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Abstract

Governments are the largest buyers in most countries and they tend to operate budgets that expire at the end of the fiscal year. They also tend to spend disproportionately large amounts right at year-end. This use-it-or-lose-it spending pattern has been observed in a number of countries and is considered a problem due to possible waste. This could be the case if firms increase their prices to profit from a government's greater demand at the end of the fiscal year. We investigate this previously unexplored possibility using a novel granular dataset of Ukrainian government procurement auctions over the period between 2017 and 2021. First, we document that the prices bid by firms are significantly higher in the last month of a fiscal year. Second, we employ a neural network technique to infer supplier costs from bidding behaviour. We estimate that suppliers charge around a 7.5% higher margin on less competitive tenders at the end of a fiscal year. Third, we demonstrate how results change depending on the type of the procured good, the length of the buyer-supplier relationship, and whether the procurement was expedited as a result of the Covid-19 pandemic. Our findings imply that substantial government funds could be saved if the extent of the year-end spending could be moderated.

JEL Codes: H57, H61, L22, L24

Keywords: government spending, procurement, fiscal year distortions, Ukraine

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1 Introduction

Heightened year-end spending has been observed in a number of countries including the United States (Liebman and Mahoney, 2017), the United Kingdom (Baumann, 2019), Germany (Fitzenberger, Furdas and Sajons, 2016), and across other OECD countries (Eichenauer, 2020). This spending pattern is often regarded as a problem by economists and policymakers since it is feared that it may be rushed and of poor value.[1] Given that 12 percent of the world's GDP is spent on public procurement (Bosio et al., 2020), and year-end spending in the final month can be more than double its monthly average (Liebman and Mahoney, 2017; Baumann, 2019), this represents a challenge for policymakers.

The increased year-end expenditure also presents an opportunity for firms. If a government is more willing to spend, why not increase prices? In this paper we examine whether firms increase the prices they offer in government procurement at the end of the fiscal year. Whilst this question has not been empirically tested before, there is some anecdotal evidence of higher prices from Hyndman, Jones and Pendlebury (2007), who conducted an extensive survey of public sector managers in the United Kingdom. These managers recognised the potential for paying more at the end of the fiscal year and tried to avert increased prices by negotiating long-term contracts where the department could order goods and services at a fixed price at any time. Unfortunately, they found this tactic faced the problem of firms being excessively busy towards the end of the fiscal year and unable to satisfy the demand of government departments. Additional anecdotal evidence that suppliers are aware of the heightened year-end spending comes from a number of media articles providing tips and recommendations to firms on how to profit from this behaviour (Federal Times, 2017; Forbes, 2020).[2]

There are multiple channels through which government departments may end up paying more for goods and services at the end of the year compared to what they would have paid

[1]There is some empirical evidence for this from the United States government procurement data (Liebman and Mahoney, 2017), which suggests that government departments use their remaining budget on lower value projects at the end of the fiscal year.

[2]An example of this is a recent lawsuit against Atlantic Diving Supply, Inc. The company, which has been awarded a contract worth up to 33 billion dollars over ten years, was accused of defrauding the Pentagon as it was participating in defence procurement intended for small firms only (POGO, 2021). One of the company's strategies involved a tradeshow - "Warrior Expo is a private tradeshow that we host in Virginia Beach and which is timed to capture the spending increase ahead of the U.S. government's September 30 fiscal year-end" (Securities and Commission, 2011; POGO, 2021).

earlier. First, the departments' increased willingness to pay can result in higher prices when these departments are bargaining contracts directly with a supplier. Second, a department may get fewer bidders per tender lot in a procurement auction given a higher number of procurements taking place in the later months of the year. This would lead to lower price competition between bidders. Third, a larger number of procurement auctions and lower competition between firms suggest that a participating firm has a better outside option if it does not win an auction. This could be expected as firms are better able to find another job that will also have less price competition and the likelihood of higher profits. As departments must pay at least firms' outside option to incentivise them to do the work, this further pushes up prices.

We use Ukrainian procurement lot level data over the period 2017 – 2021 to examine how the fiscal year-end impacts the prices that government departments pay in procurement. The Ukrainian context provides a unique set up for this question. Throughout this period the Ukrainian government solely used a procurement system called "ProZorro". It is an electronic platform that hosts all procurement procedures and is available in real time, which avoids any mistakes and biases in reporting from firms and departments. ProZorro's procurement auction format uses multiple rounds of bidding which also allows for more information elicitation than in government procurement auctions in many other countries. We are able to observe all tender participants, their bids in each round of auction and the final contract. We approach this question empirically in two distinct ways. First, we show that the quoted procurement prices for a job are at least 1% higher (relative to the department's initial price estimate) for that job at the end of the fiscal year compared to an average month. We also find that prices tend to rise most for heterogeneous good categories, relative to more homogenous good categories, at the end of the fiscal year. Our second empirical method uses a neural network model to infer firm costs of doing a job from bids in the auction for that job. Using these inferred costs we can identify that firms quote with a margin around 7.5% higher, relative to what they would charge earlier in the year, for less competitive tender lots at the year-end.

This paper contributes to two bodies of literature. The first is a small but growing literature on end of fiscal year spending, where existing research has primarily focused on explaining why such heightened spending occurs.[3] Liebman and Mahoney (2017) suggest that government departments face demand uncertainty and thus build up precautionary savings funds throughout the year. If they cannot save funds into the next year they will spend it at the end of the fiscal year, resulting in heightened spending. Drawing from the observation that spending spikes also exist in the United Kingdom, where unspent funds can be saved between fiscal years, Baumann (2019) suggests the alternative explanation that spending spikes reflect procrastination on the part of government departments. As departmental spending and performance reporting is organised on a fiscal-year basis, departments can delay exerting effort in spending funds until later in the fiscal year. A further contribution of Liebman and Mahoney (2017) is their examination of the quality of US government IT spending. They use ordered categorical quality scores of United States government IT procurement projects to find that end of fiscal year projects are between 2.2 to 5.6 times more likely to receive a quality score of "low quality". While these estimates indicate that departments are spending on goods and services which are of poor value, it does not suggest that prices are inflated. Furthermore, it is difficult to link an ordered categorical label to a more precise estimate of waste.

Our paper contributes to the literature by providing estimates of the extent to which prices are higher at the end of the fiscal year. For the most part our estimates of prices do not depend on any particular model of governmental spending. We do however offer a calibrated model in appendix A which has government departments choosing between competitive (e.g. online tender) and negotiated procurement processes. While competitive processes are cheaper in expectation, there is more uncertainty as to the outcome of the process. Therefore, at the end of the fiscal year, departments switch to negotiated procurements, which can cause heightened end of fiscal year spending. Our model depends on precautionary savings. However, unlike the model of Liebman and Mahoney (2017), the uncertainty in our model comes from the prices of suppliers, which is more measurable and in some contexts more prevalent than uncertainty coming from demand shocks. There are also new policy implications, such as imposing restrictions on the ability of departments to non-competitively negotiate with suppliers at the end of the fiscal year.

[3] A related paper to this literature is by Baumann and Klymak (2022) that uses the spending of all UK overseas embassies. As these operate under the UK fiscal year, but are located in countries with a different year-end date, this allows the authors to examine whether the year-end spike is driven by the fiscal year and higher demand in the local country.

We also contribute to the literature that concerns contracting between large buyers and smaller supplying firms (Ferraz, Finan and Szerman, 2015; Atkin, Khandelwal and Osman, 2017; Carrillo et al., 2019; Alfaro-Urena, Manelici and Vasquez, 2022), a setting that is particularly applicable to government procurement.[4] Coviello and Mariniello (2014) find that formalised procurement systems lead to lower prices in such a setting. Coviello, Guglielmo and Spagnolo (2017) examined the impact of advertising procurement auctions, with increased advertising of the auction resulted in more bidders participating and a lower price being achieved. Our paper contributes to this literature by showing the impact of a demand shock, provided by the end of the fiscal year, on prices agreed between a large buyer and a smaller suppliers. We find that in response to this demand shock the smaller supplying firms increase their prices to benefit. Additionally, when we examine the impact of expedited procurements as a result of the Covid-19 pandemic, we find supporting evidence that more intensive procurement processes lead to lower prices.

The paper proceeds as follows. Section 2 provides details on the Ukrainian government's procurement system and explains the dataset. The empirical strategy is then discussed in Section 3.1, while Section 3.2 presents a novel neural network technique for inferring job costs from the bidding decisions of prospective suppliers in procurement auctions. The results are presented in Section 4, while Section 5 considers other estimations, before Section 6 concludes.

2 Data

The public procurement sector in Ukraine represents approximately 15 percent of its GDP and has historically been criticised on the grounds of corruption. Indeed, Ukraine has been frequently named one of the most corrupt countries in Europe (Transparency International, 2020). This situation improved, however after the Ukrainian revolution of 2014 (Euromaidan). During this time, the Ministry of Economic Development and Trade, civil society and the private sector began collaborating on the development of a procurement platform "ProZorro"[5] (henceforth

[4]Related work also highlights that buyers' objectives in procurement are not necessarily the lowest costs possible (Best, Hjort and Szakonyi, 2017; Coviello and Gagliarducci, 2017; Bandiera et al., 2021).

[5]This name is derived from the word for "transparency" in the Ukrainian language.

referred to as "the platform"), which aimed to change the rules of public procurement and make it more transparent. The platform was launched in 2015 and is intended to make information about public procurement widely accessible. After the launch, it gained a lot of support from public and international organisations, received funding for further development and scaled up quickly. Furthermore, it also attracted international support and won major international government procurement awards such as World Procurement Award and Open Government Award (Open Government Partnership, 2016; Procurement Leaders, 2016). From 2016 onwards, all government authorities have been required to use the online procurement system. Between 2016 and the end of 2020, the platform was credited with saving approximately 150 billions UAH (Prozorro, 2020).[6]

If a government department would like to purchase a good, it must first estimate the price it anticipates paying a supplier. This estimate is called the *"expected price"*.[7] If a job's expected price is between 5,000 and 50,000 UAH,[8] then it can be contracted directly with a supplier of the government department's choice. If a procurement is undertaken off the platform, then a government agency still needs to report their purchase through the platform including contract details and information about a winner.[9] Jobs with an expected price greater than a *"competitive threshold"* (thereafter we call these competitive jobs) set at 50,000 UAH[10] must go through an *"online auction"* on the platform.[11]

The procedure on the online platform consists of several stages. First, a government department announces a lot it would like to purchase with all technical characteristics and the expected price. Second, firms interested in the advertised lot separately and simultaneously submit their offers, including an *"indicative price"* based on the information they received and the expected price. Once this stage is completed, the system automatically creates the day and time for an auction. The auction has three rounds. In the first round, sequentially and starting with the firm with the highest indicative price, each firm can choose to reduce its price or leave

[6] That amount corresponds to about 5.1 billion US dollars as of December 2021 exchange rate.

[7] This expected price aimed to provide guidance to what departments are expecting to pay. However, firms are allowed to bid above the expected price.

[8] 5,000 UAH approximates 176 US dollars, while 50,000 UAH corresponds to 1,760 US dollars as of December 2021 exchange rate.

[9] The only exceptions are for military or custom orders.

[10] This amount approximately equals 1,760 USD as of December 2021.

[11] Payments tend to happen upon delivery of the procured goods/services.

it unchanged. At each stage, the action can be observed immediately by all auction participants. A similar format is used for the second and third rounds, where the prices in the previous round determine the order in which firms submit price revisions. Depending on the selection criteria for a winner, which is almost always a price, the firm with the best offer from the final round wins the auction.

This paper uses data on over 10.79 million procurement lots that were concluded between January 1, 2017 until December 31, 2021 inclusive. We can observe all information reported by the government on purchases and all tender participants with an expected price of 5,000 UAH or more.[12] This includes the outcome of the auction, the identity of the bidders and the behaviour of each bidder in each round. The fiscal year in Ukraine ends in December.

