridge (2009) showed how proxy variable approaches to controlling for unobserved productivity can be implemented in a joint estimation of the parameters as in Wooldridge (1996). While providing robust standard errors and higher efficiency, this method is computationally much more demanding.

From a generic setup of identifying parameters in panel data models (Arellano & Bond 1991), and further extensions (Blundell & Bond 1998), an alternative method to estimate production functions emerged. While appealing in theory, the dynamic panel method has not been used much in practice: The estimated coefficients are often unrealistically low, possibly due to data first-differencing, which throws out variation across producers (De Loecker & Syverson 2021).

3.2.5 Critique

Einav & Levin (2010) highlight that the field of industrial organization has made dramatic advances over the last few decades in developing empirical methods for analyzing imperfect competition and the organization of markets and that the increasing access to firm-level data and, in some cases the ability to cooperate with firms or governments in experimental research designs is offering new settings and opportunities to apply these ideas in empirical work.

In the same journal issue, Angrist & Pischke (2010) describe a parallel development in applied microeconomics toward analyses that use randomized experiments to identify causal effects and challenge research in empirical industrial organization for its dependency on difficult-to-test assumptions.

Regarding markup estimation, the demand and production approaches are based on primarily unproven behavioral and practical assumptions. However, as these assumptions are mostly non-overlapping, one strategy serves as a possible validation test for the other, and De Loecker & Scott (2016) arrive at comparable results when combining the methodologies.

Specific to the production approach, after being exposed to academic scrutiny, the original methodology proposed in De Loecker & Warzynski (2012) was subsequently developed (De Loecker *et al.* 2020) and remains an active area of research (Demirer 2023). Numerous authors remain skeptical about its usage (Bond *et al.* (2020), van Dijcke (2023)). Therefore, it is essential to acknowledge its limitations (De Loecker 2021), primarily due to the problematic production function estimation. Nevertheless, it has been proven to produce reliable markup estimates (Ridder *et al.* 2021), in turn contributing to a more extensive debate on the overall state of competition, as well as helping to identify sources and implications for competition policy.

3.2.6 Applications

Although classic market power analyses such as Nevo (2001) rely on estimating market demand, the production approach to markup measurement was recently used in various applications. Notably, De Loecker *et al.* (2020) rely on this approach to show that markups of publicly traded US firms have substantially increased from the 1980s: While the weighted average markup was about 20% in the 1980s, it is about 60% today. They find that the distribution of markups has shifted considerably since 1980, with most firms having little increase while those in the upper tail are experiencing a significant increase. The increase in markups is attributed to the growth of markups within firms, new firms having high markups, and the reallocation of revenues to high-markup firms. The latter was found to be the most important, accounting for about 2/3 of the total increase, which is compatible with the superstar firm effect documented by Autor *et al.* (2020) and ties in with the documented increased concentration in US industries. Gutierrez & Philippon (2018) provide an additional explanation by considering the changes in market structure, namely the decline in antitrust enforcement. The implications are studied, for example, by De Loecker *et al.* (2021), who report an ambiguous effect on welfare: large, high-markup firms are more productive but extract more rents from the customer and affect the labor market adversely through lower wages.

Through this body of work, the production approach has connected productivity data to a larger global debate around market power, declining labor shares, increased globalization, and a variety of other labor market issues. For example, while labour markets are often considered competitive, Yeh *et al.* (2022) document that limited labour mobility and substitutability between professions leads to employers having market power in local labour markets, which in turn results in lower wages ("markdowns").

Computing markups of Czech firms active in the construction sector empirically tests whether some of the global trends in market power can be seen in Czech firm-level data as well. Additionally, as public procurement constitutes a large share of GDP, markups in procurement could significantly affect aggregate markups. Thus, the thesis also contributes to the literature on factors driving changes in aggregate markups.

3.3 Public procurement

Public procurement, a process by which governments and other public bodies purchase goods, services, and works from private sector suppliers, is a fundamental component of government spending and typically involves a complex process of planning, tendering, contracting, and delivery. Importantly, from being a neglected area of study (Thai 2001), public procurement, which accounts for about 12% of GDP and roughly 25% of general government spending in OECD countries (OECD 2023), has now a growing body of empirical research.

One related strand of literature analyzes the connection between procurement procedures or auction formats and procurement process outcomes. This literature suggests that some auction designs are more prone to allocative distortions owing to favoritism (Palguta & Pertold 2017), while also emphasizing that who is assigned a contract affects the end results of procurement procedures. Coviello *et al.* (2018), for example, find that enterprises who win contracts regularly have superior procurement outcomes. Similarly, Calvo *et al.* (2019) document that procurement officials' operational control increases cost overruns and delivery delays when contracts are awarded to less experienced providers. A closely related study of collusive conduct in public procurement tenders was pioneered by Porter & Zona (1993) and further developed in Bajari & Ye (2003), Chassang & Ortner (2015) and Conley & Decarolis (2016). Based on prosecution data, Asker (2010), De Leverano *et al.* (2020), and Kawai & Nakabayashi (2022) offer an explanation of how existing cartels work.

Another relevant body of research examines the consequences of different forms of political relationships for firms, communities, and individuals. Political links, for example, appear to help firms in a variety of ways, including stock market valuation, return on investment, and access to finance and funding (Fisman (2001), Khwaja & Mian (2005)). While they have also been demonstrated to influence people's access to welfare transfers, Han & Gao (2019), political relationships between levels of government, such as partisanship, seem to be less relevant for public expenditure allocations, Karim & Noy (2020). However, numerous studies establish that political connections have a considerable effect on public procurement markets: Goldman *et al.* (2013); Schoenherr (2019); Decarolis *et al.* (2019); Baranek & Titl (2020); Titl *et al.* (2021).

Reviewed by Narbón-Perpiñá & De Witte (2018), vast literature investigates the degree and determinants of public sector efficiency. Government accountability in Hauner & Kyobe (2010), corruption in Méon & Weill (2010), political competition in Ashworth *et al.* (2014), and the presence of direct democratic citizen initiatives in Asatryan & De Witte (2015) have all been proposed as potential drivers of the observed variation in efficiency across jurisdictions. Decarolis (2014) identifies single-bidding is identified as a source of significant market inefficiencies. Fazekas (2019) finds that about 23.2% of the public procurement contracts in the European Union member states were awarded to the only firm that submitted its bid and Kang & Miller (2022) document that in the United States, roughly 45% of government procurement contracts were granted through single-bid tenders. Further, Fazekas & Kocsis (2020) found in a cross-country analysis that a higher percentage of single-bid contracts is associated with a higher degree of perceived corruption. Titl (2021) argues that, while in cases such as patented items and natural monopolies, single bidding is justified, these are unlikely to explain such a large percentage of single-bid contracts. Coviello & Mariniello (2014) propose a lack of advertising or insufficient information regarding procurement contracts as a potential explanation, and Iossa *et al.* (2019) suggest the high share of single bidding might be due to the incumbent's cost advantage resulting from contract specifications and qualifying criteria construction.

Comparing the markups between firms primarily living on public contracts and firms working for private customers adds significantly to the literature on public procurement, specifically to the research area of public procurement efficiency. Rather than only comparing different tenders, it benchmarks the competitiveness of public procurement against markets serving private clients. Further, estimating the relationship between engagement in public procurement and markups in a multivariate regression setting controls for firm characteristics such as size, industry, and age and allows for conducting the analysis without relying on expert cost estimates, an approach that is common in the literature but has been subject to criticism.

Chapter 4

Institutional setting

4.1 Background

Public tenders represent a significant cost component within governmental budgets in the Czech Republic and play a key role in specific sectors (construction, public works, energy, telecommunications, and heavy industry). Baránek *et al.* (2020) note that public institutions in the Czech Republic award public tenders to the value of approximately 14.4% of GDP every year, and expenditures on public tenders constitute around 35% of state, regional, and local budget expenditures. The authors further emphasize that in 2010, the Czech government's National Economic Council recognized corruption and weak institutions as significant impediments to economic progress and that Transparency International's corruption perceptions index 2018 classified the Czech Republic as a high-income nation with high degrees of corruption. Public procurement is likely to be a market where these institutional issues are manifested.

