Bidding When Cost Is Uncertain: Evidence From Fresh Produce Procurement Auctions *

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Abstract

This paper empirically analyzes procurement auctions in which suppliers must decide their bid based on expectations about how future market conditions will affect their costs. While previous literature has focused on the uncertainty about winning or losing the auction, I examine the risk that is intrinsic to the contract. I use data from government procurement auctions in the State of Sao Paulo in Brazil for fresh produce to study the effect of contract risk on auction outcomes. I find that suppliers are risk averse and therefore include a risk premium in the prices they bid, which can reach 38% of the price for some goods. In addition, I show that a simple change in the payment scheme, in which the government pays a fixed amount plus 40% of the reference index of wholesale prices, could reduce the risk premium to less than 1% of the bid price for all goods analyzed.

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1 Introduction

A recurring concern for economists and policymakers is how to improve the efficiency of public sector spending. Procurement auctions are a common mechanism for governments to buy goods and services. Examples of procurement auctions abound and range from highway construction, the distribution of school milk and utility services procurement, to mention some of the most common. Therefore, understanding how the auction process affects the price the government ultimately pays is of first order importance.

A key feature of many government auctions is that the execution of the service commissioned spans a long period of time. These prolonged commitments introduce uncertainty in the suppliers' costs. Because suppliers are uncertain about how market conditions will evolve throughout the length of the contract, and how these changes will affect their costs, they must account for this risk in their bids. Intuitively, if suppliers expect higher costs in the future, their bids should reflect those predictions.

The aim of this paper is to empirically analyze how this uncertainty affects suppliers' bids, which ultimately affects the government's cost of procurement. While there is a plethora of research on risk in auctions, most of it refers to whether suppliers are going to win the auction. As such, the ex post risk that is intrinsic to contracts has largely been overlooked in the literature. Given that such long-term contracts are quite common, empirical evidence on how suppliers incorporate uncertainty into their bids has many important applications.

To address this issue, I study procurement auctions for fresh produce in the State of Sao Paulo in Brazil. The State government buys a wide range of produce in large quantities to be delivered in many installments during the contract length. Suppliers are committed to the price they offered in the auction and take into account how input prices will evolve during the length of the contract to better estimate the cost of supplying the good. In those instances, regardless of winning the auction or not, suppliers must base their bids on the distribution of future costs.

There are many features that make this setting particularly appealing. Not only is fresh produce a perishable commodity, but prices are subject to exogenous variations in weather.[2] This latter issue, besides usual seasonality, is always a source of uncertainty.

[2] Moschini and Hennessy (2001) points out four main sources of uncertainty in agricultural production: production uncertainty, that is related to uncontrollable variables such as weather; price uncertainty, related to the biological production lag between production decision and output; technological uncertainty, which may turn past investments obsolete; and policy uncertainty, since the agricultural sector

Depending on the time of year and length of contract, buying a large amount of fresh produce in advance can be more or less risky. Moreover, because these are commodity goods, wholesale market prices provide a natural measure to evaluate the risk in each contract.

Committing to a price for an extended period of time for a good that cannot be stored can be very risky. Figure 1 provides an example of the contract risk suppliers face. It plots the wholesale prices for ripe tomatoes, the duration of two contracts and their respective winning bids. In the first contract, in mid-2012, the winning bid adjusted for inflation was R$1.57.[3] The auction winner won the right to supply the good for three months and during the contract duration the wholesale price increased, reaching up to R$4, and the average wholesale price during that period was R$2.83. In contrast, the second contract in Figure 1 in mid-2013 goes in the opposite direction. The winning bid adjusted for inflation was R$2.82. A few weeks into the duration of the contract, wholesale prices started a sharp decrease and the average for the four months in which the supplier delivered the good was R$1.91. In this case, it is safe to assume that the contract was profitable for the supplier.

These cases illustrate that the main uncertainty suppliers face is the cost of buying the goods. Thus, a key feature in my empirical approach is to include market forecasts about future fluctuations in a supplier's cost function. The intuition behind this approach is that in order to maximize expected utility, suppliers must make projections about future market prices. I assume they base these projections on two sets of public information: past wholesale market prices and weather conditions in the largest production region for each of the goods I am studying. I explore the volatility in the wholesale market prices and use a standard time series approach to model the price series and make forecasts for the duration of the contract. With those forecasts, I am able to measure the risk of each contract.

Using the bidding equilibrium in a second price auction and variations in the contract risk, I uncover cost parameters relative to the contract risk as well as risk preference parameter. I estimate the coefficient on risk aversion for CARA utility bidders and find that suppliers are significantly risk averse. This aversion translates to a risk premium in the prices they bid, which can reach 38% of the price the government pays for some goods. This evidence suggests that the procurement cost can be substantially higher

is often subject of government interventions.

[3] R$ stands for the Brazilian currency (Brazilian Real).

for goods for which market conditions are less stable. In addition, I show that a simple change in the payment scheme, in which the government pays a fixed amount plus 40% of the reference index of wholesale prices, could reduce the risk premium to less than 1% of the bid price for all goods analyzed. In this exercise, the government would be able to save more than 18% of the total amount spent had it used this different payment scheme.