We begin our description of the data by presenting monthly summary statistics in Table 1. These include the mean number of bidders over all jobs and over competitive jobs (i.e., lots with an expected price greater than the competitive threshold), the fraction of competitive jobs, the total number of finalised jobs, and their total notional in each month as well as the mean price ratio. We define the price ratio, for a tender lot i, as:

$$\text{Price ratio}_i = \left(\frac{\text{Winner value}_i}{\text{Expected value}_i}\right) \times 100 \tag{1}$$

In the second and third columns of Table 1 we observe that at the year-end jobs get fewer bidders on average both over all lots and when attention is restricted to competitive lots. In the fourth column, there are far fewer lots above the competitive threshold at the end of the fiscal year. This is a strong effect with the percentage of competitive lots in December being less than half the average of other months. In the fifth and sixth columns, we observe that the number of lots and the corresponding amount of funds is highest at the end of the fiscal year. Most notably, 34% more is spent in the last month relative to the average month and 79% more jobs are finalised in this time.[13] This indicates that a large part of the end of fiscal year spending comes from more jobs and not just larger jobs.

[12] We deflated all values used in the analysis with the monthly Ukrainian CPI indices from the State Statistics Committee of Ukraine.

[13] These percentages can be calculated from the table dividing the December figure by the average of the 12 monthly figures.

The price ratio also increases sharply at the end of the fiscal year, which provides some suggestive evidence of increased prices at the end of the fiscal year. Finally, in addition to price ratios increasing around December, we also observe substantially lower price ratio around January. While government departments spend almost as much of their budget at the start of the year as in November, auctions at the year-start are more competitive. These tenders have on average 2.2 bidders and the proportion of tenders above the competitive threshold is also higher (19.1%).

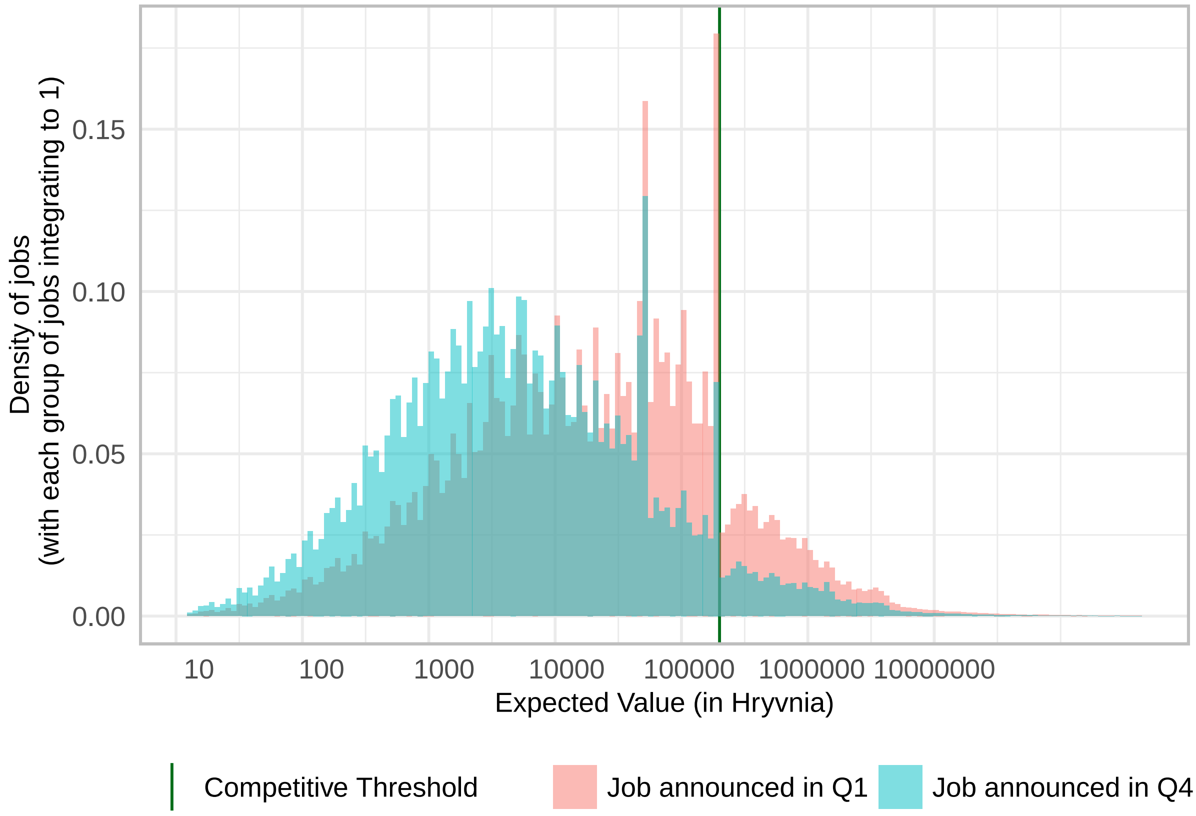
Table (1) Summary Statistics

Month	Mean Number of Bidders	Mean Number of Bidders (competitive lots)	Mean Fraction Above Competitive Threshold	Average Notional Won (Billions of Hryvnia)	Average Number Lots Won (Thousands)	Mean Price Ratio
January	2.219	4.146	19.1%	23.06	123.44	93.6%
February	2.226	4.168	19.6%	17.84	174.02	93.7%
March	2.177	4.155	20.0%	18.64	121.73	93.9%
April	2.066	3.969	19.7%	21.54	161.14	94.3%
May	1.966	3.818	17.4%	19.34	157.04	94.7%
June	1.839	3.643	16.7%	18.44	183.07	95.3%
July	1.856	3.540	18.4%	21.18	185.04	95.3%
August	1.849	3.666	18.0%	24.29	179.86	95.4%
September	1.744	3.320	15.9%	23.53	216.80	95.6%
October	1.749	3.310	16.2%	19.57	222.08	95.7%
November	1.698	3.243	15.6%	23.94	257.96	95.6%
December	1.392	3.007	8.4%	29.28	348.07	97.6%

We first investigate the increased number of smaller jobs at the end of the fiscal year and we plot a histogram in Figure 1, which shows the distribution of job sizes in the first and the last quarters of the fiscal year. It demonstrates that there is a greater density of smaller jobs in the last quarter when compared to the first. In addition, at all times of the year there is a large degree of bunching immediately below the competitive threshold. This suggests that purchasing departments in Ukraine are responsive to the competitive threshold and try to adjust the expected values of their procurements to avoid the additional steps required by larger purchases.

Next, we explore the average price ratio among jobs for each number of bidders in Figure 2.

Figure (1) Distribution of Lot Sizes



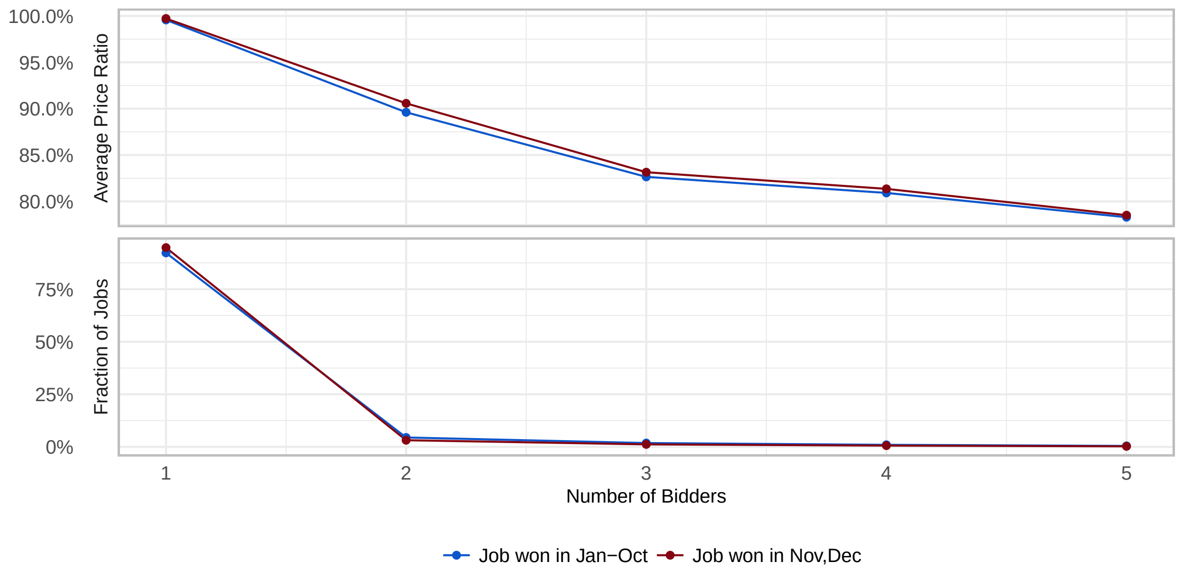
Notes: the figure demonstrates the plots of the distribution of the expected value size in the first (green) and the last (in red) quarters of the fiscal year. The competitive threshold applied for tenders above the expected value of 50,000 UAH.

We do this twice, once for jobs taking place in the first 10 months of the year and once for the last two months.[14] The top panel of the figure demonstrates that the price ratio is higher for less competitive jobs. In alignment with standard auction theory, the price ratio has a decreasing and convex shape as the number of bidders increases. In addition, for a given level of bidders there is a higher price in the last two months of the year as compared to the first ten months. This effect is robust for each of the five sets of jobs considered in the chart (with each set consisting of jobs that had a different number of bidders participating). The bottom panel of this chart shows that the percentage of jobs receiving 2, 3, 4 or 5 bidders was higher than the corresponding percentages amongst jobs taking place in the last two months of the year.

Taken together, Table 1 and Figure 2 suggest two reasons why prices might be higher at the end of the fiscal year. The first reason is that there are fewer competitive jobs at the end of the fiscal year and that competitive jobs receive fewer bidders. The second reason is that conditional

[14]We can reach similar conclusions if we isolate only December against the first 11 months.

Figure (2) Average Price Ratio per Number of Bidders



Notes: figure presents the mean price ratio (as defined in equation 1) by number of participants. Blue plots this information for tenders taking place between January and October; red is for November and December tenders.

on any given number of bidders, prices as a proportion of the expected price are higher at the end of the fiscal year.

3 Methodology

3.1 Empirical Strategy

We begin our analysis of whether government departments pay over the odds at the year-end by examining tender prices offered by firms as a proportion of expected prices. We use the following benchmark specification for estimating the total end of year price effect:

$$\text{Price ratio}_{ifdys} = \beta_0 + \beta_1 \text{Last month}_{ifdys} + \phi_d + \eta_f + \psi_y + \eta_s + \epsilon_{if} \tag{2}$$

Where the dependent variable Price ratio$_{if}$ is a per-bidder analogue of the price ratio of equation 1. It is the firm's bid normalised by the expected value of the job.

$$\text{Price ratio}_{ifdys} = \left[\frac{\text{Bid price}_{ifdys}}{\text{Expected price}_{ifdys}} \right] \times 100 \tag{3}$$

The regressor of interest Last month$_{if}$ is a dummy variable which equals one if a tender's i purchase was finalised in December and zero otherwise.[15] Therefore, if government departments spend more at the end of the fiscal year, we would expect this coefficient to be positive. We use fixed effects for the advertising department d, the bidding firm f, the year y and the industrial classification of the acquired good s, while ϵ_{if} is the statistical error term. Firm fixed effects control for the time invariant characteristics of firms as well as differences in cost bases and bidding strategies of firms. Departments fixed effect takes into account the time invariant characteristics (i.e. location, staff, procedures), but also differences in the way departments set expected prices. We also have industry fixed effects and year fixed effects. Finally, we cluster standard errors at the government department level.[16]

While the benchmark regression above provides an overall price impact, it is useful to isolate several channels which underlie it. We can identify four such channels. The first is that at the end of the year there are fewer bidders per job and so bidders face less competition. Second, bidders are busy and would face higher costs at the end of the year. The third is that the increased amount of jobs being advertised at this time also gives bidders a better outside option. The fourth is that departments may have a higher willingness to spend at the end of the fiscal year. The last three channels here lead to bidders bidding higher for a given level of competition. We can separate these three channels from the first by controlling for the number of bidders that a firm faces.