In the EU, over 250 000 public authorities spend around €2 trillion yearly on purchasing services, works, and supplies, which shows that European public procurement is a major driver for economic growth, job creation, and innovation. Therefore, the public sector should aim for resource efficiency in public procurement. Improving public procurement can yield big savings; even a 1% efficiency gain could save €20 billion per year. [1]

[1] European Commission: Directorate-General for Internal Market, Industry, Entrepreneurship, and SMEs. (2023). Public procurement. Retrieved June 22, 2023, from https://single-market-economy.ec.europa.eu/single-market/public-procurement

4.2 Legal basis

The process of granting public procurement contracts in the Czech Republic is governed by national law, namely ACT No. 134/2016 Coll. on Public Procurement. The following definitions draw from Soudek & Skuhrovec (2013):

An award of the public contract is the conclusion of a contract for pecuniary interest between a contracting authority and an economic operator, establishing the economic operator's obligation to supply supplies, provide services or execute works. Any governmental office that must follow public procurement processes in order to make purchases of goods or services is a contracting authority. A bidder is anyone who proposes the delivery of goods or services under the public procurement procedure. The auction winner enters into a contract with the contracting body and starts supplying the requested goods. The award procedure is a legal method used to choose the public procurement supplier and the most important institutional characteristic. The type of award procedure, along with the time frame and number of bids, defines how transparent and open the process will be. All bidders must meet both the minimum requirements and the professional requirements. The contracting authority has the right to impose certain conditions on suppliers regarding economic, financial, and technical qualities, such as insurance policy, the quantity of turnover, or a reference list of the major deliveries.

All procedures must also comply with the principles of EU law (Articles 26, 34, 53(1), 56, 57, 62, and 114 of the Treaty on the Functioning of the European Union). Calls for tender must correspond to different types of procedures, which are used based on a threshold system. The directives specify the methods for calculating the estimated value of each public contract and indications for the procedures to be applied. Contracting authorities must award public contracts to the 'Most Economically Advantageous Tender,' considering the quality of the works, goods, or services in question, as well as the price and life cycle costs. Procurement procedures must ensure the required transparency at all stages by publishing the essential elements of procurement procedures, information on candidates and tenderers, and all procedure steps. [2]

[2] European Parliament. (2023, April). Fact Sheets on the European Union: Public procurement contracts. Retrieved June 22, 2023, from https://www.europarl.europa.eu/factsheets/en/sheet/34/public-procurement-contracts

Chapter 5

Empirical framework

This chapter begins with a description of data handling prior to estimation. The markup formula is then derived by showing how the cost minimization criterion for a variable input not subject to adjustment costs determines a firm's markup by the input's output elasticity and the proportion of its expenditure in total sales. Next, identifying the production function necessary to obtain the elasticity of the variable input to compute the markup is discussed. Finally, the explanation of estimating the relationship between markups and public procurement is presented.

5.1 Data

5.1.1 Public procurement

One of the critical requirements of the Czech legislature states that procurers must provide information regarding contracts on a publicly accessible platform. The data used in this thesis was extracted and cleaned from this online system by a Czech private IT company Datlab. Related work using the same data source includes Baranek & Titl (2020) and Titl (2021). The data consists of contracts awarded by national, regional, local, and municipal governments as well as government-owned businesses between 2006 and 2021. Due to the difficulties associated with acquiring, cleaning, and managing the second necessary component for the analysis, firm financial statements data, the scope of this thesis focuses only on the construction industry, whose firms, as documented by Table 5.1, are awarded the majority of Czech procurement contracts.

Table 5.1: Procurement projects in the Czech Republic

	Count	Percentage
Construction	16,866	49.596
IT and telecommunication	3,584	10.539
Healthcare, social care and educational services	2,199	6.466
Transport	1,647	4.843
Legal and other advisory	1,650	4.803
Clothes, shoes and other similar equipment	1,623	4.773
Technical services	1,562	4.593
Others	1,213	3.567
Energy	841	2.473
Industrial machinery	886	2.605
Office equipment	797	2.344
Forestry and agriculture	761	2.238
Medical equipment	579	1.703
Natural resources	79	0.232
	N = 34,007	period 2006-2018

Source: Baranek & Titl (2020).

An important measurement challenge is that many procurement contracts in the construction sector last longer than a year, and information on the actual duration of each contract or the distribution of public procurement revenues across years is not available in the data. The analysis in this thesis addresses this by assuming that all contracts last for 3 years and the public procurement revenues are uniformly spread across these 3 years. As a result, the binary variable D_{it} identifies firms active in public procurement based on whether an awarded contract was recorded in the given year or the two preceding years, and the continuous measure $share_{it}$ records the share of average public procurement revenues over these three years in the total sales of a given year. Values of $share_{it}$ were restricted to lie in the closed interval from zero to one.

5.1.2 Financial statements

Information on firms active in the Czech construction industry was obtained from MagnusWeb, a firm-level dataset for Czechia. Firms' financial statements were utilized to obtain variables necessary for the estimations. Namely sales PQ (total operating revenue in Czech crowns), variable input expenditures $COGS$ (costs of goods sold in Czech crowns), and capital K (total fixed assets in book value in Czech crowns).

Since the number of available observations for these key variables differed, only firms for which all variables were non-missing constitute the final sample, resulting in an unbalanced panel of 4 450 firms with 46 577 observations, which Table 5.2 aggregates by the two-digit sector codes.

Table 5.2: Industry classification

NACE 2	Description	Number of firms	Observations
41	Construction of buildings	2,260	24,193
42	Civil engineering	194	2,545
43	Specialised activities	1,996	19,839

5.1.3 Sample statistics

The two datasets were matched based on unique firm identifiers, and the sample was then restricted to years with enough data, known industry, and public procurement engagement. Table 5.3 reports the resulting yearly number of unique firms, identified government contractors ($D_{it} = 1$), i.e. unique firms with at least one contract in the given and preceding two years, and average values of the public procurement sales to total sales proportion among firms with at least one contract ($\overline{share_{it}} \mid D_{it} = 1$).

Table 5.3: Engagement in public procurement

Year	Number of firms	$D_{it} = 1$	$\overline{share_{it}} \mid D_{it} = 1$
2006	1,828	326	0.13
2007	2,107	436	0.17
2008	2,328	525	0.20
2009	2,541	614	0.24
2010	2,661	643	0.26
2011	2,641	616	0.30
2012	2,621	686	0.33
2013	2,015	669	0.64
2014	2,358	879	0.52
2015	3,431	1447	0.21
2016	3,649	1639	0.32
2017	3,763	1840	0.35
2018	3,793	1918	0.39
2019	3,856	1990	0.42
2020	3,878	1985	0.46
2021	3,107	1556	0.55

Grouped by the activity in public procurement, the final sample summary statistics of the leading variables are presented in Table 5.4. The standard deviations highlight substantial heterogeneity of the sample. At the same time, the mean values demonstrate that firms serving only private clients seem to be smaller in size when compared to firms active in public procurement.

Table 5.4: Estimation data summary

	Mean	SD	Min	Max
Firms inactive in public procurement				
Sales	78.19	140.40	0.00	2,716.69
Cost of goods sold	38.53	72.03	0.00	1,612.83
Capital stock	36.16	406.71	0.00	15,627.91
				$N = 7,111$
Firms active in public procurement				
Sales	274.99	687.89	0.00	10,065.92
Cost of goods sold	120.58	369.90	0.00	6,927.15
Capital stock	53.20	190.99	0.00	4,938.02
				$N = 6,378$

5.2 Deriving an expression for markups

Following De Loecker *et al.* (2020), consider an economy with N firms, indexed by $i = 1 \ldots N$, 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 production function:

$$Q_{it} = Q_{it}(\Omega_{it}, \mathbf{V}_{it}, K_{it}), \tag{5.1}$$

where $\mathbf{V}_{it} = (V_{it}^1, \ldots, V_{it}^J)$ is the vector of variable inputs of production (including labor, intermediate inputs, materials,...), K_{it} is the capital stock and Ω_{it} is productivity (output unexplained by inputs of production). Within one period, variable inputs are assumed to adjust frictionlessly, whereas capital is subject to adjustment costs and other frictions. In the implementation, information on a bundle of variable inputs is used instead of the individual inputs. The vector $\mathbf{V}_{it}$ will therefore be treated as a scalar V_{it} in the following derivation.