To verify if the results hold under different specifications, I run three additional tests. First, because the main interest of the paper is on how much the government actually pays, the main analysis focuses on winning bids only. To determine whether results also hold for all other bids, I include other bids besides the winning bid. Second, the main analysis focuses on suppliers that participate regularly in the auctions. To test if results are not being driven by those frequent suppliers, I also include bidders that participated in fewer auctions. The results in both tests confirm that suppliers are risk averse and therefore include a risk premium in the price they bid. Third, I provide an additional test to determine whether bidding behavior is driven by risk preferences by performing the same analysis for root vegetables. Root vegetables present a stark contrast with fruits because they usually last longer and are easier to store. As such, the risk of buying these types of goods should be much lower because suppliers can buy when prices are lower and store until delivery. Indeed, I find that for these types of goods, suppliers bid as if they are risk neutral.

Unlike the most common approach in the literature, in which the uncertainty suppliers face refers to whether they are going to win the auction, I examine the risk that is intrinsic to the contract. As mentioned earlier, the prevalence of this type of ex post risk in real world auctions is ubiquitous, although it has received little attention in the literature. Here, however, there are two notable exceptions. The first is Bajari, Houghton, and Tadelis (2014), which study highway procurement auctions in California.[4] In their setting, suppliers anticipate how actual quantities will differ from estimated ones and include adaptation costs in their bids. When the difference is substantial, suppliers and government procurers renegotiate compensation around those differences. In my setting suppliers are committed to the price they bid. Similar to my results, they find that uncertainty carries a premium. In their case, they found that adaptation costs can increase

[4] On the theoretical side, Esö and White (2004) study contract risk in auctions and find that in a interdependent values auction and random ex post risk, CARA bidders require an amount equal to the risk premium to compensate the marginal utility of income for an increase in risk.

the cost of procurement for highways construction up to 14%.

The second paper (Haile (2001)) studies the effects of resale opportunities in bidders' valuations in timber auctions. Haile (2001) finds evidence that bidders' valuations are higher when the value of selling in the resale market is higher. In his setting, bidders infer how valuable resale opportunities will be in the future from the number of participants in the auction. While both Bajari, Houghton, and Tadelis (2014) and Haile (2001) address uncertainty about the contract value, they assume that bidders are risk neutral. In this paper, I estimate the presence and significance of expectations about input prices fluctuations in the winning bid and estimate suppliers' risk preferences.

Indeed, most of the studies on auctions rely on the assumption that bidders are risk neutral, but there have been efforts to test this hypothesis when uncertainty refers to the odds of winning the auction. In ascending bid auctions, the bidding strategy is the same for risk neutral and risk averse bidders. Therefore, risk preferences cannot be identified by observing bids only (Athey and Haile (2007)). Because of this difficulty, most of the papers that estimate risk preferences focus on first-price sealed-bid auctions (Bajari and Hortaçsu (2005), Lu and Perrigne (2008), Campo, Guerre, Perrigne, and Vuong (2011), Campo (2012) among others). More recently though, Fang and Tang (2014) and Li, Lu, and Zhao (2015) use entry behavior to construct tests for risk attitudes in ascending bid auctions.

My study contributes to several streams of research in the literature. First, risk preferences and decision-making under uncertainty are two essential features of agriculture production and many authors have studied farmers' attitudes towards risk.[5] The range of risk aversion estimates in this strand of literature is very wide, but one pattern seems to be consistent: farmers in developing countries are more risk averse than their counterparts in developed countries. And because most of the studies do not control for the availability of risk-management instruments, the difference can be even greater (Young (1979)). This is consistent with my finding of a high degree of risk aversion among suppliers. Although they are intermediaries (not farmers), suppliers in my data are working in a developing country known for weak institutions and lack of credit access.

Second, my findings relate to a large empirical literature that is broadly concerned with the reduction of government spending in procurement auctions. A very common concern when studying the cost of procurement is the possibility of collusion. Two classic references in this literature are Porter and Zona (1993) and Porter and Zona (1999),

[5] For a survey on risk attitudes in agricultural production, see Moschini and Hennessy (2001).

which are based on pre-existing suspicions on bid rigging activity. However, the market for fresh produce is very competitive and the online procurement process is transparent (which makes corruption difficult). Besides that, there has been no suggestion of irregular activity in these auctions, which would make any exercise to try to find evidence of collusion impractical (Harrington (2008)). Finally, another branch of the literature considers the effect of entry in procurement auctions (see, for example, Li and Zheng (2009) and Krasnokutskaya and Seim (2011)). Because entry costs are negligible in the auctions I am studying, I take participation as exogenous.

The remainder of this paper is organized as follows: Section 2 provides institutional background on the online procurement process and introduces the data. Section 3 presents the model of bidding behavior when costs are uncertain. Section 4 outlines the empirical strategy and presents the main estimates of the size of risk premia paid by the government. A counterfactual involving risk-sharing with the government is conducted in Section 5. Section 6 concludes.

2 Institutional Background and Data

In this section, I describe the procurement process and the data. The two most important components of my empirical approach are the equilibrium bid strategy in a second-price auction and the measure of contract risk. I will input the contract risk in the suppliers' cost function and use the result that suppliers bid truthfully to uncover the cost and risk preference parameters.