Separating these last three channels is however more challenging, as how busy firms are and firm outside options are not readily observable. We do however construct proxy variables for each of these. For how busy firms are, we create a proxy by calculating the average daily notional (or cash value) of all government jobs awarded in that industry over the previous 30 days for each region and the broad industrial classification of the procured good. We then divide this by the annual average daily notional for that industrial code for the calendar year. Finally, we then standardise this variable and use it as a proxy for how busy firms are, which we define as firm *"busy-ness"*.[17] We similarly construct a variable for the *"outside option"* by considering

[15] We also perform a set of regressions using the date of a tender being published rather than finalised. These findings are available in the Appendix.

[16] We do this in all regressions of this paper except where noted.

[17] Note that a linear transformation will only change the magnitude of the coefficients estimated in regressions

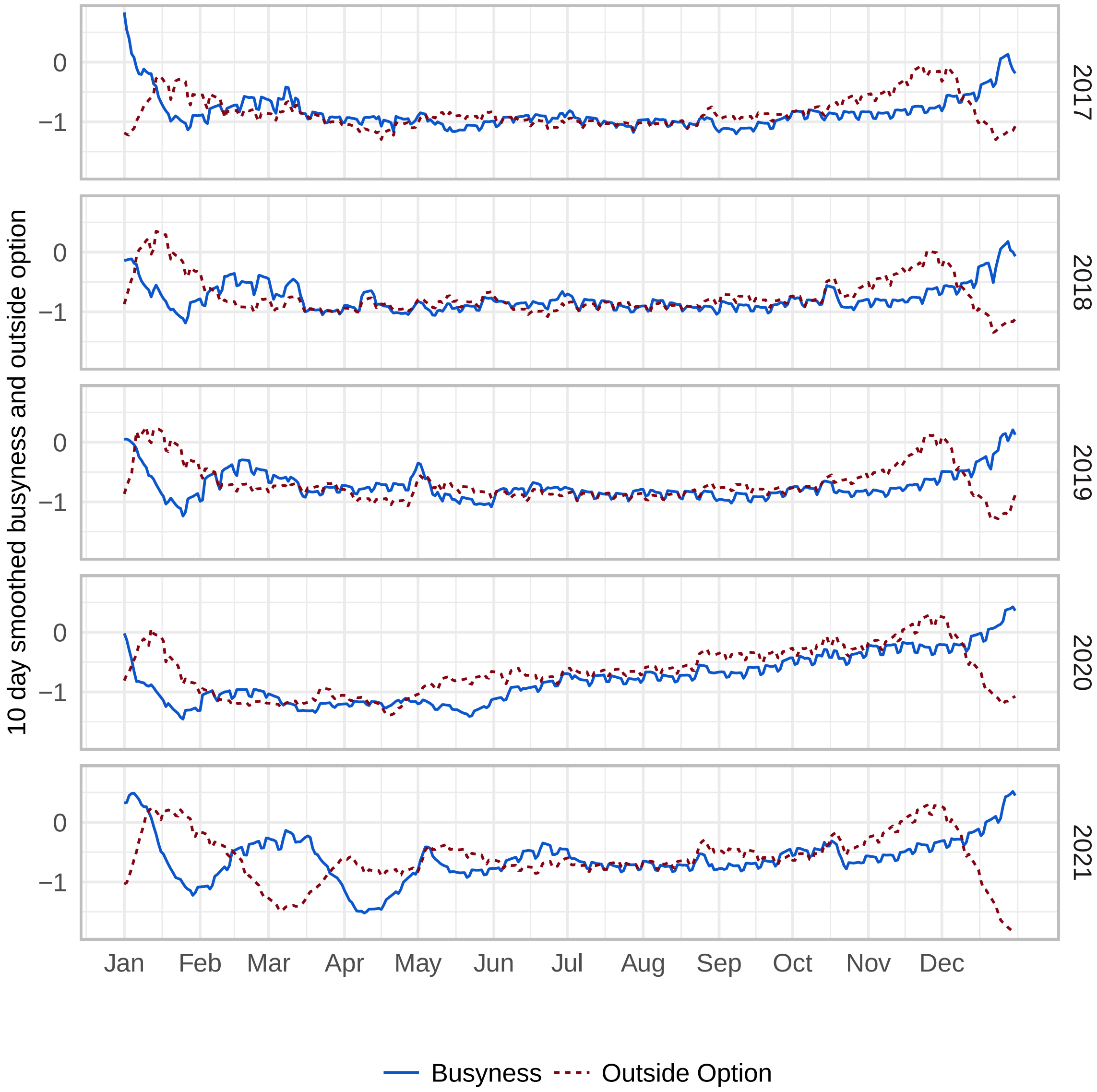


Figure (3) Busy-ness and Outside Option over the year

the future 30 days rather than the past 30 days. While the total cash value of jobs that will be awarded in an industry in the next 30 days will not yet be known to a bidding firm, they are likely to have some expectation, and hence this would function as a proxy for the value of their outside option. The average (across industries) daily busy-ness and outside option values are plotted in Figure 3. We can see that these variables reflect the same clustering of jobs at either end of the year.

While our benchmark specification uses price ratio, a natural concern is that government agencies may increase the expected price at the end of the fiscal year in order to reflect higher

but not the significance.

purchasing prices generally experienced at that time. This possibility acts against finding price ratio increases at the end of the fiscal year and hence our results are likely to underestimate the true price impact of fiscal year distortions. As a result of this possibility, we additionally employ an alternative approach and try to infer firm costs of doing jobs from their bids. By using these implied firm costs (rather than expected price) as a benchmark for prices we can avoid this issue. This approach is presented in the subsequent subsection.

3.2 Inferring Costs from Bids

We use a deep learning model to infer firm costs from the bids they place in auctions.[18] We train a log-concave function that models the probability that a firm wins an auction with a certain bid $b_{3,f}$ conditional on what each firm can observe at the time they make the bid. Our implicit assumption is that the firms bidding in an auction will be choosing bids optimally based on their calculations of the profit margin and probability of winning for each potential bid.

We will denote the position of a firm within the bidding sequence in the third round as being after $N_{3,a}$ firms and preceding $N_{3,b}$ firms. We use seven observables to train our model. These are: $N_{3,a}$; $N_{3,b}$; the best bid (from all bidders) in the second round; the best bid of the preceding $N_{3,a}$ firms in the third round;[19] the logarithm of the expected price of the auction and the number of "inactive bidders" who have not varied their price between the preliminary round and the second round. The final input to our model is the bid b as a proportion of the expected price however as a restriction to ensure monotonicity and log concavity, this does not directly enter the neural network.

We first train a Neural Network that takes as an input 6 input variables (all aforementioned variables except the bid). Then there are 8 fully connected hidden layers of widths (6,5,4,4,4,4,4,4), all of which are of leaky ReLU type and a final output layer of 4 outputs (that

[18] A more direct technique of trying to solve for bidder's optimal strategies is not possible in this case for several reasons. The auction format is highly complicated. For instance, in order to choose a bid in the first round, each bidder needs to consider their beliefs concerning other bidders from preliminary round bids and from bids already undertaken in the first round. They also need to consider the effect that lowering a bid would have on their future bidding position, on their smaller range of future allowed actions (in that bids cannot later be increased) and in their impact on other bidder's beliefs. Hence, it is not feasible to solve for equilibrium and it is possible the model may have many equilibria.

[19] If firm f is first, then we duplicate the best bid in the second round for this model input.

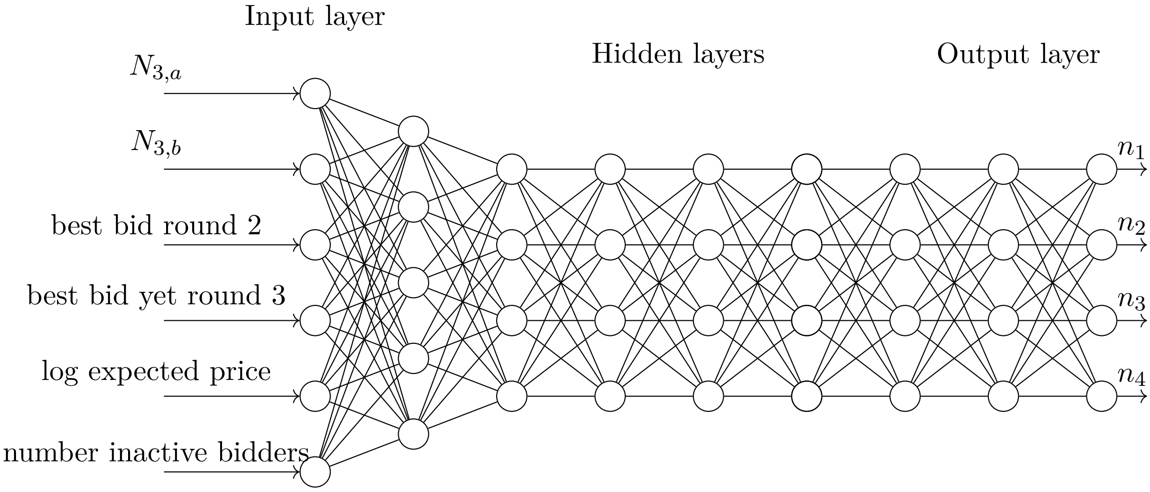


Figure (4) Probability of winning neural network

will be denoted n_1, n_2, n_3, n_4).[20] To predict the probability of a firm winning an auction we input these 4 outputs as well as a firm's bid into the expression:

$$\text{Prob of Winning}(b) = n_1 \exp\left(-n_2 \times (b^{n_3}) + n_4\right) \tag{4}$$

One way to view this estimation technique is that the neural network produces four parameters describing the *state* that a bidder finds itself in. These parameters representing the state are combined with the bid (which is a *choice*) in Equation 4 to give the probability of winning the auction. One limitation is that this log-concave probability function is unlikely to be accurate for bidders who bid last in the final round, as these bidders likely have a stepped demand function as they will win if they undercut the previous bidders by an epsilon. As a result, we do not consider these bidders in training or evaluating this model.

Equation 4 is easily differentiable and thus the neural network can be trained to optimize the accuracy of Equation 4.[21] Furthermore, this functional form is constrained so that the resultant

[20] This architecture was chosen as being sufficiently deep to get good performance and generalisation. We use leaky ReLU to allow for faster convergence and to avoid dead neurons (Maas, Hannun and Ng, 2013).

[21] The neural networks method is the obvious choice for providing the four state variables that enter Equation 4. The reason is that they can return multiple variables, are functionally flexible and we can train the neural network by back-propagating through Equation 4 to optimise this Equation's predictions on the training set. We did the training using the Flux.jl package of Julia (Innes, 2018). This training was performed on the database of Ukrainian tenders with a unit of observation being a bidder-tender. We exclude jobs with more than 10 bidders as there were too few such orders to adequately train the neural network. We also dropped jobs that did not undergo a competitive tender process as bidding never occurred. For data availability reasons we only include orders from 2017 to 2019. Bidders that did not change their bid between the preliminary and the second round were also excluded. This left us with 307,752 observations of which 50,000 were taken as a test set with the training set comprising of the remainder. The training was accomplished using stochastic gradient descent to minimise the

probability of winning function is log-concave and monotonically decreasing in the bid that is offered. The log-concavity also ensures that there is one particular unique best bid for any state. We constrain the parameter values so that costs lie between zero and the bid.[22] Given our trained neural network, we can extract estimates of costs as follows. We can first write each firms optimal bidding decision problem:

$$\pi_{3,f} = \max_{b}(b - c_f)p(b) \tag{5}$$

where p(b) is the probability of winning given a bid. From the profit maximisation of firms we assume that the bids in our dataset reflect optimal choices:

$$b_{3,f} = \arg\max_{b}(b - c_f)p(b) \tag{6}$$

Assuming that the bids in our dataset reflect optimal choices, we can take first order conditions and rearrange to give an expression which we can use to back firm costs out of their bid in the final round:

$$\hat{c}_{3,f} = b_{3,f} - \frac{p(b_{3,f})}{-p'(b_{3,f})} \tag{7}$$

This can be easily calculated using the automatic derivative of Equation 4.