The following Lagrangian objective function is then associated with the firm's cost minimization:

$$\mathcal{L}_{it}(V_{it}, K_{it}, \Omega_{it}) = P^V_{it} V_{it} + r_{it} K_{it} + F_{it} - \lambda_{it}(Q_{it}(\cdot) - \bar{Q}_{it}), \tag{5.2}$$

where P^V_{it} is the price of the variable input, r is the user cost of capital, F_{it} is the fixed cost, $Q(\cdot)$ is the technology specified in 5.1, $\bar{Q}_{it}$ is a scalar and λ is the Lagrange multiplier. Assuming that variable input prices are given to the firm, the first-order condition with respect to the variable input V is given by:

$$\frac{\partial \mathcal{L}_{it}}{\partial V_{it}} = P^V_{it} - \lambda_{it} \frac{\partial Q_{it}(\cdot)}{\partial V_{it}} = 0. \tag{5.3}$$

multiplying all terms by $\frac{V_{it}}{Q_{it}}$ and rearranging, De Loecker *et al.* (2020) arrive at an expression for the output elasticity of input V:

$$\frac{\partial Q_{it}}{\partial V_{it}} \frac{V_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P^V_{it} V_{it}}{Q_{it}.} \tag{5.4}$$

The authors note that the Lagrange multiplier λ traces out the value of the objective function when the output constraint is relaxed, thus directly measuring the marginal cost. The markup price–marginal cost ratio then becomes $\mu_{it} = \frac{P}{\lambda}$, where P is the output price. Substituting marginal cost for the markup-to-price ratio, they obtain an expression for the markup:

$$\mu_{it} = \theta^V_{it} \frac{P_{it} Q_{it}}{P^V_{it} V_{it}} = \theta^V_{it} (s^V_{it})^{-1}, \tag{5.5}$$

and highlight that the expression of the markup is derived without specifying conduct or a particular demand system. Its two necessary components are the revenue share of the variable input, $s^V_{it} = \frac{P^V_{it} V_{it}}{P_{it} Q_{it}}$ and the output elasticity of the variable input θ^V_{it}. While the former is easy to calculate from the data, obtaining the latter requires estimating the production function (the relationship between the factors of production and the output produced). For the benchmark specification, consider a sector-year-specific Cobb-Douglas production function with a variable input bundle and capital as inputs of the form:

$$y_{it} = \theta^V_t v_{it} + \theta^K_t k_{it} + \omega_{it} + \epsilon_{it}, \tag{5.6}$$

where lower cases denote logs, $\omega_{it} = ln(\Omega_{it})$, y_{it} is a measure of realized firm's output, and ϵ_{it} denotes measurement error in output, i.e. $y_{it} = ln(Q_{it} exp(\epsilon_{it}))$.

In the application, after being deflated by the appropriate deflators, the data summarized in Table 5.4 were used as a measure of quantity, and the following gross output production function was estimated:

$$ln(P_{sit}Q_{sit}) = \theta_s^V ln(COGS)_{sit} + \theta_s^K ln(K)_{sit} + \tau_{st} + \omega_{sit} + \epsilon_{sit}, \tag{5.7}$$

where τ_{stm} stands for year t fixed effects included to capture common trends. Differences in technologies were controlled by performing regressions separately for each 2-digit sector s.

5.3 Estimating output elasticities and markups

De Loecker *et al.* (2020) group the challenges in estimating production functions into two main categories: dealing with unobserved productivity shocks ω_{it}, and extracting units of output and inputs from revenue and expenditure data (the omitted price variable bias) and rely on methods that aim to deliver consistently estimated output elasticities. Following the literature, they control for the simultaneity and selection bias, inherently present in the estimating equation 5.6, using the two-stage control function approach, paired with a law of motion for productivity, to estimate the output elasticity of the variable input. The method accounts for the fact that the variable factor of production V adjusts in response to a productivity shock, while the fixed factor K does not react to contemporaneous shocks to productivity, but it is correlated with the persistent productivity term.

5.3.1 Control function

Building on the insights of Olley & Pakes (1996) and Levinsohn (2003), unobserved productivity can be expressed as an unknown function of the firm's state variables and observables by taking the inverse of input demand:

$$\omega_{it} = h_t(d_{it}, k_{it}, \mathbf{z}_{it}), \tag{5.8}$$

where d_{it} is the control variable (for example v_{it}), and $\mathbf{z}_{it}$ denotes output and input market factors that generate variation in factor demand (for input d_{it}) across firms, conditional on the level of productivity and capital. The latter allows for imperfect competition in product markets, and thus markup heterogeneity across firms (De Loecker & Warzynski 2012).

In the first stage of this method, the measurement error and unanticipated shocks to output are purged using a nonparametric output projection on the inputs and the control variable. With a static control, $d_{it} = v_{it}$, this gives rise to:

$$y_{it} = \phi_t(v_{it}, k_{it}, \mathbf{z}_{it}) + \epsilon_{it}. \tag{5.9}$$

In the second stage, the productivity process $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$ is considered to derive the industry-year-specific output elasticity using the following moment condition:

$$\mathbb{E}\left(\xi_{it}(\theta_t)\begin{bmatrix} v_{it-1} \\ k_{it} \end{bmatrix}\right) = 0, \tag{5.10}$$

where ξ_{it} is generated by projecting productivity $\omega_{it}(\theta_t)$ on its lag $\omega_{it-1}(\theta_t)$, with $\theta_t = \{\theta_t^V, \theta_t^K\}$, and productivity is in turn computed from $\phi_{it} - \theta_t^V v_{it} - \theta_t^K k_{it}$ using the first-stage regression estimate ϕ_{it}. The output elasticity of a variable input is identified under the assumption that variable input use responds to productivity shocks, but lagged values do not, and that lagged variable input use is correlated with current variable input use via serially correlated input and output market conditions captured in z_{it}.

Finally, since $y_{it} = ln(Q_{it}exp(\epsilon_{it}))$, the second component of markups in equation 5.5, i.e. the revenue share of the variable input $\alpha_{it}^V = \frac{P_{it}^V V_{it}}{P_{it} Q_{it}}$, must be corrected for the residuals of the first stage (Ackerberg *et al.* 2015). The residuals fitted in 5.9 allow for deriving the corrected shares as:

$$s_{it}^{V*} = \frac{P_{it}^V V_{it}}{P_{it}\frac{Q_{it}}{exp(\epsilon_{it})}} = \frac{P_{it}^V V_{it}}{P_{it} y_{it}}, \tag{5.11}$$

and estimating the markups:

$$\hat{\mu}_{it} = \hat{\theta}_{it}^V (s_{it}^{V*})^{-1}. \tag{5.12}$$

The two-step control function approach described above was applied to overcome the production factor endogeneity. Cost of goods sold ($COGS$) was used as the variable factor of production (v) to compute the markup from equation 5.5 and also as the control variable (d) in equation 5.8. To allow for differences in factor demand under imperfect competition, the public procurement dummy variable was used as the additional instrument $\mathbf{z}$ in the first stage equation 5.9.

5.3.2 Units

As pointed out in De Loecker *et al.* (2020), standard production data record revenue and expenditures rather than physical production and input use, and using this (deflated) data as a proxy for physical quantity presents an additional source of endogeneity. The error term can contain output and input prices, and the correlation of input expenditures to the error results in biased estimates of the output elasticity.

However, De Loecker & Warzynski (2012) show that adopting a proxy for productivity helps against not observing prices as price variation correlated with variation in productivity will be controlled for. Notably, the authors emphasize that unobserved prices will only affect the estimations of the magnitude of the markup and not the correlation of markups with other variables. Therefore, while price variation caused by demand shocks that are not correlated with the output projection $\phi(\cdot)$ could arguably bias the output elasticity estimates, the main conclusions about the relationship between markups and public procurement should remain unaffected.

5.4 Relating markups and public procurement

To examine the relationship between markups and public procurement, the percentage difference between markups charged by firms engaged in public tenders and those serving only private clients is estimated.

In a regression framework with logged markups being the dependent variable, the effect of public procurement activity corresponds to the coefficient of the public procurement engagement measures.

This approach is beneficial in that the results are unchanged even if variable inputs considered to compute markups are subject to adjustment costs, as long as firms active in public procurement are not more or less subject to these adjustment costs (De Loecker & Warzynski 2012).

5.4.1 Pooled OLS

The following cross sectional regression estimates the markup percentage difference between government contractors and firms serving private clients:

$$ln\hat{\mu}_{it} = \alpha_0 + \alpha_1 PP_{it} + \delta z_{it} + v_{it}, \tag{5.13}$$

where $PP_{it} = \{D_{it}, share_{it}\}$ is either a public procurement dummy (D_{it}) or the share of public tender sales in total sales ($share_{it}$). Controlling for the costs of goods sold and capital to capture differences in size and factor intensity, as well as the year (T)-industry (I) dummies to take out aggregate trends in markups and collect them all in z_{it} with δ the corresponding vector of coefficients. The percentage markup premium for government contractors is measured by α_1. Note that, rather than a causal parameter, it indicates whether government contractors have different markups on average.