Three main data sources are used to execute this empirical strategy. The first dataset is new to the literature and consists of the reports of the procurement auctions that are publicly available online.[6,7] Since 2008, the State of Sao Paulo in Brazil has bought a wide range of goods and services through electronic procurement auctions combined with post-auction bargaining. The State is the most populated Brazilian state and produces almost one third of the country's GDP, which makes it an important local economy.[8] Although I have all the auctions from 2008 to 2014, I focus the description on the fresh

[6] Ferraz, Finan, and Szerman (2015) also use Brazilian procurement auctions but their study is about Federal government purchases.

[7] All the reports and auction details can be found at http://www.bec.sp.gov.br (in Portuguese).

[8] During the period studied (2008-2014), there were two administrations with governors elected from the same political party so there is no concern about radical political changes. There were three governors during this period. The first one was elected and began his mandate in 2007 but renounced to run for president and the vice-governor assumed. The third one was elected and began his mandate in 2011.

produce items commissioned, which are the main interest of this study.

The procurement process has three main stages. The government agency first publicly announces the auction and describes the goods it wants to buy. In the case of fresh produce, the description is very detailed, including width or length ranges that are acceptable, overall quality (cleanliness, ripeness, firmness of flesh, no damage, etc.) and transportation condition requirements. If the good delivered does not meet the requirements, the government agency may reject the delivery and require another delivery or terminate the contract, in which case the firm is subject to penalties. The public announcement also specifies the total quantity being commissioned, the length of the contract and the schedule of deliveries.[9] Moreover, it describes the day and time the auction will take place and the minimum increment between bids required.

Prospective suppliers submit initial offers before the auction takes place to indicate interest in participating in the procurement process. On the auction day, the number of interested and qualified bidders are revealed and the second stage is the auction itself that follows a reverse English auction protocol.[10] Each supplier is given a random identifying name so identities are not known to the agency and other bidders, but all bids and identifiers are observed. The bidding stage lasts for 15 minutes, unless there is a valid bid in the last three minutes.[11] In such cases, the bidding phase is extended for three more minutes and continues until there are no more valid bids. The winner is the one who submitted the lowest bid.[12]

The last stage is a bargaining phase where the auctioneer bargains with the winner of the auction stage. In principle the bargaining stage adds a challenge to my empirical strategy because, when choosing their bids, suppliers anticipate the bargaining stage and might shade their reservation price. However, for the case of fresh produce, the final price for more than 82% of the auctions is equal to the winning bid, meaning that

[9] Most of the contracts have a well defined schedule for deliveries, but the amount of each installment can be defined "as needed until the completion of the total quantity". Nevertheless, the public announcement always provides an expected time frame for the duration of the contract.

[10] Initial offers may not qualify in case there is any kind of information in the document submitted with the proposal that identifies the supplier. For instance, the government provides instructions in order to hide the firm name from Microsoft Office and Acrobat Reader products.

[11] A valid bid is any bid that is lower than the supplier's last bid and satisfies the minimum difference between bids required in the public announcement.

[12] There is one exception to this rule. In case a firm is classified as a small firm (depending on gross revenue) and its bid is very close to the winning bid (usually no more than 5% higher), this firm is given preference. For an analysis of preference programs in procurement auctions, see Krasnokutskaya and Seim (2011). The setting I am studying is slightly different from theirs though, since the supplier must be able to contract at least at the price the lowest bidder submitted and entry costs are negligible.

there were no further reductions in the price in the bargaining stage.[13] Moreover, for this particular set of goods, differences between each bid are very small (the median is R$ 0.02) and jump bids are rare.[14] Indeed, around 80% of all differences between bids are equal to the minimal bid requirement, which is almost always less than R$0.05. Larsen (2014) makes similar points to argue that the auction in his setting is similar to a button auction, which is a general framework to describe English auctions, in which prices decrease continuously and bidders hold a button to indicate interest. When a bidder decides to release the button, the price at which he/she exited is his/her bid. Furthermore, Larsen (2014) shows that if the auction is a button auction, the bargaining stage does not affect the bidding strategies in the auction stage.

The assumption that the auction in my setting is a button auction is important in the empirical analysis as it allows me to identify the bidding strategy. In this type of auction, bidders bid truthfully, that is, they exit the auction at their true valuation. When there are only two bidders left and one leaves the auction, the price at which he/she exited is the winning bid and is equal to his/her valuation. Therefore, the winning bid will be the second-order statistic from the distribution of costs. From this result, I can determine how the winning bid will be related to the second-lowest bidder cost. Hence, from now I will focus the analysis on the second-lowest bidder cost and the winning bid in each auction.

The other important aspect of my empirical approach is how to construct a measure of the risk in each contract. The risk suppliers face in my setting refers to how much the good will cost when the time comes to deliver it. I will assume that suppliers make forecasts about future fluctuations in prices, taking into account past prices and weather conditions in the largest production regions for each of the goods. The following datasets are used with that objective in mind. I will use a series of wholesale prices for fresh produce since 2005 and also collect weather variables from the main production regions for each good that I am analyzing.

The wholesale prices data for fresh produce is a daily series from Ceagesp, the most important market for produce in the State. The prices collected by Ceagesp are an important part in calculating price indexes. In fact, the online auction system requires

[13] Even when there was bargaining, it does not necessarily mean that there was a reduction in price. It could be the case that the winner was disqualified for some reason and the government bought from (bargained with) the second-lowest bidder.