There is a substantial amount of randomness associated with the use of neural networks.[23] To overcome this issue we do the preceding procedure 10 times. In each case, the model generally attained a correlation (on the test set) of around 45% between the probability of winning and the dummy variable representing whether a bidder actually won. There is a high degree of correlation between the inferred costs calculated by each neural network (of the ten we estimate) with an average pairwise correlation of 99.4%.

We can infer costs for all bidders except the final bidder and any bidders who do not vary

mean absolute error of prediction. Training stopped when accuracy on the test set stopped improving and started to worsen by overfitting.

[22] The constraints we impose are $0 < n_3 < 1$ and $\frac{2}{n_3} < n_2 < 4 + \frac{2}{n_3}$.

[23] As there are typically multiple local optima in optimising a neural network, the random initialisation of weights and the use of stochastic gradient descent imply that different trainings of the same model will result in different weights and different predictions.

their bids in any rounds. For those bidders that we can estimate costs, the margin that bidder f is seeking for job i is:

$$\text{Margin}_{if} = \left(\frac{\text{Bid}_{if}}{\text{Implied cost}_{if}}\right) \times 100 \tag{8}$$

Notably, however many of the winners of auctions go into the final round in a position to bid last and hence we cannot infer costs for a large group of successful bidders. For this reason, for every tender we average each implied cost that has been calculated to get a variable indicating the cost of a job. We can then calculate *margin common cost* as:

$$\text{Margin common cost}_{if} = \left(\frac{\text{Bid}_{if}}{\text{Average cost of job across bidders}_i}\right) \times 100 \tag{9}$$

One issue with the Margin common cost_{if} variable however is that the estimated cost will differ depending on the number of bidders participating in an auction. On one hand, consider a job with two bidders. In this case the calculated average cost would be the implied cost of the losing bidder. The data generation process for this value could be described as the second order statistic of two draws of the true distribution of costs. If on the other hand we have ten bidders, then calculated average cost is the average of our estimated cost of the 9 losing bidders. The data generation process for this value could be described as the average of the 2nd, 3rd, ... 10th order statistic from ten draws of the true distribution of costs.[24]

As a result, we will always use the Margin common cost_{if} value in regressions with the number of bidders being fixed. As the number of bidders is endogenous to the end of the fiscal year this precludes estimation of the unconditional expectation of end of fiscal year margin changes. However we can estimate to what extent bidders increase their prices for a given number of competing firms. The specification in the following section for margin estimations will be:

$$\text{Margin common cost}_{ifydg} = \gamma_0 + \gamma_1 \text{Last Month}_{ifydg} + \psi_y + \tau_d + \delta_g + \upsilon_{if} \tag{10}$$

[24]Note that this issue cannot be easily reconciled by only taking the cost of the 2nd place bidder, as the second order statistic from two draws is higher than the second order statistic from ten.

where *Last Month*$_{ifydg}$ corresponds to the auction i taken place in December in year y organised by department d for a purchase of a good in sector g.

4 Results

4.1 Estimations with Price Ratio

We present the results of a series of estimations based on equation 2 in Table 2. This table contains the final prices agreed for each tender lot advertised by the government with unit of observation being the tender lot. A firm's bid is included in this dataset only if it is a winning bid, and hence these regression results are indicative of the price the government paid.

The top panel does not take into account the number of bidders that participated in the procurement process, while the bottom panel does. We begin our analysis with a specification that includes our regressor of interest only, and we gradually add year, governments' buying unit, firm and industry fixed effects. The final estimate in column (5) corresponds to equation 2. The results of the top panel indicate that costs are substantially higher at the end of the fiscal year, with prices around 0.5% higher depending on the fixed effects.

The bottom panel of Table 2 controls for the number of bidders. As expected, this approach provides smaller coefficients for last month when conditioned on the number of bidders than when we do not condition on it. We also condition on how busy firms in that region/industry (i.e. busy-ness) are and the value of their outside option using the proxy variables discussed in section 3.1. The estimated coefficients are still significantly positive with a magnitude around 0.15%. This result indicates that the majority of the higher prices effect operates through the channel of less competitive jobs at the end of the fiscal year.

Taken together, Table 2 reveals that end of fiscal year prices are higher with both fewer bidders per auction and higher bids per level of competition in an auction being significant channels for this effect. Our findings also indicate that all four channels (i.e. level of competition, firm busy-ness and outside option) are potentially contributing to the higher prices at the end of the fiscal year. However, since we rely on proxies for the latter two channels, this limits the

Table (2) Benchmark Results

	Dependent variable:				
	Price ratio				
	(1)	(2)	(3)	(4)	(5)
Panel A: All lots					
Last Month	0.654***	0.493***	0.477***	0.432***	0.422***
	(0.018)	(0.013)	(0.011)	(0.010)	(0.010)
Observations	11,616,801	11,616,801	11,616,801	11,616,801	11,616,801
R^2	0.023	0.137	0.229	0.281	0.285
Panel B: All lots conditioning on number of bidders					
Last Month	0.181***	0.145***	0.163***	0.145***	0.133***
	(0.013)	(0.013)	(0.010)	(0.010)	(0.010)
Busy-ness	0.072***	0.044***	0.041***	0.026***	0.044***
	(0.008)	(0.007)	(0.006)	(0.005)	(0.006)
Outside Option	0.022***	0.033***	0.019***	0.024***	0.038***
	(0.008)	(0.007)	(0.006)	(0.005)	(0.006)
2 bidders	−9.616***	−8.951***	−9.334***	−8.881***	−9.005***
	(0.095)	(0.073)	(0.066)	(0.061)	(0.062)
3 bidders	−16.596***	−15.759***	−15.276***	−14.782***	−14.857***
	(0.118)	(0.089)	(0.089)	(0.079)	(0.079)
4 bidders	−18.351***	−17.711***	−17.057***	−16.684***	−16.773***
	(0.187)	(0.140)	(0.140)	(0.124)	(0.124)
5 bidders	−20.993***	−20.338***	−19.329***	−18.973***	−19.056***
	(0.246)	(0.191)	(0.182)	(0.165)	(0.163)
6+ bidders	−13.788***	−14.531***	−13.900***	−14.437***	−14.580***
	(0.514)	(0.350)	(0.328)	(0.261)	(0.261)
Observations	11,611,308	11,611,308	11,611,308	11,611,308	11,611,308
R^2	0.321	0.365	0.414	0.442	0.445
Year FE	Yes	Yes	Yes	Yes	Yes
Buyer FE	No	Yes	No	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses, and are clustered by government departments. FE refers to fixed effects. The dependent variable in all columns is a price ratio as defined in equation 3. Last month is a dummy variable that takes the value 1 if the tender was finalised in December and 0 otherwise. All coefficients should be interpreted as percentage changes to the price (relative to expected price).

extent to which these can be disentangled from an increased willingness to spend on the part of government departments.

We next repeat the regressions of Table 2 but with the unit of observation being the bidder $\times$ tender lot. All bids are included in this data (including losing bids), and so these results are indicative of prices quoted to the government rather than prices paid by the government. This is presented in Table 3. While Table 2 shows how the prices paid by governments change at the end of the fiscal year, Table 3 shows how the bids posted by firms change at the end of the fiscal year. Looking at the unconditional results in the top panel, we can see that prices bid are around 1% higher. The significant increase in posted bids is robust in every regression.[25]

We then test whether results change if instead of examining the last month of the fiscal year (i.e. December) we control for other months as well. We therefore replicate the benchmark specification (2) but additionally include a dummy variable for each month (with January being the baseline). We present the coefficients this generates in Figure 5,[26] where the top panel shows the case where we do not condition on the number of bidders while we condition in the bottom panel. Our results indicate that generally, the prices paid as a proportion of expected value increase as the year goes on. The rate of increase is greater in the top panel as we have two effects that change throughout the year: fewer bidders per job; and higher bidding per level of competition. The bottom panel removes the former effect but we still see an increase which reflects the channel of higher bidding for a given level of competition.

Our results hold when we consider industrial and regional heterogeneity. Previous papers have found a greater end of fiscal year spending in certain classes of goods (Liebman and Mahoney, 2017; Baumann, 2019). These goods include computers and furniture, presumably because they are relatively expensive, available off the shelf, and allow funds to be spent quickly. The emerging question is whether the prices of goods with more end of year spending increases to a greater extent than other goods. To test for this, we aggregate our industrial classification to broader categories and repeat our estimation of Equation 2 on each. We record the coefficient and 95%

[25]As a robustness check, we also separate the price ratio and use the logarithm of the winning value as the dependent variable, while controlling for the expected value. We present the results in table C.1. The clear picture is that prices are between 1.9% and 1.2% higher at the end of the fiscal year, while the winners charge approximately 0.6% higher prices for their goods and services.

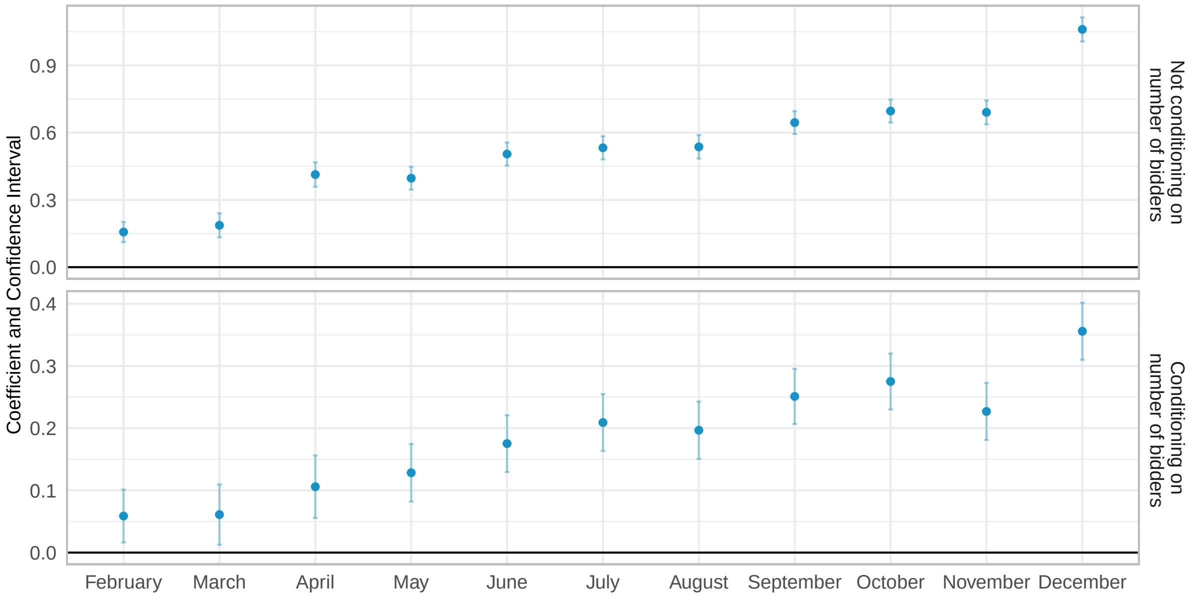
[26]We provide the regression output in the Appendix Table B.2.