5.4.2 Fixed effects

Using the panel data structure to examine whether there is a specific pattern of markups for firms before and after they become a government contractor, a similar regression to the one above but with a firm fixed effect σ_i is taken to the data:

$$ln\hat{\mu}_{it} = \beta_0 + \beta_1 PP_{it} + \delta z_{it} + \sigma_i + u_{it}, \tag{5.14}$$

where the definition of PP_{it} stays, while β_1 denotes the percentage markup premium associated with entering the public procurement market. Note that the fixed effects estimator uses the within transformation and, by time demeaning the variables for each observation, eliminates σ_i.

Chapter 6

Results

Results were obtained using Stata/MP 15.1, together with the prodest[1] and markupest[2] packages for estimating the production function and markups. All reported standard errors are firm-clustered.

6.1 Firm level markups

Estimating the output elasticity of a bundle of variable inputs, together with the first-order condition of input demand and data on input spending, allows for computing the implied markups. Reported markups $\hat{\mu}$ were obtained using a sector-specific homogeneous gross output production function specified above by equation 5.7. Additionally, estimating the production function separately for firms active in public procurement and those inactive, i.e. allowing for greater heterogeneity between government contractors and private serving firms, gave rise to markups $\hat{\mu}_{pp}$. Additionally, markups resulting from an OLS estimation of the production function $\hat{\mu}_{OLS}$ are compared.

6.1.1 Production function estimates

Table 6.1 presents the estimated sector-specific production factor elasticities. The linear regression (OLS) results of log output on free and state variables are presented as a benchmark for the implemented control-function (CF) approach. The main parameter of interest is the elasticity of the variable input (θ^V) as it is used for the following markup computation.

[1]Rovigatti, G. and Mollisi, V. (2018) Theory and practice of total-factor productivity estimation: The control function approach using Stata The Stata Journal 18.3: 618-662

[2]Rovigatti, G. (2020). Markup estimation using Stata: Micro and Macro approaches with markupest Working Paper

In line with Levinsohn (2003), who argue that OLS overestimates the parameters of free variables, the control function approach resulted in slightly lower estimated output elasticities of the variable input across all sectors. Notably, the control function methodology yielded smaller standard errors of the estimated coefficients. The only exception is the capital parameter for sector 42 (civil engineering), which both OLS and CF estimations did not reject from being equal to zero. Overall, the effect of capital on produced output, similarly in the other sectors, was estimated to be negligible. Further, civil engineering production was estimated to be closest to constant returns to scale, i.e. output increasing by the exact proportional change as all inputs, in this case, amounting only to the variable input. Sectors 41 (construction of buildings) and 43 (specialized activities) were estimated to have decreasing returns to scale, i.e. output increasing by less than the proportional change in all inputs. When interpreting this result, one might argue that civil engineering projects may face fewer management difficulties associated with production scaling. In contrast, the lack of coordination in all stages of production in the construction of buildings and specialized activities may lead to decreasing efficiency.

Table 6.1: Sector-specific production factor elasticities

	Sector 41		Sector 42		Sector 43	
	OLS	CF	OLS	CF	OLS	CF
$\hat{\theta}_s^K$	0.079^{***}	0.067^{***}	0.029	0.023	0.103^{***}	0.101^{***}
	(0.013)	(0.011)	(0.036)	(0.039)	(0.018)	(0.013)
$\hat{\theta}_s^V$	0.848^{***}	0.826^{***}	1.003^{***}	0.985^{***}	0.791^{***}	0.783^{***}
	(0.026)	(0.001)	(0.046)	(0.006)	(0.026)	(0.005)
N	7,064	7,064	1,068	1,068	5,132	5,132

Note: *** p<0.01, ** p<0.05, * p<0.10.

To allow for a specific production process of public procurement contracts, the regression was run once more, this time separately for identified government contractors ($D^{pp} = 1$) and firms serving private clients only ($D^{pp} = 0$). Table 6.2 presents the resulting estimated coefficients and documents that the variable inputs output elasticities were estimated higher for firms active in public procurement, while for the capital parameter, the opposite holds. The results suggest that it is the civil engineering sector where the most profound difference between public tender and private sector production occurs.

Table 6.2: Sector-market-specific factor elasticities

	Sector 41		Sector 42		Sector 43	
	$D = 1$	$D = 0$	$D = 1$	$D = 0$	$D = 1$	$D = 0$
$\hat{\theta}^K_{sm}$	0.056***	0.045*	−0.013	0.084	0.093*	0.077***
	(0.010)	(0.019)	(0.031)	(0.068)	(0.039)	(0.003)
$\hat{\theta}^V_{sm}$	0.895***	0.797***	1.050***	0.878***	0.878***	0.749***
	(0.005)	(0.003)	(0.005)	(0.075)	(0.020)	(0.006)
N	3,746	3,318	787	281	1,811	3,321

Note: *** p<0.01, ** p<0.05, * p<0.10.

As it relates to calculating the markup, the heterogeneity of estimated elasticities will directly influence the resulting markup distribution. From equation 5.12, it is clear that keeping the cost of goods sold revenue share fixed, higher elasticities of the variable input imply higher markups.

6.1.2 Markup estimates

Grouped by the indicator variable D_{it}, the summary statistics of the estimated markups, after trimming 1% of the values from the top and bottom of their distributions, for the whole construction industry, are given in Table 6.3.

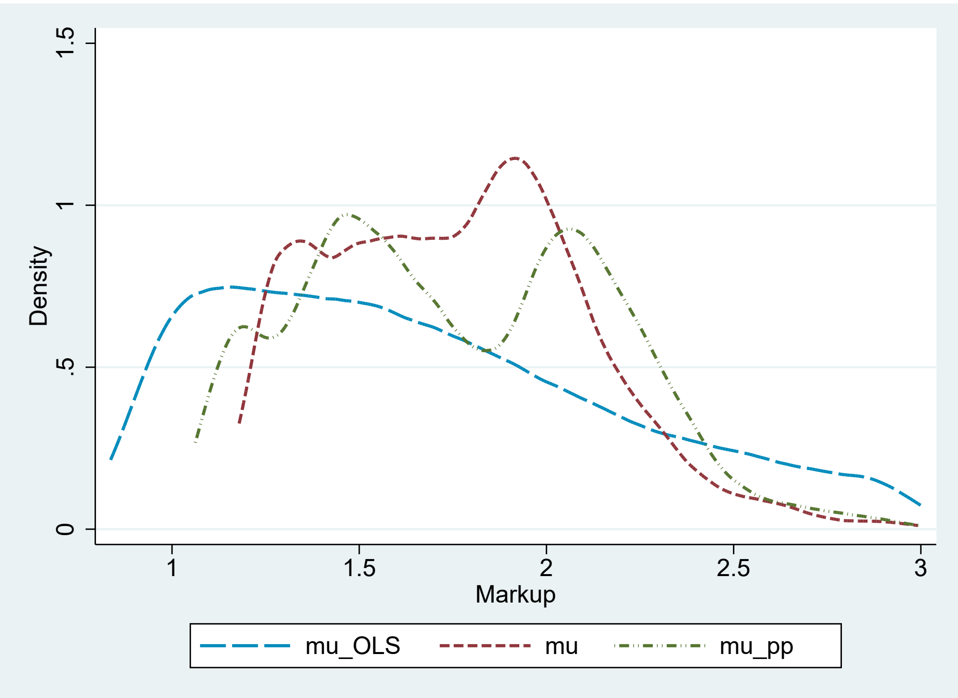
Table 6.3: Markup summary

	$\hat{\mu}_{OLS}$		$\hat{\mu}$		$\hat{\mu}_{pp}$	
	$D = 1$	$D = 0$	$D = 1$	$D = 0$	$D = 1$	$D = 0$
Mean	2.20	2.05	1.94	1.71	2.07	1.61
SD	1.28	1.66	0.37	0.43	0.33	0.50
p10	1.15	1.00	1.41	1.26	1.60	1.16
p25	1.44	1.17	1.74	1.42	1.92	1.31
p50	1.87	1.54	1.95	1.64	2.08	1.51
p75	2.54	2.17	2.13	1.88	2.24	1.76
p90	3.54	3.44	2.35	2.20	2.43	2.11
N	7,232	8,049	6,330	6,670	6,218	6,782

All approaches resulted in differences between the distributions of estimated markups charged by government contractors ($D = 1$) and firms inactive in the public procurement market ($D = 0$), as shown in Appendix A Figures 3, 5, 7.