[14] Jump bid happens when bidders place a bid that is larger than necessary to be the current winning bidder. For a model that rationalizes this kind of behavior, see Avery (1998).

suppliers to specify the brand of the good they are selling when submitting initial offers. Because brand is not clearly defined for fresh produce, many of the suppliers list Ceagesp as a brand, which seems to be strong evidence that they are actually buying the goods from this market. The description of the goods in the Ceagesp wholesale prices series match satisfactorily well the description in the auction dataset.[15] Prices since 2005 for all goods are available from the Ceagesp website.[16]

Finally, I also collected information from all weather stations in the country from the National Institute of Meteorology (INMET) to include weather changes in the forecasts. From each weather station, I collected daily amounts of rain, hours of sun exposure, average temperature and relative humidity. From these variables, I compute the average per day and State. Then, I construct a moving average of the past 15 and 30 days and compute squares, lags and interactions using these moving averages. Lastly, to determine which States are the largest producers of each good in the country, I complement this dataset with a report from the Brazilian Institute of Geography and Statistics (IBGE), which contains crops production information by city.[17] The motivation for this strategy is the intuition that if weather changes affect the production in the largest producer State, then it will likely have an effect on prices nationwide.

For those goods that I have data on 1) auctions, 2) wholesale prices and 3) production, I use the five that were most frequently bought through the auctions and are not root vegetables, which are: bananas, ripe tomatoes, green (unripened) tomatoes, large oranges and limes. The motivation for looking at fruits as opposed to root vegetables, such as potatos, carrots, onions and garlic, is that root vegetables last longer on average and are easier to store. Because my main interest is in estimating the risk premium when contracts are risky, these two features of root vegetables make them less attractive for the analysis.[18,19]

Table 1 provides summary statistics about each good. The contract price the government pays is on average lower than the wholesale price. The quantity varies substantially

[15]Ceagesp has a program called Hortiescolha that helps government agencies describe in a very precise way the goods they want to buy. Therefore, it is very likely that the description in the auction public announcements is actually inspired by the Ceagesp's descriptions to make it easier to reference to.

[16]http://www.ceagesp.gov.br (in Portuguese).

[17]I used the most recent report, from 2013.

[18]Root vegetables refer to any vegetable that grows under earth and it may include bulbs (onion, garlic), modified plant stem (potatoes) and true roots (yuca).

[19]For reference on how long some fruits and vegetables can be stored, see http://www.gardening.cornell.edu/factsheets/vegetables/storage.pdf

and the contracts last for 3.5 months on average. In total, there are 5,983 auctions for these goods. From 2008 to 2014, the most frequently purchased product are bananas with 1,742 auctions, and the least frequently purchased product are limes, with 519 auctions. The goods were purchased by 137 different government agencies, most of them (around 90%) are penitentiaries. During this period, the government bought around US$8 m of these goods.

The most striking feature of Table 1 is the large difference between the winning bid and wholesale market prices. One possible explanation is that the government buys very large quantities, so volume discounts might be present. Consistent with that explanation is that limes have the smallest volume and winning bids are closer to wholesale prices than any other good. Another possible explanation is that Table 1 presents means for the period and therefore does not take into account that suppliers decide their bids based on beliefs about future prices.

Furthermore, a very reasonable explanation is that suppliers buy goods directly from farmers below wholesale prices. Table 2 shows the prices received by farmers for bananas, oranges and tomatoes collected by the Agricultural Economics Institute in the State of Sao Paulo (IEA).[20] Winning bids are in between the prices received by farmers and the wholesale market prices, which makes it clear that suppliers have margins to work with when bidding on the contracts with the government. Although the farmers' prices are a natural measure of input prices suppliers face, the description is not as precise as in the wholesale market price series and prices are aggregated.[21] Therefore, in the main analysis I will use the wholesale market price series as a proxy for the input prices paid by the suppliers, as it captures the fluctuations in the input cost.

Finally, a plausible concern that arises when looking at the differences between wholesale prices and winning bids is whether the government agencies are getting lower-quality products. Informal interviews with some suppliers resulted in ambiguous reports: while some did say that they might mix goods of different quality, others said that the agencies' requirements are very strict, therefore goods' quality is well above average. A program called "Hortiescolha" sponsored by Ceagesp aims to help agencies to get high-quality products. One way they help is to provide these agencies with a very precise description

[20] Unfortunately, prices for limes were not available.