Table (3) The Last Month Effect for Winners and Losers

	Dependent variable:				
	Price Ratio				
	(1)	(2)	(3)	(4)	(5)
Panel A: All lots					
Last Month	1.758***	1.194***	1.129***	0.945***	0.920***
	(0.035)	(0.022)	(0.019)	(0.016)	(0.016)
Observations	13,824,208	13,824,208	13,824,208	13,824,208	13,824,208
R^2	0.041	0.174	0.292	0.342	0.349
Panel B: All lots conditioning on number of bidders					
Last Month	0.167***	0.126***	0.165***	0.137***	0.114***
	(0.020)	(0.017)	(0.015)	(0.014)	(0.014)
Busy-ness	0.089***	0.053***	0.054***	0.036***	0.068***
	(0.012)	(0.009)	(0.008)	(0.007)	(0.009)
Outside Option	0.013	0.032***	0.023***	0.029***	0.052***
	(0.013)	(0.010)	(0.008)	(0.007)	(0.008)
2 bidders	−9.153***	−8.582***	−9.287***	−8.825***	−9.040***
	(0.091)	(0.067)	(0.063)	(0.058)	(0.058)
3 bidders	−15.339***	−14.539***	−14.316***	−13.793***	−13.933***
	(0.090)	(0.064)	(0.067)	(0.060)	(0.060)
4 bidders	−17.346***	−16.637***	−16.212***	−15.732***	−15.874***
	(0.125)	(0.083)	(0.091)	(0.078)	(0.078)
5 bidders	−20.086***	−19.290***	−18.423***	−17.920***	−18.034***
	(0.133)	(0.100)	(0.102)	(0.092)	(0.092)
6+ bidders	−17.336***	−17.831***	−16.988***	−17.139***	−17.300***
	(0.444)	(0.219)	(0.239)	(0.170)	(0.170)
Observations	13,117,858	13,117,858	13,117,858	13,117,858	13,117,858
R^2	0.376	0.412	0.477	0.496	0.501
Year FE	Yes	Yes	Yes	Yes	Yes
Buyer FE	No	Yes	No	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses, and are clustered by government departments. FE refers to fixed effects. The dependent variable in all columns is a price ratio as defined in equation 3. Last month is a dummy variable that takes the value 1 if the tender was finalised in December and 0 otherwise. All coefficients should be interpreted as percentage changes to the price (relative to expected price).

Figure (5) Coefficient of each month



Note: The dependent variable is the price ratio defined in Equation 3. Each month is a dummy variable corresponding to when a tender was finalised with January being a baseline month. Please note, coefficients should be interpreted as percentage changes to the price (relative to expected price). All regressions include firm, department, industry, and year fixed effects. Standard errors are robust and clustered by departments.

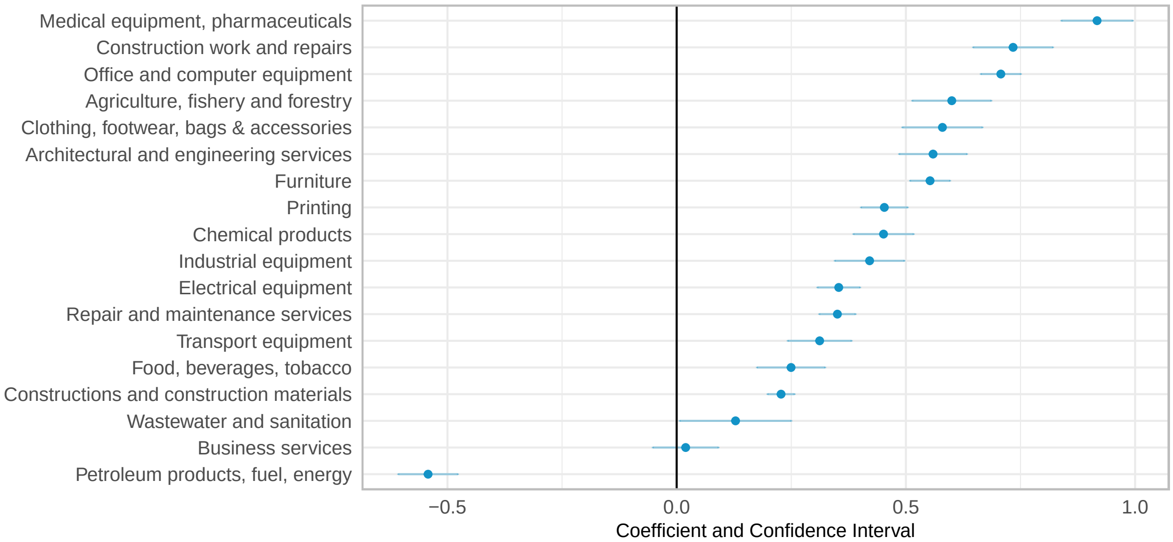
confidence interval for each regression and plot these in figure 6.[27] Our findings confirm that the government faces higher prices for almost all good categories.

Next, we demonstrate that results are robust at the regional level. This can be seen in figure 7. To create this plot we used the main specification for price ratio on all procurements in each buyer region separately. We record the coefficients of the last month and map them. Darker colours represent a greater coefficient on the last month while lighter colours represent lower coefficients.[28] The maps shows that Kyiv which hosts the capital and Sicheslav region (one of biggest industrial regions in the country) have had higher end of year price increases than other regions.

[27]We also include summary statistics for each of these aggregated industries in the Appendix's B table B.1.

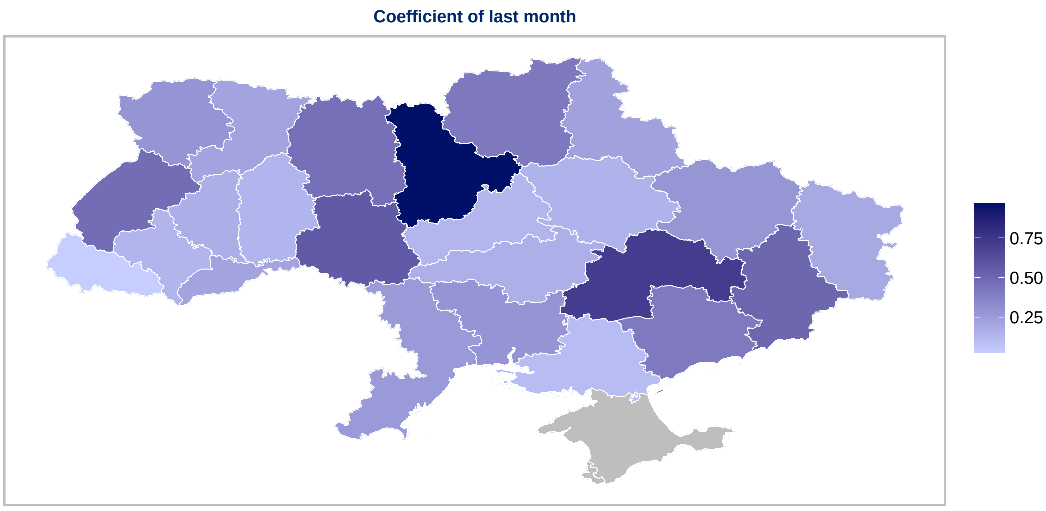
[28]As Crimea was not reflected in our data, this region is plotted as grey.

Figure (6) Coefficient of last month by industries



Note: The figure presents coefficients estimate and confidence intervals for benchmark specification performed on each aggregated industry. The dependent variable is the price ratio defined in Equation 3. Each industry group is a dummy variable corresponding an industry in which tender was adverstised. Please note, coefficients should be interpreted as percentage changes to the price (relative to expected price). All regressions include firm, department, industry and year fixed effects. Standard errors are robust and clustered by departments.

Figure (7) Coefficient of last month for each buyer regions



Note: The figure represents the intensity of government spending the last month of fiscal year by each buyer region. We replicate the benchmark regression for each buyer region and map the coefficients. The dependent variable is the price ratio defined in Equation 3. All regressions include firm, department, industry and year fixed effects. Standard errors are robust and clustered by departments. Darker colour represents higher waste and lighter colours are lower end of fiscal year waste. There is no information on Crimea's spending and therefore it is plotted as grey.

4.2 Estimations with Margin

We next explore how the margins that bidders seek change at the year-end. We start by running a series of regressions of all tenders with two bidders. We rely on the specification presented in Equation 10 and these presented in Table 4. Due to the small sample size, we only impose year fixed effects. The first column reports a coefficient of the regression for all bidders, while the second column restricts our sample to the subset of winning bidders and the third column contains only losing bidders. There is a greater number of losers reflecting the fact that bidders who are last in the final round typically win and we cannot infer costs for these bidders. The results indicate that the margins are approximately 7.5% higher at the end for fiscal year for both winners and losers.

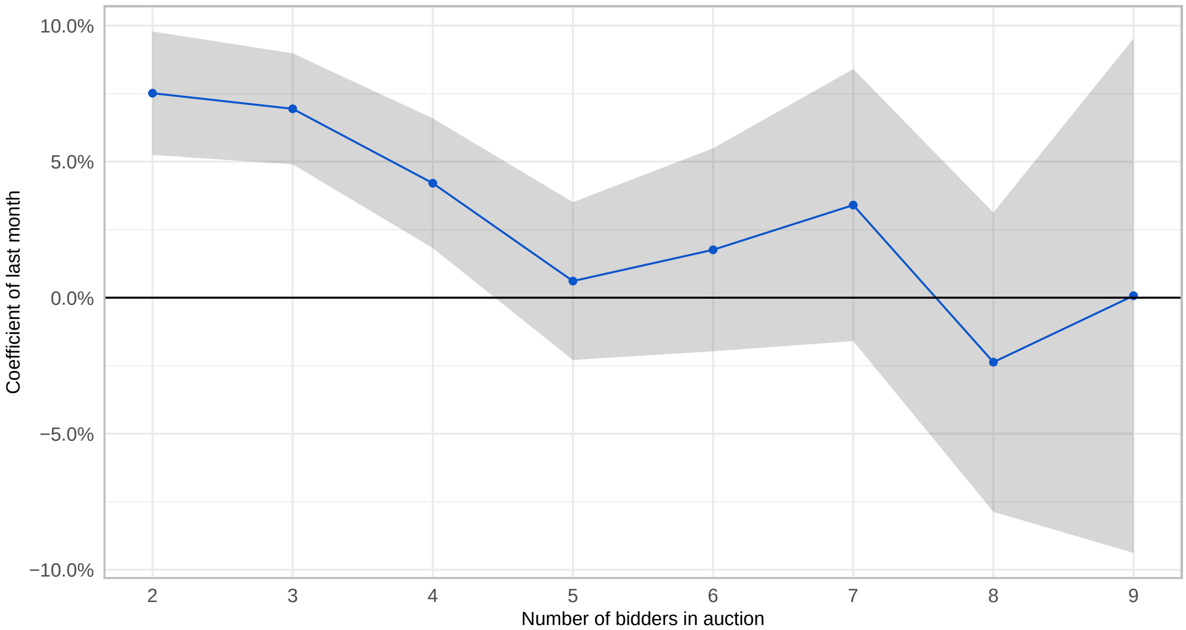
Table (4) Auctions with Two Participants

	Dependent variable: Margin common cost		
	All	Winner	Loser
	(1)	(2)	(3)
Last Month	7.516***	8.457***	7.234***
	(2.250)	(2.462)	(2.350)
Observations	9,896	2,321	7,575
R^2	0.100	0.064	0.114

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses, and are clustered by good class level. FE refers to fixed effects. The dependent variable in all columns is a margin common cost as defined in equation 9. Last month is a dummy variable that takes the value 1 if the tender was finalised in December and 0 otherwise.

We then perform similar regressions for auctions with three participants, with four participants and so on. We record the coefficients of last month as well as the standard errors and plot these against the number of participants. This is presented in Figure 8. We can observe that for smaller auctions with two or three participants, the margins that are sought are around 7.5% higher in the last month of the year relative to other months. If there are four participants, then the margins are around 5% higher. For auctions with five or more participants, firms generally bid higher but the effect is no longer statistically significant.

Figure (8) Coefficient of Last Month in Regressions



Note: The figure presents coefficients and confidence intervals of last month based on the specification 10 performed separately for two, three, four, five, six, seven, eight and nine bidders. Standard errors are robust and clustered by departments.