Overall, the OLS estimates exhibit higher mean values, and their standard deviations are almost four-fold compared to the control function estimates. As expected, allowing the estimated elasticities to differ based on public procurement activity ($\hat{\mu}_{pp}$) resulted in a greater variation among the distribution of estimated markups for the Czech construction firms than under the assumption of only sector-specific production functions ($\hat{\mu}$). Figure 6.1 depicts the estimated markup distribution of the whole Czech construction industry over the sample period and illustrates that the control function approaches achieved to capture the heterogeneity of the sample, as seen by their multimodality, more than the OLS estimation (see Appendix A Figures 2, 4 and 6). The distribution estimated with least squares ($\hat{\mu}_{OLS}$) is skewed to the right and starts from "markdowns" of less than one. In contrast, the CF estimation markups begin from approximately 1.2 and are centered at around 1.3 and 1.9 for the sector-specific estimates and near 1.5 and 2.2 when assuming markups calculated from differing production processes for public procurement projects. The logged estimated markup distributions are visualized in Appendix A Figure 1.

Figure 6.1: Estimated markup distributions



Note: Markups over three are excluded from the figure.
$\hat{\mu}_{OLS}$ and $\hat{\mu}$ obtained from estimating sector-specific production functions,
$\hat{\mu}_{pp}$ allowed for coefficients to vary also based on activity in public procurement.

6.2 Markups and public procurement

Having estimated the markups $\hat{\mu}$ and $\hat{\mu}_{pp}$ allows for turning to the main focus of the application: To establish whether markups differ between firms active in public procurement and those working for private customers only and test whether a firms markup evolves upon entry into the public procurement market. Respectively, the percentage markup premiums α_1 and β_1, corresponding to the coefficients of the public procurement dummy variable in the regression framework described in the methodology section 5.4, provide insight into each of these questions. The coefficients α_1^{share} and β_1^{share} allow for inspecting this relationship from another perspective, as they were obtained by replacing the public procurement dummy with the share of public tender sales in total sales, thus indicating the relationship between a firms markup and the intensity with which it engages in public procurement. With conventional significance notation and corresponding firm-clustered standard errors in parentheses, Table 6.4 reports the pooled OLS regression estimates of $\hat{\alpha}_1$, while Table 6.5 shows $\hat{\alpha}_1^{share}$. Similarly, Table 6.6 presents the within firm fixed effects regression estimates $\hat{\beta}_1$ and $\hat{\beta}_1^{share}$ is given in Table 6.7. Additional results using markups from the production function estimated by OLS ($\hat{\mu}_{OLS}$), as well as from regressions without controls, are additionally shown for comparison and robustness.

6.2.1 Cross sectional relationship

Both the indicator variable $D = \{0, 1\}$ and the continuous measure of the intensity of public procurement engagement $share \in [0, 1]$ approaches result in obtaining statistically significant estimates similar in magnitude, in turn showing that, on average, government contractors have higher markups.

Table 6.4: Pooled OLS: Public procurement activity

$N = 13,000$	$l\hat{\mu}_{OLS}$		$l\hat{\mu}$		$l\hat{\mu}_{pp}$	
Indicator variable	0.07***	0.13***	0.08***	0.13***	0.22***	0.28***
($D = \{0, 1\}$)	(0.019)	(0.019)	(0.007)	(0.005)	(0.007)	(0.005)
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Controls	No	Yes	No	Yes	No	Yes
R^2	0.08	0.15	0.38	0.72	0.49	0.74

Note: *** p<0.01, ** p<0.05, * p<0.10. SE in parentheses are adjusted for clusters. Time-sector FE are interaction dummies. Controls are costs of goods sold and capital.

When regressing markups estimated from a homogenous production function ($l\hat{\mu}$), the parameters α_1 and α_1^{share} were estimated to be around 0.14. Considering different technologies for government contractors and private serving firms ($l\hat{\mu_{pp}}$), the markup percentage premium was estimated to be approximately twice as high. The dummy models explained more of the logged markup variation when considering both production function frameworks, while their standard errors are half of the ones obtained using the continuous share measure. Controlling for capital and cost of goods sold resulted in higher values of estimated parameters. This negative omitted variable bias likely stems from the higher expenditures of government contractors, as documented in Table 5.4 and their negative relationship with markups, as given by equation 5.13.

Table 6.5: Pooled OLS: Public procurement intensity

$N = 13,000$	$l\hat{\mu}_{OLS}$		$l\hat{\mu}$		$l\hat{\mu}_{pp}$	
Share of procurement sales	0.14***	0.31***	0.10***	0.15***	0.22***	0.26***
in total sales ($share \in [0,1]$)	(0.019)	(0.035)	(0.015)	(0.010)	(0.015)	(0.012)
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Controls	No	Yes	No	Yes	No	Yes
R^2	0.08	0.16	0.36	0.67	0.37	0.56

Note: *** p<0.01, ** p<0.05, * p<0.10. SE in parentheses are adjusted for clusters. Time-sector FE are interaction dummies. Controls are costs of goods sold and capital.

6.2.2 Within analysis

With firm fixed effects estimation, the public procurement dummy (D) remained associated with a significant difference in markups, and the parameter α_1 was estimated similarly as in the pooled OLS regression.

Table 6.6: Panel fixed effects: Public procurement activity

$N = 13,000$	$l\hat{\mu}_{OLS}$		$l\hat{\mu}$		$l\hat{\mu}_{pp}$	
Indicator variable	0.03***	0.04***	0.13***	0.14***	0.28***	0.29***
($D = \{0, 1\}$)	(0.011)	(0.011)	(0.005)	(0.003)	(0.006)	(0.005)
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
within R^2	0.02	0.10	0.19	0.59	0.45	0.69

Note: *** p<0.01, ** p<0.05, * p<0.10. SE in parentheses are adjusted for clusters. Time-sector FE are interaction dummies. Controls are costs of goods sold and capital.

The best models in terms of explanatory power included the indicator variable, and most of the overall variation of the logged markups was explained under the differentiated elasticities framework ($l\hat{\mu}_{pp}$). In contrast, the continuous measure ($share$) model explained only about two-fifths of the deviations from the mean values of the dependent variable in the sector-specific and a third in the sector-market-specific frameworks.

Table 6.7: Panel fixed effects: Public procurement intensity

$N = 13,000$	$l\hat{\mu}_{OLS}$		$l\hat{\mu}$		$l\hat{\mu}_{pp}$	
Share of procurement sales	0.00	0.01	0.03**	0.03***	0.03**	0.03***
in total sales ($share \in [0,1]$)	(0.011)	(0.030)	(0.011)	(0.08)	(0.014)	(0.012)
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
R^2	0.02	0.10	0.04	0.43	0.09	0.30

Note: *** p<0.01, ** p<0.05, * p<0.10. SE in parentheses are adjusted for clusters. Time-sector FE are interaction dummies. Controls are costs of goods sold and capital.

Assuming a homogeneous production function for each construction sector ($l\hat{\mu}$), the estimated coefficients of the public tender sales proportion measure $\hat{\alpha}_1^{share}$ became much lower, around 0.03. Similarly, in the case of the production function estimates heterogeneous based on public procurement activity ($\hat{\mu}_{pp}$), the markup premium was estimated to be around 3%.

The discrepancy between the fixed effects estimation results using the indicator variable and the proportion of public procurement sales in total sales approaches deserves its attention. A plausible explanation could be that the definition of the continuous measure of the intensity of engagement in public procurement $share$ suffers from the lack of information on the duration of the contracts. It was defined as the proportion of average awarded tender prices over a three-year period and total sales of a given year. As such, the measure of the intensity of engagement in public procurement is prone not to capture the exact distribution of revenues from public procurement over time for all firms. Further analysis of the relationship between markups and public procurement may therefore benefit from changing the 3-year identification window to a shorter or longer period. Splitting the sample into small and large firms and according to the type of contract or tender are other possible extensions that could provide more insight into the degree of public procurement efficiency.

6.3 Robustness

6.3.1 Estimating the production function

The main issue with estimating markups is recovering unbiased estimates of the production function, specifically the output elasticity of the variable input used in the markup formula given by equation 5.13. Apart from the two-step control function identification strategy, described in the methodology section 5.3, two additional methods were considered. Further, the assumed specification of the production function (equations 5.6 and 5.7), was varied. Table 6.8 lists the obtained estimates $\hat{\theta}^V$ and documents that the estimation approaches are consistent with the results presented in the main section.