[21] For instance, in the wholesale market price series I find the price for "large oranges of variety pera" which is the same good I find in the auctions data, while in the farmers' price series the good is defined just as "oranges". Moreover, the data contains only monthly averages and not daily prices for some of the goods.

of each good in terms of size, weight, and transportation conditions, among other characteristics. All the descriptions are easily found on their website.[22] Moreover, the program instructs agency staff on what cannot be received by providing pictures of poor-quality goods. Figure 2 shows an example for oranges and ripe tomatoes. Therefore, while I cannot know if the government is receiving lower-quality goods, it is certainly working to receive high-quality products.[23]

With respect to suppliers, I considered those who bid in at least 30 auctions and on two different goods, leaving 47 different suppliers that were ranked second-lowest bidder in any auction. Almost all of the firms (44) bid in all five goods I am analyzing. On average, these firms participated in 1,563 online procurement auctions in total and in 127 auctions for the five goods that I am studying. Although I am focusing on the auctions where the suppliers were ranked second, it is worth mentioning that on average they won 33% of the auctions that they participated in for these goods. The average distance from the supplier to the buying agency is 118 km (73 miles), which translates to about an hour and 30 minutes one way drive.[24]

More than 80% of the firms (38 out of 47) are small firms, as defined by their annual gross revenue.[25] They have been operating for 12 years on average, although two of them are out of business according to their records in the Brazilian IRS. For reference, the country's average is 10.1 years of operation and about 50% of firms close their business after three years.[26]

It is important to emphasize that the firms that participate in the auctions for fresh produce are intermediaries, as they classify themselves as being either produce wholesalers or grocery stores.[27] That means that they are not producing the goods themselves, rather they buy from farmers and sell to the public/firms/government. Their ownership

[22]http:// www.hortiescolha.com.br (in Portuguese).

[23]Lewis-Faupel, Neggers, Olken, and Pande (2014) study the effect of the introduction of electronic procurement auctions on prices and quality in India and Indonesia for road constructions and public work projects, respectfully. They find that although prices paid by the government do not seem to be different, quality has improved.

[24]Distances and travel times were computed using Google Maps and actual roads (not minimum distance from one point to another) during no rush hours.

[25]To be considered a small firm, the firm's annual gross revenue does not exceed R$3.6 m (approximately US$1.1 m).

[26]According to the most recent report (2012) on firms demographics from the Brazilian Institute of of Geography and Statistics (IBGE): http://ibge.gov.br/home/estatistica/economia/demografiaempresa/2012/default.shtm (in Portuguese).

[27]For the two firms that closed their business, I could not find their economic activity in the Brazilian IRS records. But I believe it is safe to assume that they belong to the same activity as the other firms.

structure is either limited liability partnership (30 out of 47) or sole proprietorship. In the case of LLP, I do not know from the data who - for example, business owner or employer - is bidding in the auction. This could make a difference in terms of risk behavior and incentive schemes. Because I am unable to identify the person who is placing the bid, I am assuming that his/her objective is aligned with the owner to maximize profits.

In sum, the majority of firms are small and they have participated in many auctions. Ferraz, Finan, and Szerman (2015) study Brazilian procurement auctions commissioned by the Federal government. In their study, they have a much larger set of suppliers, which may include the firms I am analyzing. They found that winning a contract with the government boosts firm growth and that this effect lasts beyond the length of the contract. Their result provides evidence that contracts with government agencies are important for the suppliers to increase firm growth.

Throughout the paper, I use and report monetary amounts in Brazilian Real (R$). Cumulative inflation over the years I am studying (2008-2014) was 55%, as measured by the Broad National Consumer Price Index (IPCA). To make prices comparable among the years, I deflated all bids and wholesale prices to 2005 prices using IPCA. Because the unit of observation is my data is days, from the monthly inflation rate I computed the daily inflation rate using the number of business days in each month-year.[28]

3 Model of Bidding Behavior with Unknown Costs

This section presents a model of firms' profit function and bidding strategy that takes into account expectations about market conditions. I will assume that each supplier i has CARA utility of the form

$$U_{ijt}\left(\left(p_{ijt}-c_{ijt'}\right)q_{jt'}\right)=\frac{-e^{-\alpha\left(\left(p_{ijt}-c_{ijt'}\right)q_{jt'}\right)}}{\alpha}$$

where p_{ijt} is the price the government pays for good j in case supplier i wins the auction, $c_{ijt'}\left(q_{jt'}\right)$ is the cost at t', the time the good is delivered, $q_{jt'}$ is the total quantity commissioned by the government, and α is the coefficient of absolute risk aversion.[29] CARA utility function may be a strict assumption. Nonetheless, it is not only very tractable

[28]Let r be the inflation rate in a specific month. The cumulative daily inflation was computed as $i_t=(1+\frac{r}{100})^{1/d}\cdot i_{t-1}$ where d is the number of business days in that month.

[29]Henceforth, I will abbreviate $c_{ijt'}\left(q_{jt'}\right)$ by $c_{ijt'}$.

and straightforward, but is also a benchmark utility function that has been widely used (see Lapan and Moschini (1994) for an example that studies agricultural production and Easley and O'hara (2004) for an example in Finance). More importantly, CARA focuses on absolute risk aversion, which allows me to measure the curvature of the utility function at a particular wealth level, abstaining from the recent discussion about the empirical relevance of expected utility theory (Rabin (2000)).[30]

The important thing to note is that the cost $c_{ijt'}$ is unknown at the day of the auction t because the good has yet to be purchased.[31] I assume it has mainly two components: the part of the cost that is specific to the firm and the part that is common to all bidders. The latter is common to all firms participating in the auction. More formally:

$$c_{ijt'} = \phi_{ij} + \beta_1 d_{it} + \beta_2 X_t + \gamma_j Z_{jt'} + \varepsilon_{ijt} \tag{1}$$

where ϕ_{ij} are firm-good fixed effects, d_{it} is the distance from the supplier to the agency buying the good, X_t are the auction/contract's observable characteristics (number of bidders competing in the auction and total quantity being commissioned) and ε_{ijt} is the part of the firm's cost that is unobserved to the econometrician but it is known to the firm at time t.[32] The fixed effects ϕ_{ij} aim to account for any time-independent variable, such as the firm's size and productivity, that may affect the costs, as well as storage infrastructure and the presence or absence of long-term contracts with farmers.