Furthermore, we perform a series of regressions to verify the robustness of this result in Table 5. We first restrict our sample to winners of tenders in which two or three firms were competing. We then perform regressions with a dummy for three bidders (with two bidder tenders being the baseline) and varying combinations of fixed effects. Reflecting the smaller sample size compared to the price ratio regressions we apply fixed effects at broader levels including year fixed effects; region of purchasing department (out of 26 oblasts of Ukraine); good category (out of the 18 industries shown in figure 6). We find a significant increase in margin towards the end of the fiscal year.

Table (5) Auctions with Two or Three participants

	Dependent variable: Margin common cost			
	(1)	(2)	(3)	(4)
Last Month	7.339***	7.487***	5.945*	4.940*
	(1.953)	(1.916)	(3.049)	(2.517)
ThreeParticipants	−1.236	−1.259	−0.538	−0.850
	(0.899)	(0.906)	(0.900)	(0.874)
Year FE	Yes	Yes	Yes	Yes
Department Region FE	No	Yes	No	Yes
Good Class FE	No	No	Yes	Yes
Firm Region FE	No	No	No	Yes
Observations	6,088	6,088	6,088	5,506
R^2	0.057	0.064	0.094	0.107

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses, and are clustered by good class level. FE refers to fixed effects. The dependent variable in all columns is a margin common cost as defined in equation 9. Last month is a dummy variable that takes the value 1 if the tender was finalised in December and 0 otherwise.

5 Other Estimations

5.1 Homogeneous Goods

We might expect firms bidding on selling homogenous goods to exhibit different behaviour at an end of year context as the lack of differentiation means markets for these goods are closer to perfect competition than monopolistic competition.[29] In the extreme cases, the presence of liquid commodity markets in some good areas may reduce or eliminate the end of fiscal year price change effect (as we observed for petroleum products, fuel, energy products).

We classified the good codes in our sample based on their level of heterogeneity. We assign a good code as homogeneous when there is relatively little vertical or horizontal heterogeneity within the good category.[30] Some examples of homogenous goods are “printer paper”, “rice”, “golf balls” and “cement”, while “crustaceans”, “trucks” and “golf clubs” are classified as being heterogeneous.

[29] Bandiera, Prat and Valletti (2009) consider an Italian procurement system and find heterogeneity in prices paid by government agencies for homogenous goods. These differences in prices were mostly due to “passive waste”, where buyers do not make full use of a centralised purchasing system in which favourable prices are pre-negotiated with suppliers.

[30] This method of categorisation is not perfect but it is sufficient such that the good we identify as homogeneous is more homogeneous than other goods. Due to inability to perfectly separate homogeneous from heterogeneous goods however we draw attention to the difference between the two interaction coefficients in the regressions rather than their absolute levels.

We interact the homogeneous and heterogeneous categorisation of a good category with last month dummy and present the results in Table 6. We observe that while the aforementioned strong last month effect is apparent for heterogeneous good categories, this rise in prices at the end of the year is much lower for homogeneous goods.

Table (6) Results for Homogeneous and Heterogeneous Goods

	Dependent variable:				
	Price Ratio				
	(1)	(2)	(3)	(4)	(5)
Panel A: All tenders					
Last Month × Heterogeneous Goods	1.037***	0.783***	0.721***	0.641***	0.629***
	(0.021)	(0.014)	(0.013)	(0.011)	(0.011)
Last Month × Homogeneous Goods	0.479***	0.347***	0.329***	0.302***	0.303***
	(0.028)	(0.024)	(0.019)	(0.019)	(0.019)
Homogeneous Goods	−0.234***	−0.445***	0.096***	−0.012	
	(0.023)	(0.015)	(0.012)	(0.009)	
Observations	11,616,801	11,616,801	11,616,801	11,616,801	11,616,801
R^2	0.024	0.138	0.229	0.282	0.286
Panel B: All tenders conditioning on number of bidders					
Last Month × Heterogeneous Goods	0.273***	0.222***	0.253***	0.222***	0.220***
	(0.013)	(0.011)	(0.009)	(0.008)	(0.008)
Last Month × Homogeneous Goods	0.080***	0.045*	0.020	0.013	0.003
	(0.026)	(0.025)	(0.020)	(0.019)	(0.019)
Homogeneous Goods	0.132***	0.113***	0.077***	0.040***	
	(0.022)	(0.016)	(0.011)	(0.009)	
Observations	11,616,801	11,616,801	11,616,801	11,616,801	11,616,801
R^2	0.321	0.365	0.414	0.442	0.445
Year FE	Yes	Yes	Yes	Yes	Yes
Buyer FE	No	Yes	No	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses, and are clustered by government departments. FE refers to fixed effects. The dependent variable in all columns is a price ratio as defined in equation 3. Last month is a dummy variable that takes the value 1 if the tender was finalised in December and 0 otherwise. Homogeneous/heterogeneous goods are dummy variables taking value 1 if a good is homogeneous/heterogeneous and 0 otherwise. All coefficients should be interpreted as percentage changes to the price (relative to expected price).

5.2 The Effect of Covid-19 in Ukraine

Similar to many other governments throughout the world, the Ukrainian government was concerned about the effects of the Covid-19 pandemic. They believed that the additional time that more elaborate procurement mechanisms take could hamper their response to the pandemic. As a result, the government began to allow procurements with values above the competitive threshold to be finalised without requiring an auction. If a government department could state that a procurement was related to the pandemic response, then they could negotiate a purchase with a supplier or accept a single quotation for a procurement item.

These government purchases give us an additional way to test whether the less rigorous procurement techniques lead to higher final price achieved by a department. We replicate our main specification (equation 2) with the addition of a dummy for whether the good or service made use of a Covid-19 exemption to avoid the full procurement method. In addition, we interact this dummy with last month dummy to ascertain whether there is a different end of fiscal year effect for these procurements.

In Table 7, we split procurement lots between Covid-19 related lots, that had a more lenient procurement process, and other lots, where the full procurement procedure took place. We observe that the Covid-19 procurements were between 1%-2% more expensive than non-Covid-19 tenders. This finding is in broad agreement with the procurement systems literature discussed previously. When we consider how the end of the fiscal year impacts prices of Covid-19 tenders, we can see that there is a smaller increase in cost at the end of the fiscal year than other jobs. This comparatively smaller effect may reflect that they are already attracting few bidders and achieving poor prices so there is not a large change to this pattern at the end of the fiscal year.

5.3 Contract Renegotiation

Given the sharp increase in the number of tenders being advertised at the end of the fiscal year, it is possible that some of these tenders have been rushed. For example, Liebman and Mahoney (2017) suggested this as a reason why the end of fiscal year spending might have been of lower quality than other spending.

Table (7) Covid-19 Procurements

	Dependent variable:				
	Price ratio				
	(1)	(2)	(3)	(4)	(5)
Panel A: All tenders					
Last Month × Covid	-0.800^{***}	-0.609^{***}	-0.538^{***}	-0.544^{***}	-0.523^{***}
	(0.023)	(0.031)	(0.031)	(0.033)	(0.033)
Last Month	0.951^{***}	0.716^{***}	0.660^{***}	0.589^{***}	0.578^{***}
	(0.021)	(0.014)	(0.012)	(0.011)	(0.011)
Covid	1.089^{***}	1.493^{***}	1.812^{***}	1.932^{***}	2.175^{***}
	(0.025)	(0.046)	(0.055)	(0.053)	(0.058)
Observations	11,616,801	11,616,801	11,616,801	11,616,801	11,616,801
R^2	0.024	0.138	0.230	0.283	0.287
Panel B: All tenders conditioning on number of bidders					
Last Month × Covid	-0.146^{***}	-0.124^{***}	-0.202^{***}	-0.203^{***}	-0.203^{***}
	(0.018)	(0.022)	(0.024)	(0.024)	(0.024)
Last Month	0.243^{***}	0.193^{***}	0.215^{***}	0.188^{***}	0.185^{***}
	(0.013)	(0.011)	(0.009)	(0.009)	(0.009)
Covid	0.250^{***}	0.366^{***}	0.355^{***}	0.410^{***}	0.362^{***}
	(0.016)	(0.027)	(0.035)	(0.033)	(0.036)
Observations	11,616,801	11,616,801	11,616,801	11,616,801	11,616,801
R^2	0.320	0.365	0.414	0.442	0.445
Year FE	Yes	Yes	Yes	Yes	Yes
Buyer FE	No	Yes	No	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses, and are clustered by government departments. FE refers to fixed effects. The dependent variable in all columns is a price ratio as defined in equation 3. Last month is a dummy variable that takes the value 1 if the tender was finalised in December and 0 otherwise. All coefficients should be interpreted as percentage changes to the price (relative to expected price).

We investigate this possibility using two variables that are likely to be related to rushing. First, the final price paid by the government could have changed after the contract was awarded. Second, a contract could be renegotiated after its award, which may or may not be accompanied by a change in price. We estimate the percentage price change between awarded and the final price, a flattened variable variable indicating whether price has changed,[31] and whether or not a contract was renegotiated in the three panels of Table 8. These regressions are all estimated on competitive lots as we only we have this information for these tenders, and we do condition on the number of bidders.

Table (8) Contract Renegotiation

	Dependent variable (DV):				
	(1)	(2)	(3)	(4)	(5)
Panel A: Percentage price change DV					
Last Month	-0.009^{***}	-0.005^{***}	-0.003^{**}	-0.002^{*}	-0.002^{*}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	524,029	524,029	524,029	524,029	524,029
R^2	0.008	0.149	0.142	0.233	0.243
Panel B: Binary price change DV					
Last Month	-0.029^{***}	-0.015^{***}	-0.012^{***}	-0.006^{*}	-0.006^{*}
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
Observations	524,029	524,029	524,029	524,029	524,029
R^2	0.015	0.152	0.157	0.243	0.250
Panel C: Contract renegotiation DV					
Last Month	0.015^{***}	0.003	-0.016^{***}	-0.019^{***}	-0.018^{***}
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
Observations	524,029	524,029	524,029	524,029	524,029
R^2	0.379	0.456	0.491	0.537	0.546
Year FE	Yes	Yes	Yes	Yes	Yes
Buyer FE	No	Yes	No	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses, and are clustered by government departments. FE refers to fixed effects. Last month is a dummy variable that takes the value 1 if the tender was finalised in December and 0 otherwise. All coefficients should be interpreted as percentage changes to the price (relative to expected price).

The results show that price decreases are more likely at the end of the fiscal year, which could be a result of elevated prices at the time of the advertisement. We also cannot find any robust

[31] The sign of the price change: +1 for a price increase, 0 for no change and −1 for a decrease.

evidence for a different likelihood of renegotiation for contracts awarded at the end of the fiscal year.

5.4 New Firms

Hyndman, Jones and Pendlebury (2007) reported that UK budget managers were not able to use lower-cost firms as they were too busy at the end of the fiscal year. As a result, they switched to new firms that were more expensive. We test for this hypothesis by comparing prices charged by new and existing firms. We first define a "new firm" as one that a government department has not awarded a job to in the preceding 365 days. Otherwise, firms are denoted as "old firms" as there was a business relationship within the last year. We perform a number of regressions to predict the price ratio. We interact the last month dummy variable with new firms and old firms and present the results in the Table below.[32]

In short, we cannot find any support for Hyndman, Jones and Pendlebury's (2007) survey findings in our sample of Ukrainian public procurement lots. We only observe that new firms do not tend to be robustly more expensive than existing suppliers. Both new firms and old firms bid higher at the end of the fiscal year, with there being a greater increase in prices for new firms. This may reflect busyness of the existing suppliers meaning new firms do not need to cut prices as much to get the sale.