First, the factor share approach, which relies on the condition for static cost minimization: an input's output elasticity equals the product of that input's cost share and the scale elasticity, was tested. Empirical applications often assume the scale elasticity to be equal to 1 and compute the resulting elasticity as: $\hat{\theta}^V_{CS} = \frac{P^V_{it} V_{it}}{P^V_{it} V_{it} + P^K_{it} K_{it}}$. Next, as referenced in the literature section 3.2.4, the Wooldridge (2009) single-step joint estimation of the production function parameters was performed, giving rise to $\hat{\theta}^V_{WRDG}$. Second, the standard Cobb-Douglas production function restricts the output elasticities to be independent of input use intensity and implies a constant elasticity across producers and time, in turn attributing variation in technology to variation in markups and potentially biases the public procurement effect (De Loecker & Warzynski 2012). In contrast, the translog production function is a specification that includes additional second order and interaction terms of the production factors: $y_{it} = \theta_v v_{it} + \theta_k k_{it} + +\theta_{vv} v_{it}^2 + \theta_{kk} k_{it}^2 + \theta_{vk} v_{it} k_{it} + \omega_{it} + \epsilon_{it}$, allows for variation in output elasticities across individuals: $\hat{\theta}^V_{TRANS} = \hat{\theta}_v + 2\hat{\theta}_{vv} v_{it} + \hat{\theta}_{vk} k_{it}$.

Table 6.8: Output elasticity of the variable input

$\hat{\theta}^V_{CS}$		$\hat{\theta}^V_{WRDG}$		$\hat{\theta}^V_{TRANS}$	
$D=1$	$D=0$	$D=1$	$D=0$	$D=1$	$D=0$
0.747	0.767	0.910***	0.776***	0.943***	0.833***
0.181	0.218	(0.014)	(0.017)	(0.010)	(0.012)

Note: *** p<0.01, ** p<0.05, * p<0.10. Sample means and standard deviations are shown instead of regression point estimates and standard errors for $\hat{\theta}^V_{CS}$. N = 13,000.

6.3.2 Controlling for productivity

Do firms active in public procurement charge higher markups simply because they are more productive? Importantly, the public procurement effect is still present even after controlling for productivity differences.

Documented by Table 6.9, including both the firm's procurement status and productivity (estimated by the control function procedure, see 5.3.1) in the pooled OLS cross sectional estimation (5.13), the coefficient on the procurement dummy, expressed in percentages, actually goes slightly up, 0.14 for markups generated under the assumption of sector-specific production functions, and when rounded to two decimals stays the same, 0.28 when considering sector-market specific production functions, while the R-squared increases from 0.72 to 0.91 for the former and from 0.74 to 0.90 for the latter model. Similar results hold for the share methodology.

Table 6.9: Pooled OLS with productivity estimates

$N = 13,000$	$l\hat{\mu}_{OLS}$		$l\hat{\mu}$		$l\hat{\mu}_{pp}$	
Indicator variable ($D = \{0,1\}$)	0.13***		0.14***		0.28***	
	(0.019)		(0.003)		(0.004)	
Share of procurement sales		0.30***		0.14***		0.24***
in total sales ($share \in [0,1]$)		(0.036)		(0.008)		(0.011)
Productivity estimate ($\hat{\omega}$)	0.61***	0.59***	0.94***	0.92***	0.91***	0.88***
	(0.089)	(0.090)	(0.040)	(0.045)	(0.050)	(0.058)
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.18	0.18	0.91	0.86	0.90	0.72

Note: *** p<0.01, ** p<0.05, * p<0.10. SE in parentheses are adjusted for clusters. Time-sector FE are interaction dummies. Controls are costs of goods sold and capital.

Controlling for productivity with firm fixed effects (5.14) still results in obtaining a substantial positive impact of public procurement entry under the indicator variable framework. The share methodology effect is estimated to be the same as in the main text, considerably smaller, yet statistically significant, as Table 6.10 presents.

Table 6.10: Panel fixed effects with productivity estimates

$N = 13,000$	$l\hat{\mu}_{OLS}$		$l\hat{\mu}$		$l\hat{\mu}_{pp}$	
Indicator variable ($D = \{0,1\}$)	0.04***		0.13***		0.28***	
	(0.011)		(0.002)		(0.004)	
Share of procurement sales		0.01		0.03***		0.03***
in total sales ($share \in [0,1]$)		(0.031)		(0.006)		(0.012)
Productivity estimate ($\hat{\omega}$)	0.26***	0.27***	0.98***	1.04***	0.90***	1.01***
	(0.079)	(0.079)	(0.029)	(0.033)	(0.041)	(0.049)
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
within R^2	0.10	0.10	0.89	0.75	0.85	0.50

Note: *** p<0.01, ** p<0.05, * p<0.10. SE in parentheses are adjusted for clusters. Time-sector FE are interaction dummies. Controls are costs of goods sold and capital.

Having productivity in the same regression framework with highly positive coefficient estimates of around 0.9 for pooled OLS and 1 for fixed effects estimations aligns with a wide range of theory models, confirming that more productive firms have higher markups.

However, given that measured productivity is a simple residual of a sales-generating production function, it contains unobserved quality differences in both inputs and output, as well as market power effects, and might be a poor measures of marginal cost. Other factors, reflected in price differences such as the elasticity of demand or product quality, can thus play an important role in explaining the estimated markup premia (De Loecker & Warzynski 2012).

Chapter 7

Conclusion

This thesis aims to add transparency to public procurement, a substantial part of general government spending, by applying the production approach of markup estimation and multivariate regression analysis to investigate the relationship between markups and public procurement empirically. Data on Czech construction firms and public tenders from 2006 to 2021 are used to test whether government contractors charge different markups than their private sector oriented counterparts and whether markups differ after a firm enters the public procurement market. While controlling for aggregate trends, government contractors are found to charge statistically and economically higher markups than similar firms servicing private clients, and econometric evidence of firms increasing markup upon public procurement entrance is established.

The relationship between markups and public procurement was examined via the estimated percentage markup premium of government contractors in a regression framework. With logged estimated markups as the dependent variable, the procurement effect was estimated as the coefficient of the explanatory variable measuring engagement in public procurement while controlling for technological change, industry effects, cost of goods sold, and capital. To account for the duration of construction contracts, the binary variable identified firms active in public procurement based on whether a public contract was recorded within a given year or the two preceding years. Similarly, the continuous measure of the intensity of engagement in public procurement was defined as the proportion of the average firm sales from public procurement over these three years and its total revenues in a given year.

In sum, two important conclusions are presented. First, controlling for aggregate demand and supply effects, government contractors in the Czech construction industry have, on average, higher markups than their private sector serving counterparts. Both measures of engagement in public procurement provided significant evidence for rejecting the null of no difference. Second, this relationship was found to hold also when taking into account the unobserved heterogeneity associated with firm-specific fixed effects, in turn establishing that markups increase after firms become engaged in public procurement. The estimated markup premium in the indicator measure framework is 14% or 29%, based on the assumptions of the underlying markup distribution. In the case of the continuous measure, the markups were estimated by about 3%.

However, the question of why government contractors charge higher markups remains. From the perspective of industrial organization, various models of competition predict that more efficient producers are more likely to charge lower prices, beat rivals, and establish higher markups. Government contractors may therefore benefit from a cost advantage. Alternatively, the results could be due to differences in demand elasticities or quality in private and public procurement markets. Last but not least, public procurement literature provides an additional aspect to consider when interpreting the results in that possible bid tendering inefficiencies, such as favorable contracting, manipulating the evaluation criteria, political connections, or corruption, could explain the markup premia found.

The significant contribution of this approach to the research area of public procurement efficiency is its ability to benchmark the competitiveness of public procurement against markets serving private clients rather than only making comparisons between different tenders. Furthermore, using multivariate regression allows for analyzing the relationship without relying on data on expert cost estimates, in turn circumventing potential subjective biases and inaccuracies. Additionally, as public procurement constitutes a large share of total GDP, the findings also contribute to studying factors driving the changes in aggregate markups. Possible extensions of the work include extending the sample period for robustness and considering multiple industries in the analysis to achieve more general results. While valuable for academics and policymakers, the findings are just the first step in examining the root causes behind the markup premiums of government contracting firms, a scope beyond this work's focus.