Finally, $Z_{jt'}$ is a measure of product j's cost that is not known to the firm on the day of the auction. This variable represents the uncertainty suppliers face about their own cost since they do not know the price of the good on the day they are supposed to deliver it. As such, we can interpret it as proxy for the suppliers' opportunity cost. Therefore, different from the auction theory literature, the bidders' own cost or valuation is unknown.

[30] This point is also raised in Cohen and Einav (2007).

[31] Papers that study bidders' participation decision such as Krasnokutskaya and Seim (2011) and Fang and Tang (2014) assume that bidders do not know their cost when deciding to participate or not, but learn it before the auction day. In my setting, suppliers learn the cost only after the bidding takes place. Besides having to be pre-registered in the government potential suppliers database, which requires some document preparation regarding tax compliance among other requirements but no fee, once the bidders are registered, they can participate in any procurement auction. Essentially, there are no entry costs besides a one time document preparation requirement that is not specific to the good being commissioned. Therefore, I am not looking at entry decisions.

[32] Because I am not modeling the distribution of costs among suppliers, including the number of bidders in the cost function is a way to control for changes in the underlying distribution when the number of bidders change.

Consequently, suppliers must make conjectures about $Z_{jt'}$ in order to compute their expected profit. I am assuming they make their inferences based on two sets of information: one that is private and includes $\{\phi_{ij}, \varepsilon_{ijt}, d_{it}\}$, which I denote by $\mathcal{W}_{ijt}$, and a set of public information, denoted by $\mathcal{I}_t$, that not only includes the auction/contract characteristics X_t, but also any other information that is relevant in order to make forecasts about future price fluctuations, like past prices and weather variables.

Suppose $Z_{jt'}$ is normally distributed. Then $c_{ijt'}$ is normally distributed with mean $\mu_{ijt'}$ and variance $\sigma^2_{ijt'}$, which are given by

$$\begin{aligned}
\mu_{ijt'} &= \mathbb{E}_t\left[c_{ijt'}|\,\mathcal{W}_{ijt},\mathcal{I}_t\right] = \phi_{ij} + \beta_1 d_{it} + \beta_2 X_t + \gamma_j \mathbb{E}_t\left[Z_{jt'}|\,\mathcal{W}_{ijt},\mathcal{I}_t\right] + \varepsilon_{ijt} \\
\sigma^2_{ijt'} &= V_t\left[c_{ijt'}|\,\mathcal{W}_{ijt},\mathcal{I}_t\right] = \gamma_j^2 V_t\left[Z_{jt'}|\,\mathcal{W}_{ijt},\mathcal{I}_t\right]
\end{aligned}$$

Therefore, the expected profits are given by[33]

$$\mathbb{E}_t\left[U_{ijt}\left(\left(p_{ijt} - c_{ijt'}\right) q_{jt'}\right)|\,\mathcal{W}_{ijt},\mathcal{I}_t\right] = -\frac{e^{-\alpha\left(\left(p_{ijt}-\mu_{ijt'}-\frac{1}{2}\alpha q_{jt'}\sigma^2_{ijt'}\right)q_{jt'}\right)}}{\alpha}$$

Furthermore, I am assuming that, in order to make forecasts about future prices, all suppliers have the same set of information $\mathcal{I}_t$ and that inference about future price and volatility are independent of $\mathcal{W}_{it}$, that is, $\mathbb{E}_t\left[Z_{jt'}|\,\mathcal{W}_{ijt},\mathcal{I}_t\right] = \mathbb{E}_t\left[Z_{jt'}|\,\mathcal{I}_t\right]$ and $V_t\left[Z_{jt'}|\,\mathcal{W}_{ijt},\mathcal{I}_t\right] = V_t\left[Z_{jt'}|\,\mathcal{I}_t\right]$. Essentially, this hypothesis means that suppliers use the same forecasts to compute their expected costs. Since the series of past prices and weather information are publicly available and suppliers are small compared to market size, these forecasts could be interpreted as market expectations. From now on, because the forecast for the variance of the price does not depend on any variable that is i-dependent, I will omit the subscript i from $\sigma^2_{ijt'}$.

Note that although forecasts are a "common" factor in each supplier's cost, those are public signals that are the same for each supplier. Therefore, this is not a common values auctions setting since the other suppliers' costs are not relevant to determining supplier i's own cost (Athey and Haile (2007)), but it certainly adds correlation between valuations.