[32] In addition, we test whether a new firm is likely to win an auction and whether that likelihood changes in the year-end. The results are presented in Table B.3

Table (9) New and Old Firms

	Dependent variable:				
	Price ratio				
	(1)	(2)	(3)	(4)	(5)
Panel A: All tenders					
New Firm × Last Month	0.624***	0.601***	0.410***	0.434***	0.446***
	(0.024)	(0.023)	(0.020)	(0.019)	(0.019)
Last Month	0.770***	0.558***	0.570***	0.489***	0.478***
	(0.020)	(0.013)	(0.012)	(0.010)	(0.010)
New Firm	−1.596***	−1.262***	−0.851***	−0.942***	−0.956***
	(0.023)	(0.015)	(0.016)	(0.013)	(0.013)
Observations	11,616,801	11,616,801	11,616,801	11,616,801	11,616,801
R^2	0.031	0.142	0.231	0.283	0.287
Panel B: All tenders conditioning on number of bidders					
New Firm × Last Month	0.082***	0.085***	0.053***	0.075***	0.100***
	(0.020)	(0.018)	(0.018)	(0.017)	(0.017)
Last Month	0.201***	0.154***	0.182***	0.151***	0.143***
	(0.013)	(0.011)	(0.009)	(0.008)	(0.008)
New Firm	−0.619***	−0.517***	−0.613***	−0.595***	−0.631***
	(0.020)	(0.013)	(0.013)	(0.011)	(0.011)
Observations	11,616,801	11,616,801	11,616,801	11,616,801	11,616,801
R^2	0.322	0.365	0.415	0.442	0.446
Year FE	Yes	Yes	Yes	Yes	Yes
Buyer FE	No	Yes	No	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses, and are clustered by government departments. FE refers to fixed effects. The dependent variable in all columns is a price ratio as defined in equation 3. Last month is a dummy variable that takes the value 1 if the tender was finalised in December and 0 otherwise. All coefficients should be interpreted as percentage changes to the price (relative to expected price).

6 Conclusion

At the end of the year government departments typically spend more than in prior months, which raises the possibility that governments could be overpaying in procurement. The overpaying could be a result of the greater willingness to spend of government departments, fewer firms available and willing to bid on a project, as well as a better outside option available to firms given a large number of procurements. In addition, the greater number of tenders at the end of the year also implies that government departments have less resources on scrutinising each job. This is the first paper to explore such issue and estimate the extent of overpaying.

We use a novel detailed dataset of Ukrainian government procurement auctions between 2017 and 2021. Our paper reveals that government departments pay higher prices at the end of the fiscal year than they do in an average month. This effect is robust across all different regions of Ukraine and most categories of goods. We also use a neural network to estimate the cost for a supplier of doing a job. We can use these implied costs together with supplier bids to find that the margins charged by firms at the end of the fiscal year are around 7.5% higher at the end of the fiscal year relative to other times.

We also perform a number of extensions to explore how our results change in different settings. We consider whether firms selling homogeneous goods might increase prices less at the end of the fiscal year given it is easier for the government to find close substitutes. We find this is the case. Part of our data overlaps with the Covid-19 pandemic, where the Ukrainian government allowed simplified procurements for goods related to the pandemic response. We found that the Covid-19 procurements were between 1%-2% more expensive than non-Covid-19 tenders overall. When we examine how the end of the fiscal year impacts prices of covid tenders we can see that there is a smaller increase in cost at the end of the fiscal year than other jobs. We then test a number of implications of the literature. The first is that new supplying firms offer higher prices at the end of the fiscal year while the second is that end of fiscal year contracts are rushed and hence more likely to be later renegotiated. We cannot find robust evidence for either of these two effects.

The clear policy implication of our paper is that heightened end of fiscal year spending results in higher prices for governments. This suggests that should governments be able to smooth spending throughout the year they could buy more given the same expenditure level. There may be a case for parliaments to restrict the ability of government departments to engaging in noncompetitive procurement processes at the end of the fiscal year.

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Appendices

A The Model

Two models have previously been proposed in the literature, namely the precautionary savings model of Liebman and Mahoney (2017) and the procrastination model of Baumann (2019). The precautionary savings model considers government departments that face demand shocks each month. As a result, they create precautionary savings funds throughout the year. At the end they cannot save these funds into the subsequent year and hence spend it all in the last month. The implication is that allowing departments to save funds between years would remove the incentive to spend quickly at the end of the fiscal year.

Two key reasons suggest however that other factors may be at work aside from precautionary savings. The first is that the UK has allowed government departments to save across fiscal years which has not noticeably decreased end of fiscal year spending. The second reason is that it is not clear if the month-to-month uncertainty required to explain the size of spending seen in practice is credible. As a result of these concerns Baumann (2019) suggested procrastination as a driving factor. Government departments typically have fiscal and performance reporting on a fiscal year basis. Budgetary managers in government departments need to incur effort costs in order to spend funds. As a result of these factors they may backload effort until later in the fiscal year which results in end of fiscal year spending spikes.

Ukrainian government departments (and most world government departments) face stochastic costs of procurement. This suggests a third mechanism that drives end of fiscal year spending in this context. Our *stochastic costs* model is driven by government departments which in the early months of the year choose projects with considerable uncertainty as to the final cost. Later in the year departments would prefer to avoid these risky projects as they are faced with the possibility of not being able to afford expensive procurements or having funds left over if projects come in cheaper than expected. As a result they have an incentive to switch to less risky projects that have a higher expected cost. The behaviour we can see in the Ukrainian context, where departments choose more and smaller procurement jobs at the end of the fiscal year may be a result of these incentives. While the more and smaller jobs are likely to face higher contracting costs the procurement risk is more diversified.

There is some evidence of this occurring from the UK where Hyndman, Jones and Pendlebury (2007) found that a popular tactic amongst managers was to maintain a list of off the shelf projects that could be used if there was no better use of the funds before the end of the fiscal year. We can clearly see in the Ukrainian data that departments are much more likely to engage in uncompetitive bargaining procedures in the final months of the fiscal year. In addition, they are more likely to split jobs so that there are several small jobs that can be negotiated directly with suppliers rather than one large job that requires a competitive tender process.

The main agent in our model is a government department. A department chooses an expected value, x, for a procurement in each period. The realised price, p, of the procurement can differ from the expected value. There are two types of projects that can be undertaken. The first has a random cost where with 50% probability, the price is equal to x while with 50% probability the price is θx where $\theta < 1$. The second has a deterministic cost where the price will be $\gamma \frac{1+\theta}{2}$ for $1 < \gamma < \frac{2}{1+\theta}$ with certainty. Therefore the deterministic project has a higher expected price than the random cost project but is cheaper than if the random cost project is expensive. The department can divide their spending between the two types of project in each month.

A department cannot engage in a procurement where it is possible that they will not be able to pay in the event of a high price.[33] In each month they get a utility equal to an increasing concave function of the expected value, $u(x_m) = x_m^\delta$. The department has an annual budget normalised to 1 that they can spend over a year.

This setting can be summarized as:

$$V_m(B_m) = \max_{d_m \in [0,1], x_m \in [0, \frac{B_m}{d_m \gamma + (1-d_m)}]} [u(x_m) + \beta V_{m'}(B_{m'}(\bar{x}_m))] \tag{A.1}$$

$$\text{Where} \qquad \bar{x}_m = d_m \gamma x_m + (1 - d_m) \times (x_m \quad \text{or} \quad \theta x_m)$$

$$B_{m'}(\bar{x}_m) = 1 + \lambda(B_{m'} - \bar{x}_m) \qquad \text{if } m \equiv M$$

$$= B_{m'} - \bar{x}_m \qquad \text{if } m \not\equiv M$$

[33] In a real setting any price is possible and it therefore possible that a department will need to pull out of a procurement for cost reasons. This simple model captures the essential behaviour however that departments face stochastic costs in procurements and need to budget for these stochastic costs.

Where the annual budget is 1, M is the number of months in the year, λ is the amount of rollover that is allowed, m and m' are the indices for this month and next month respectively. d_m is the proportion of monthly spending devoted to deterministic projects while x_m is the total expected spending.

This model is a standard consumption smoothing problem and with a suitable parameterisation it exhibits end of fiscal year spending spikes. As the prices paid in early months are stochastic and leave an uncertain amount for later months the department will spend less in early months leading to precautionary savings. Later in the year there is more chance of having leftover funds that may not be spent if random projects are selected. Hence the department switches to deterministic projects. As there is no more uncertainty in procurement prices as well as no way to save precautionary savings between fiscal years, these savings are spent which results in heightened end of fiscal year spending.

We calibrated this model to the Ukrainian spending series in the following way. First, we calibrate θ such that the distribution of price ratios in the model matches those in our data. This results in a figure of $\theta = 0.545$. Second, we then impose that deterministic projects are 2% more expensive (in expectation) than the stochastic project.[34] This corresponds to a value of $\gamma = 0.796$. We impose $\beta = 0.996$ which implies 5% annual discounting. Third, we calibrate the curvature of the utility function so that the ratio of last month to year average spending equals the 1.57 ratio that we see in the data (see table 1). This implies a value of $\delta = 0.58$. The spending profile that this generates over the year can be seen in figure A.1. In this case, in the early months of the fiscal year the department purely engages in the risky project. In the later months of the year the department shifts to a greater fraction of spending is in the deterministic project. In the final month of the year the department purely spends in a deterministic fashion.

This mechanism has some similarities with the precautionary savings model of Liebman and Mahoney (2017). Both models are driven by uncertainty regarding future marginal utility from spending. Similarly to that model, allowing departments to rollover unspent funds prevents end

[34] This is in line with the regression results presented earlier in this paper. This low value also highlights that the model does not depend on an exogenous increase (from higher θ) in costs to drive end of fiscal year spending. End of fiscal year spending is not purely driven by engaging in projects that are more expensive in expectation, but rather by how departments change their behaviour between risky and deterministic projects.

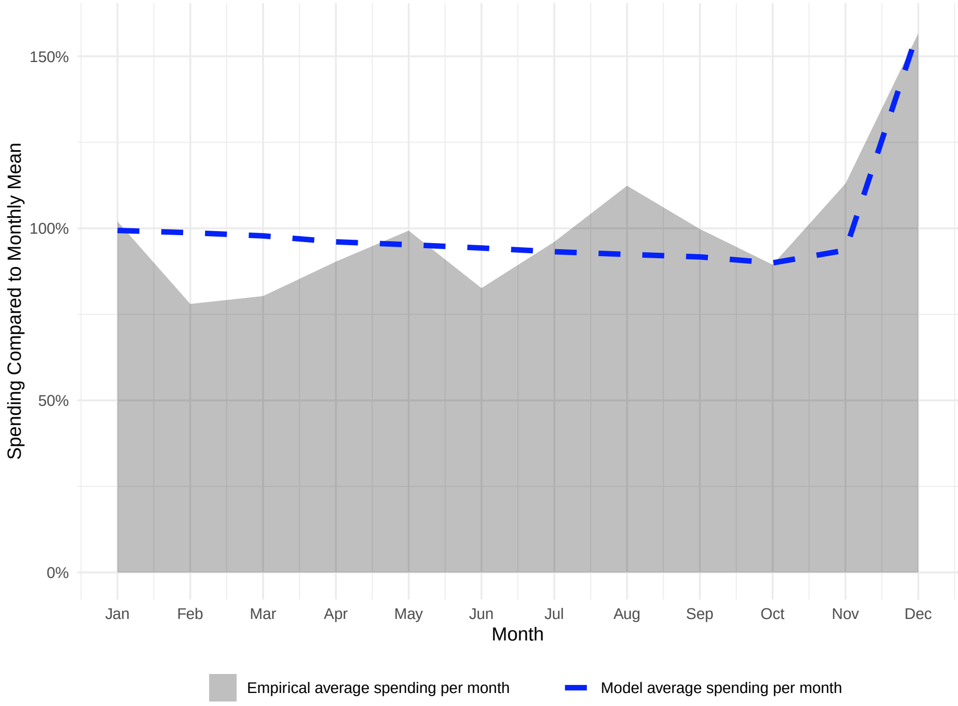

Figure (A.1) Model fit to data

of fiscal year spending spikes. There are several keys differences however when we consider the stochastic costs model. The first difference is that the uncertainty comes from procurement prices rather than demand shocks which is a more measurable and, in some contexts, more credible source of uncertainty. In the calibration of the model it was possible to base the parameters governing the variability of cost on data observables. This is particularly important as it was unclear if the volatility required for the Liebman-Mahoney calibration to fit the data was credible given the uncertainty in demand faced by real government departments.