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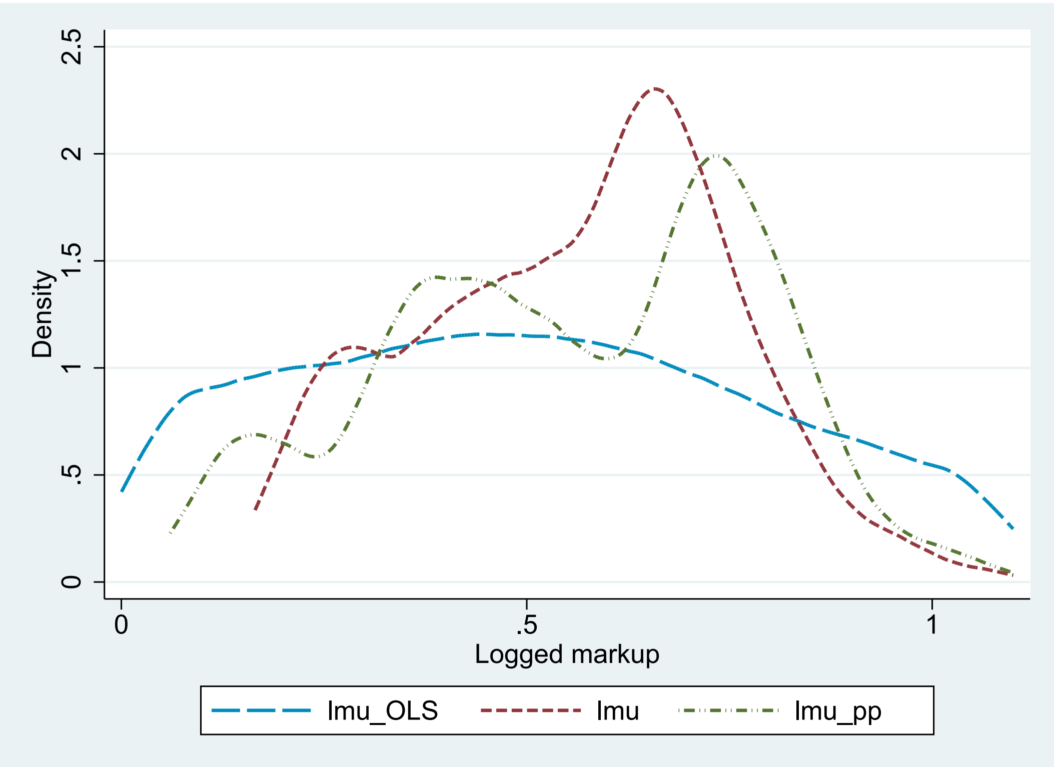
Appendix A

Additional figures

Figure A.1: Estimated log markups



Note: Logged markups over 1.1 are excluded from the figure.
$l\hat{\mu}_{OLS}$ obtained from an OLS sector-specific production estimation,
$l\hat{\mu}$ obtained from estimating sector-specific production function elasticities,
$l\hat{\mu}_{pp}$ also allowed for coefficients to vary based on activity in public procurement.

Figure A.2: $\hat{\mu}_{OLS}$ by sector

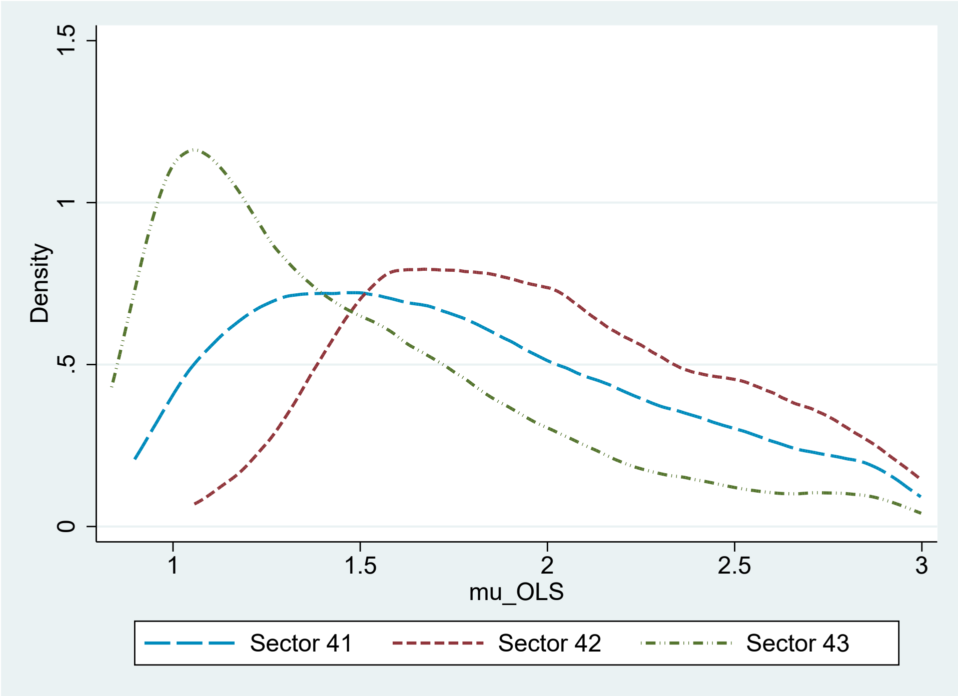
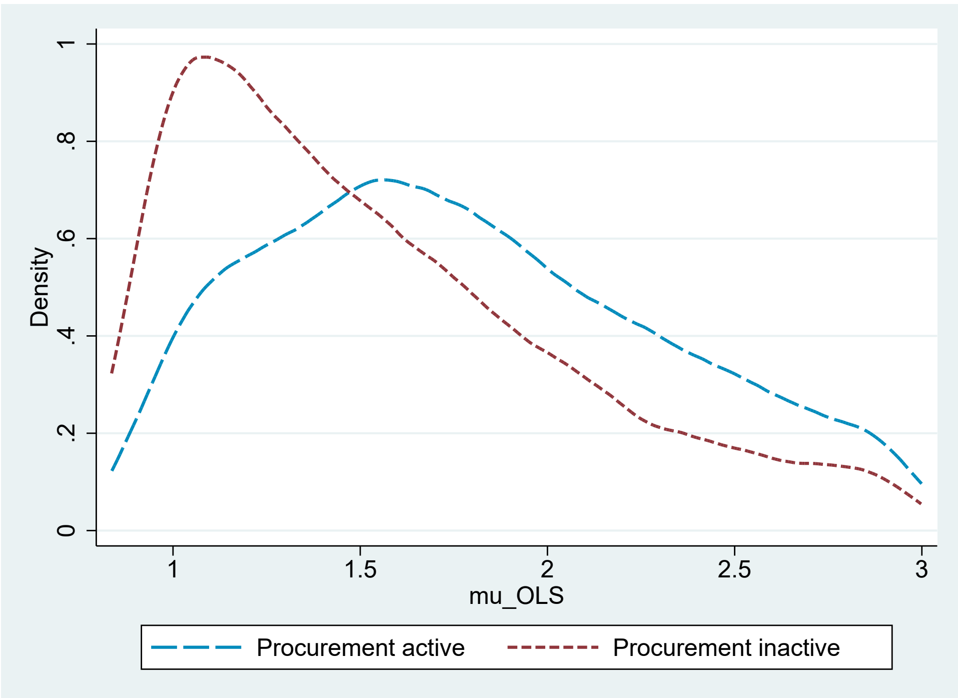


Figure A.3: $\hat{\mu}_{OLS}$ by procurement



Note: Markups over three are excluded from the figures.
$\hat{\mu}_{OLS}$ obtained from an OLS sector-specific production estimation