Finally, the rationale for choosing a bid will be that supplier i places bid p_{ijt} as long

[33] See Appendix for the derivation of this result.

as the price the government pays exceeds its reservation price, that is

$$p_{ijt} \geq \mu_{ijt'} + \frac{1}{2}\alpha q_{jt'}\sigma^2_{jt'} \tag{2}$$

As argued in Section 2, there are compelling reasons to assume that the online procurement auction is well-approximated by a button auction framework: increments are very small (the median is R$ 0.02) and jump bids are rare (see Larsen (2014)). This means that the equilibrium bid strategy is to bid the true cost which implies Equation (2) holds with equality for the last bid placed by each bidder that did not win the auction. This means that the winning bid will be the second-order statistic from the distribution of (expected) costs.

Therefore, (2) becomes

$$p^{(1)}_{ijt} = \phi^{(2)}_{ij} + \beta_1 d^{(2)}_{it} + \beta_2 X_t + \gamma_j \mathbb{E}_t\left[Z_{jt'}|\mathcal{I}_t\right] + \frac{1}{2}\alpha\gamma_j^2 q_{jt'} V_t\left[Z_{jt'}|\mathcal{I}_t\right] + \varepsilon^{(2)}_{ijt} \tag{3}$$

Equation (3) is the main regression equation. On the left side there is the bid placed by the winner p^1_{ijt} and on the right side there are variables that are observable and unobservable characteristics of the second-lowest bidder $\left(\phi^2_{ij}, d^2_{it}, \varepsilon^2_{ijt}\right)$, auction characteristics $(X_t, q_{jt'})$ and the forecasts $\mathbb{E}_t\left[Z_{jt'}|\mathcal{I}_t\right]$ and $V_t\left[Z_{jt'}|\mathcal{I}_t\right]$. Identification of the parameter α comes from variation in the risk for each contract: the forecast $V_t\left[Z_{jt'}|\mathcal{I}_t\right]$ is different for each good, auction day and contract length.

The main interest is to estimate how much risk the suppliers bear, that is, the risk premium included in their bid as given by

$$\text{Risk premium} = \frac{1}{2}\alpha\gamma_j^2 q_{jt'} V_t\left[Z_{jt'}|\mathcal{I}_t\right] \tag{4}$$

Note that in case I cannot reject that α, the coefficient of absolute risk aversion, is equal to zero, we are back to the usual setting of risk neutrality and the risk premium is equal to zero.

4 Empirical Analysis

This section presents the main estimates of the coefficient on risk aversion and implied risk premium when contracts are risky. I first show how the forecasts $\mathbb{E}_t\left[Z_{jt'}|\mathcal{I}_t\right]$ and $V_t\left[Z_{jt'}|\mathcal{I}_t\right]$ were computed using time series analysis in which I explore the volatility in the series. Then, I present the main analysis that uses the forecasts as explanatory variables for the bids suppliers place. The estimated parameters imply that suppliers are risk averse and that the risk premium can be substantial when market conditions are volatile.

4.1 Wholesale price forecasts

Figures 3-7 plot the complete series of wholesale prices for the five goods I am studying. The continuous line in the top panel is a cubic spline fit for better visualization of the changes in the series. The bottom panel in each figure shows the daily percentage change in prices. The series presents a common phenomenon in financial data, which is the fact that there are periods in which the volatility is high followed by some periods where the prices are relatively stable.

Motivated by exploring the volatility as a measure of the risks suppliers face, in order to compute the forecasts $\mathbb{E}_t\left[Z_{jt'}|\mathcal{I}_t\right]$ and $V_t\left[Z_{jt'}|\mathcal{I}_t\right]$, I model each series as ARMA(p,q)-GARCH$(1,1)$ model using standard time series techniques, where p is the number of autoregressive lags and q is the number of moving average lags. Formally, the ARMA(p,q)-GARCH$(1,1)$ model is formulated as:

$$y_t = c + \eta_1 y_{t-1} + \ldots + \eta_p y_{t-p} + u_t + \theta_1 u_{t-1} + \ldots + \theta_q u_{t-q}$$

$$u_t = \sqrt{h_t} \cdot \nu_t$$

$$h_t = \zeta + \alpha_1 u_{t-1}^2$$

where ν_t is i.i.d with mean zero and variance equal to 1.[34]

For each good, I used the complete series (since 2005) to find the best fit using Akaike and Schwarz information criteria.[35] Table 3 presents the models chosen for each of the goods using these criteria.

[34] For an introduction to ARMA-GARCH models, see Hamilton (1994).

[35] The information criteria are statistical measures that assess the model goodness fit. Let k be the number of parameters of the model, L be the value of the likelihood and n the number of observations. The two criteria are defined as

$$AIC = 2k - 2\ln(L) \qquad BIC = k \cdot \ln(n) - 2\ln(L)$$

The lower the criteria, the better, that is, AIC and BIC penalizes models that have too many parameters.

In addition, since weather conditions may have a considerable effect on supply of fresh produce, I include weather-related variables when computing the forecasts. First, I ran a principal component analysis of the weather variables described in Section 2 using polynomials, lags and interactions. In the ARMA-GARCH model, I included the five most important factors that represent together more than 98% of the variation of those variables for each good.

Finally, from the estimation of the ARMA-GARCH model, I computed daily forecasts for the mean and variance of the series for each auction, from the day it was scheduled to the duration of the contract (adjusted for the number of business days). Therefore, for each auction, the forecasts $\mathbb{E}_t\left[Z_{jt'}|\mathcal{I}_t\right]$ and $V_t\left[Z_{jt'}|\mathcal{I}_t\right]$ are different, unless the auctions were scheduled on the same day and had the same contract length. From those daily forecasts, I am using the mean of the predictions. The forecasts were calculated dynamically, that is, using only the information that was available on the day of the auction and not the whole series.