The second is that the stochastic costs mechanism requires the availability of a risk free way to spend funds. In the absence of such an option end of fiscal year spending is prevented due to the necessity to hold funds in reserve in case a project comes in at an expensive price. While departments build up a precautionary savings fund and would like to spend it at the end of the year, this requirement prevents them. The third is that new policy implications become apparent.

One new policy implication is that spending spikes may be assuaged by reducing the procurement price risk that departments face. This may be achievable through a centralised insurance system where departments that got many bidders on their projects make transfer payments to departments that had fewer bidders participating in their auctions. With the current calibration if the uncertainty in the risky project was reduced so that $\theta = 0.6$, with a corresponding increase in γ so that it remains 2% above the expectation of the risky project we get final month spending at 1.5 times the monthly average. Hence while there is still end of fiscal year spending there is less than in the calibrated case (where last month spending is 1.57 times higher). While insurance is in principal a solution to the original Liebman-Mahoney model, there is the practical problem that demand shocks are less observable and thus harder for departments to agree insurance arrangements against them.

The second policy implication is that end of fiscal year spending may be averted by cutting back on department's opportunities for deterministic procurements at the end of the fiscal year. This is to some extent counterintuitive as having a list of ready to go projects has been cited as an effective way to respond to fiscal year budgeting constraints (Hyndman, Jones and Pendlebury, 2007). This may involve restrictions on departments engaging in reported procurements at the year-end in a Ukrainian context. Alternatively a government might be able to deter departments by effectively charging them a tax (or in alternative terms a budgetary reduction) from engaging in deterministic projects. In the Ukrainian context deterministic projects may be considered to be all procurements that do not involve a competitive auction process. As an example if they engaged in an uncompetitive tender project at the end of the fiscal year and spent an amount to money x then ψx (for some $\psi > 1$) would be deducted from their budget with $(\psi - 1)x$ of this money being directly returned to treasury.[35]

To see this we take the benchmark calibration and increase γ by 10% so that it is 0.867. The result is that end of fiscal year spending is deterred significantly relative to the benchmark case with final month spending being 1.31 times more than the average month. While this example shows that governments charging taxes to departments may deter end of fiscal year spending, it also shows that heightened prices from suppliers at the end of the fiscal year may themselves deter end of fiscal year spending.

Finally and similarly to the Liebman and Mahoney (2017) model, allowing departments to

[35] This is similar to the time variant budgetary tax policy recommendation of Baumann (2019) with the difference being these taxes are levied based on the competitiveness of the purchase rather than when in the year it was undertaken. This may also be simpler to understand and implement than time variant taxes.

rollover funds between fiscal years would prevent end of fiscal year spending. While uncertainty in costs would still drive departments to build up precautionary savings, there would not be any shift to spend these funds at the end of the year as this precautionary savings fund could be carried over to the following year. This policy implication has some practical limitations however. The first is that rollover was implemented in the United Kingdom and did not lead to any discernible decrease in end of fiscal year spending (Crawford, Emmerson and Tetlow, 2009). This may imply that there are other forces leading to end of fiscal year spending in the UK and potentially also in Ukraine. For instance stochastic costs may not be the only mechanism leading to end of fiscal year spending. The second complication is that the central government allowing rollover will not be felt by lower level budgetary managers if their "savings" are taken from them by higher level budgetary managers. It is not clear if this would be a problem in the Ukrainian public sector.

A.1 Two period version of model

We consider a two period version of the model introduced in section A. Rather than a concrete utility function we instead consider an arbitrary increasing concave utility function $f(x)$ and consider the case where there is no rollover ($\lambda = 0$).

We can first establish that the department will spend their entire budget using determnistic projects in the second and final period of the year.

Lemma 1. *The department will spend their entire remaining budget using deterministic projects in the last period of the fiscal year.*

Proof. Utility is increasing in the total expected value, x_E, that is spent. As the department needs to have enough funds to be able to covers expensives if costs end up being expensive the constraint for the department is $d\gamma x_E + (1-d)x_E < B_2$ where B_2 is the budget available in the second period of the year. As $\gamma < 1$ the total spend is maximized when $d = 1$ and all funds are spend with deterministic projects.

Now we can write an expression for the maximisation problem for a department at the start of the first period:

$$\max_{d\in[0,1],x\in[0,\frac{B_1}{d\gamma+(1-d)}]} f(x)+\frac{\beta}{2}\left[\overbrace{f(B_1-d\gamma x-(1-d)\theta x)}^{\text{If Stochastic Project Cheap}}+\overbrace{f(B_1-d\gamma x-(1-d)x)}^{\text{If Stochastic Project Expensive}}\right] \quad \text{(A.2)}$$

Now given this we can show that there exist parameterisations such that the department will, in expectation, spend more in the second round than the first round.

Using the parameters $\beta = 0.975$, $\theta = 0.5$, $\gamma = 0.8$, $B = 1$ and a log utility function $f(x) = \log(x)$ we can numerically solve for the department spending a fraction $d = 0.34$ in the first period. The expected value in the first period is 0.633. This implies that in expectation 0.486 will be spent in the first period and the remaining 0.514 will be spent deterministically in the second period.

B Additional Analysis

Table (B.1) Summary statistics by procurement type

Industry	Total Notional (Billions of Hryvnia)	Number of tenders	Success Rate	Mean number bidders
Agriculture, fishery and forestry products	7.367	252,394	0.997	1.209
Architectural, construction, engineering and inspection services	18.171	521,089	0.998	1.112
Business services: legal, marketing, consulting, staffing, printing and security	13.853	353,818	0.998	1.143
Chemical products	12.298	243,419	0.998	1.165
Clothing, footwear, bags and accessories	7.104	189,412	0.998	1.194
Construction work and ongoing repairs	536.216	774,082	0.994	1.206
Constructions and construction materials	35.311	1,139,505	0.999	1.097
Electrical equipment	19.940	444,594	0.998	1.158
Food, beverages, tobacco	23.541	877,882	0.998	1.201
Furniture (including office furniture), furniture-decorative products	11.588	715,893	0.998	1.134
Industrial equipment	19.646	210,534	0.997	1.228
Medical equipment, pharmaceuticals	39.402	585,843	0.997	1.585
Office and computer equipment	14.785	599,827	0.997	1.209
Petroleum products, fuel, electricity and other energy sources	224.448	592,519	0.972	1.625
Printed and related products	3.964	380,317	0.999	1.077
Repair and maintenance services	30.449	733,984	0.998	1.125
Transport equipment	55.720	288,875	0.996	1.302
Wastewater and waste management, sanitation	11.820	201,137	0.992	1.223

The LM (last month) spending ratio is the december spending figure divided by the monthly average

Table (B.2) Month by Month Regression

	Dependent variable:	
	Price ratio	
	(1)	(2)
February	0.157***	0.059***
	(0.023)	(0.022)
March	0.187***	0.061**
	(0.027)	(0.025)
April	0.413***	0.106***
	(0.028)	(0.026)
May	0.397***	0.128***
	(0.026)	(0.024)
June	0.505***	0.175***
	(0.026)	(0.023)
July	0.532***	0.209***
	(0.026)	(0.023)
August	0.536***	0.197***
	(0.027)	(0.024)
September	0.645***	0.251***
	(0.026)	(0.023)
October	0.696***	0.275***
	(0.026)	(0.023)
November	0.691***	0.227***
	(0.027)	(0.023)
December	1.061***	0.356***
	(0.028)	(0.023)
2 bidders		−8.991***
		(0.062)
3 bidders		−14.845***
		(0.079)
4 bidders		−16.757***
		(0.124)
5 bidders		−19.041***
		(0.164)
6 or more bidders		−14.546***
		(0.261)
Year FE	Yes	Yes
Buyer FE	Yes	Yes
Firm FE	Yes	Yes
Industry FE	Yes	Yes
Observations	11,616,727	11,616,727
R^2	0.285	0.444

Note: ***p<0.01. Standard errors are (in parentheses) clustered by government departments. FE refers to fixed effects. The dependent variable in all columns is a price ratio as defined in equation 3.

Table (B.3) New Firms

	Dependent variable:				
	Winner Lot				
	(1)	(2)	(3)	(4)	(5)
Last Month	0.035***	0.012***	0.012***	0.007***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
New Firm	−0.136***	−0.169***	−0.191***	−0.208***	−0.206***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Last Month x New Firm	0.082***	0.069***	0.057***	0.051***	0.049***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	13,874,837	13,874,837	13,874,837	13,874,837	13,874,837
R^2	0.084	0.253	0.358	0.413	0.424
Year FE	Yes	Yes	Yes	Yes	Yes
Buyer FE	No	Yes	No	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses, and are clustered by government departments. FE refers to fixed effects. The dependent variable in all columns is a winner lot which takes value of 1 if tender participant won the auction. Last month is a dummy variable that takes the value 1 if the tender was finalised in December and 0 otherwise. All coefficients should be interpreted as percentage changes to the price (relative to expected price).

C Alternative Empirical Approach

We present an alternative empirical approach that examines whether government departments pay over the odds at the year-end. The specification we use is as follows:

$$\text{Log bid price}_{if} = \beta_0 + \beta_1 \text{Last month}_{if} + \beta_2 \text{Log expected price}_{if} + \phi_d + \eta_f + \psi_y + \eta_s + u_{if} \tag{C.1}$$

The regressor of interest Last month$_{if}$ is an indicator variable that equals one if a tender's i purchase was finalised at the last month of the fiscal year and zero otherwise. As in the benchmark specification 2 presented in section 3.1, we apply fixed effects at the level of the advertising department d, the bidding firm f, the year y and the industry of the purchased good s.

The key difference between the benchmark specification and the model above is that we separate the price ratio variable. We use the logarithm of bid price as our dependent variable and control for the logarithm of the expected price. Specification 10 imposes less structure than the preceding regressions of this paper.

We demonstrate our results in Table C.1. Panel A presents results for all tenders while Panel B restricts the sample to winners only. All specifications control for the logarithm of the expected value and all fixed effects applied are listed at the bottom of the table. The findings suggest that firms participating in auctions bid between 1.9% and 1.2% higher prices in the last month of the fiscal year. Whilst the winners (i.e. the price paid by the department) were between 0.9% and 0.6% higher in the last month, which is consistent with our previous estimates.

Table (C.1) The Last Month Effect for Winners and Losers with Alternative Specification

	Dependent variable:				
	Log Bid Value				
	(1)	(2)	(3)	(4)	(5)
Panel A: All lots					
Last Month	0.019***	0.015***	0.014***	0.012***	0.012***
	(0.001)	(0.0004)	(0.0004)	(0.0004)	(0.0003)
Log Expected Price	0.986***	0.988***	0.986***	0.987***	0.985***
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Observations	13,874,837	13,874,837	13,874,837	13,874,837	13,874,837
R^2	0.993	0.993	0.993	0.994	0.994
Panel B: All winning bids					
Last Month	0.009***	0.008***	0.007***	0.007***	0.006***
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Log Expected Price	0.991***	0.992***	0.991***	0.991***	0.989***
	(0.0003)	(0.0002)	(0.0004)	(0.0003)	(0.0004)
Observations	11,651,222	11,651,222	11,651,222	11,651,222	11,651,222
R^2	0.994	0.994	0.994	0.995	0.995
Year FE	Yes	Yes	Yes	Yes	Yes
Buyer FE	No	Yes	No	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses, and are clustered by government departments. FE refers to fixed effects. The dependent variable in all columns is a logarithm of winning value. Last month is a dummy variable that takes the value 1 if the tender was finalised in December and 0 otherwise.