Figure A.4: $\hat{\mu}$ by sector

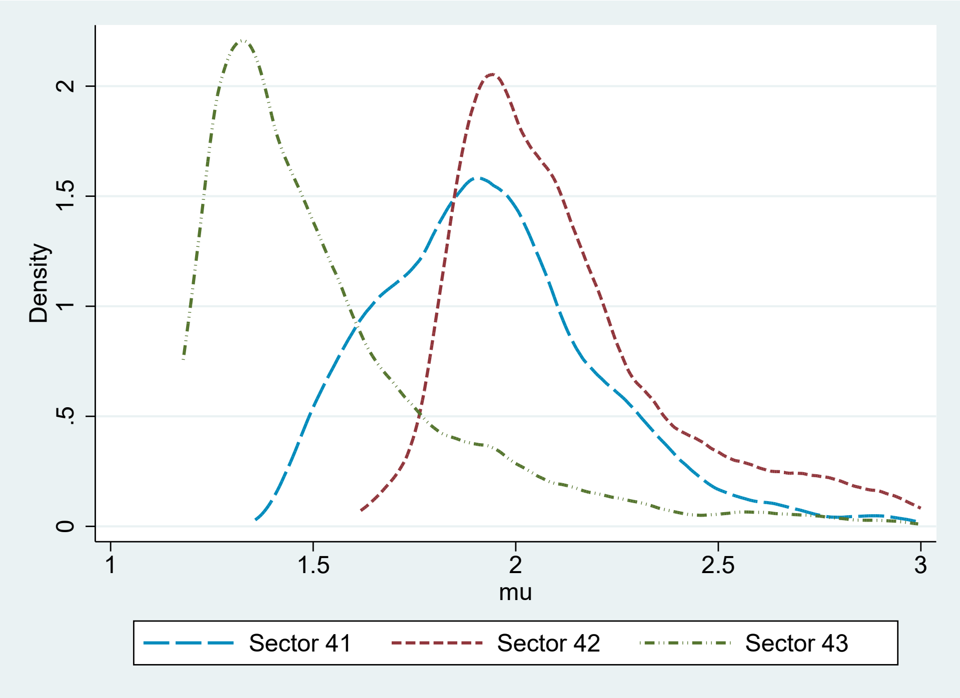
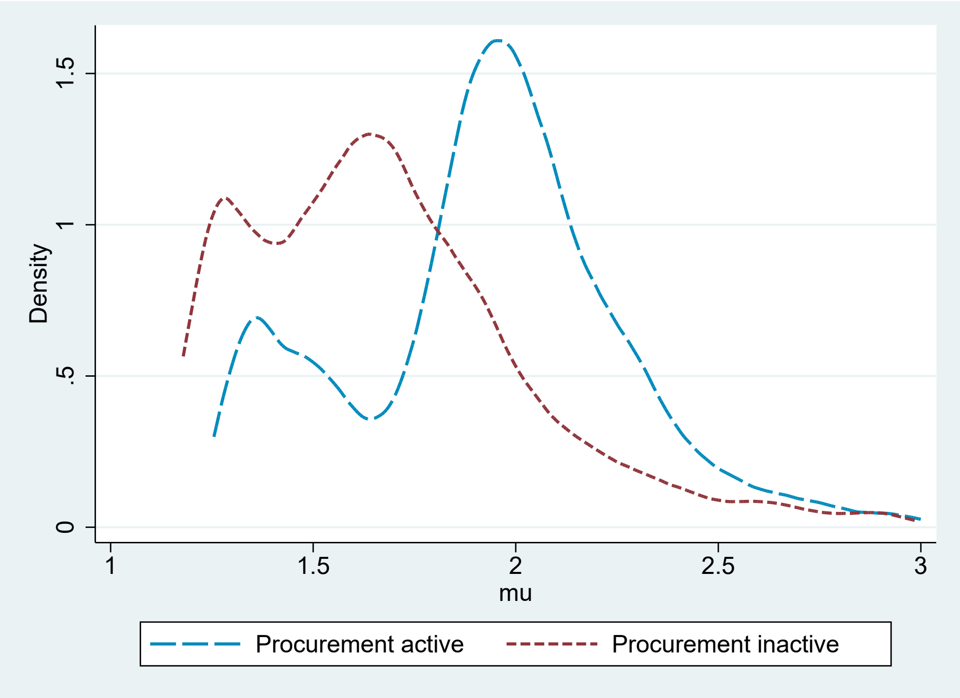


Figure A.5: $\hat{\mu}$ by procurement



Note: Markups over three are excluded from the figures.
$\hat{\mu}$ obtained from a control function sector-specific production estimation.

Figure A.6: $\hat{\mu}_{pp}$ by sector

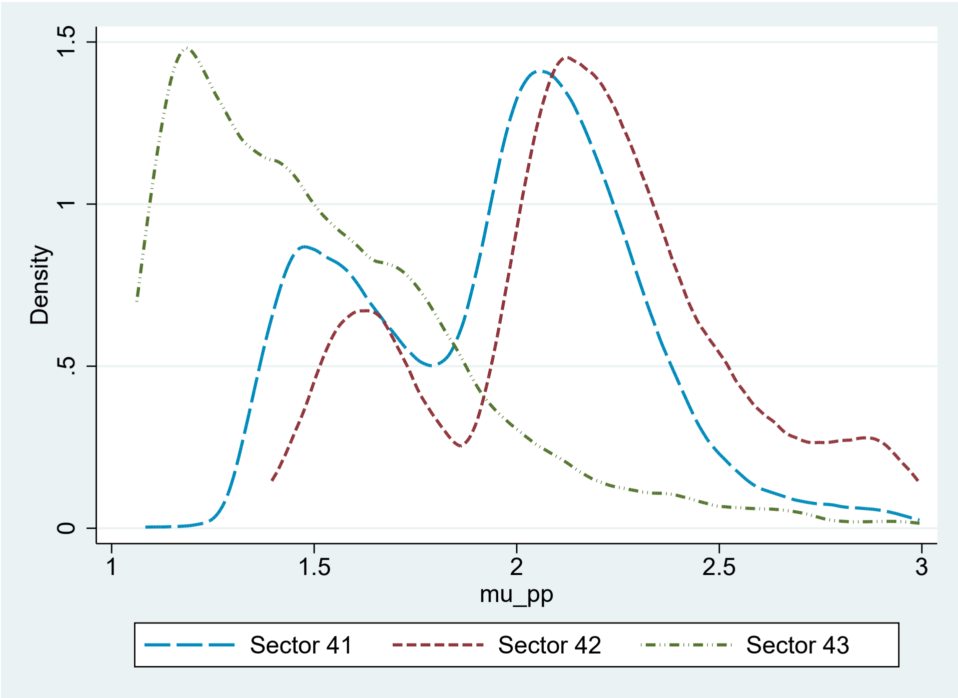
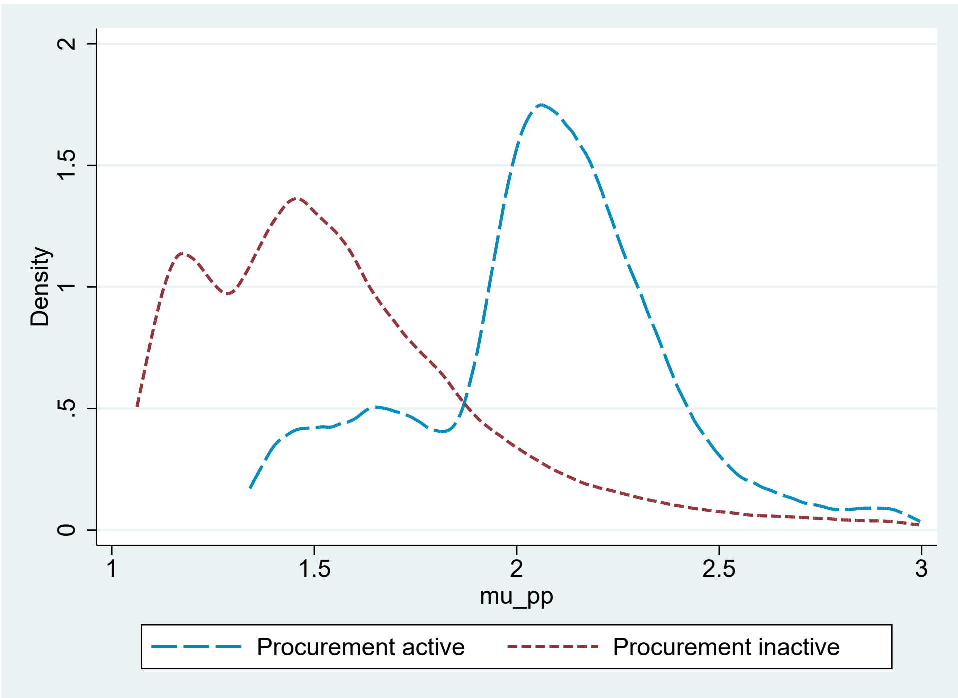


Figure A.7: $\hat{\mu}_{pp}$ by procurement



Note: Markups over three are excluded from the figures.
$\hat{\mu}_{pp}$ obtained from a control function sector-specific production estimation and allowed for coefficients to vary also based on activity in public procurement