The estimated forecasts were noticeably good, when compared to the actual series. Table 4 presents the correlations between the actual wholesale prices series and the forecasts $\mathbb{E}_t\left[Z_{jt'}|\mathcal{I}_t\right]$ and $V_t\left[Z_{jt'}|\mathcal{I}_t\right]$. The forecasts for the means are very close to the actual series, with correlation ranging from 0.85 (limes) to 0.97 (bananas). For the variance, it is not as high, but still very close, with correlations ranging from 0.66 (ripe tomatoes) to 0.78 (limes).

4.2 Estimation of the risk premium

With the forecasts computed, I can investigate the effect of the expected volatility of the prices in the winning bid. For a graphical visualization first, Figure 8 plots the mean expected prices for the duration of the contract and winning bids for one government agency and four of these goods.[36] The plots show that bids roughly follow the pattern of expected prices and are usually lower than the forecasts, except for limes for which bids seem to be, in general, higher than the expected prices.

I now turn to my main objective which is to estimate the risk premium (Equation (4)). First, I estimate the coefficients from Equation (3) using the winning bid and the second-lowest bidder traits. The results are summarized in Table 5. The estimated

[36] The agency is the Prof Ataliba Nogueira Penitentiary in Campinas. It is the agency that has bought these goods most often: 118 auctions in total for bananas, limes, oranges and green tomatoes. However, it did not commission any auction to buy ripe tomatoes.

coefficient on absolute risk aversion is 0.0174. Following Cohen and Einav (2007) to interpret this estimate, this coefficient would mean that suppliers are indifferent between a 50-50 gamble of gaining US$100 and losing US$15.[37] This implies a very high level of risk aversion. Dillon and Scandizzo (1978) study small Brazilian farmers and estimated their coefficient on absolute risk aversion from experimental data. They find coefficients in the 0.0016-0.0034 range, which is lower than what I find. However, they suggest some interviewer biases that Binswanger (1980) tries to overcome in a very influential paper. Binswanger (1980) finds that the estimated risk aversion in rural India ranges from 0.32 to 1.74. This implies a even higher degree of risk aversion than what I estimate, which could be understandable since farmers are likely more risk averse than intermediaries. Finally, Love and Buccola (1991) estimate risk and technology choice jointly for Iowa corn farmers with CARA utility functions and find a range 0.016 - 0.14 for the coefficient, which is very close to my findings. Nonetheless, it is worth mentioning that farmers in developing countries are found to be more risk averse than their counterparts in developed economies due to less access to risk-management instruments (Young (1979)). Brazil is known for being a country that has very bureaucratic regulations and bad law enforcement. Out of 189 economies, Brazil is ranked 120 in ease of doing business according to a World Bank report.[38] Therefore, it is not surprising to find that Brazilian firms are more risk averse when compared to other countries, since they are less shielded against adverse conditions.

Furthermore, as Rabin (2000) identifies, the comparison between risk preferences across different contexts and stakes can be very problematic. In the case of Cohen and Einav (2007), the mean individual with CARA utility function would pay US$ 76.51 for the same gamble. However, the context of their study is auto insurance in which the bet involves losing the total value of the car. In my setting, suppliers may lose one contract out of others they can sign. Hence, I believe the framework I study is closer to financial markets than insurance markets.

Considering this interpretation, I also computed the relative risk aversion implied by the model's estimates. In order to do that, I multiplied the estimated coefficient of risk aversion by the contract value, which is the winning bid multiplied by the total quantity commissioned. Table 6 presents the average contract value for each good and the implied median and mean relative risk aversion. With the exception of limes, the coefficients are

[37] This number is found by solving for x such that $u(w) = \frac{1}{2}u(w+100) + \frac{1}{2}u(w-x)$.

[38] http://www.doingbusiness.org/data/exploreeconomies/brazil

many times greater than 10, which is a usual upper bound in the financial literature. However, when compared to the estimates found in Campbell (2003) for many developed countries, they actually look small. In Campbell (2003), the relative risk aversion ranges from 58.11 (Australia) to 1713.19 (Sweden) in an asset pricing model.[39]

The remaining estimates from Table 5 are statistically significant and have the expected sign, except for distances. The winning bid increases when the mean expected price for the duration of the contract increases, and decreases with quantity and number of bidders.

It remains to show the implied risk premium suppliers require when bidding from Equation (4). Table 7 shows statistics for the implied risk premium, computing Equation (4) as a percentage of the winning bid. For bananas, limes and oranges, the cost of the risk to the government is around 2% on average. However, for ripe tomatoes and green tomatoes, the two most volatile goods, the risk accounts for 38% and 26% on average, respectively. This evidence shows that the procurement cost due to contract risk can be substantial.

Finally, Table 8 presents the correlation between the suppliers' estimated fixed effects per good. The correlations are all positive but far from perfect, which provides another reason to include the interaction ϕ_{ij} in the model. This means that firms' fixed effects only would not capture that firms might be more competitive in one good than another. The highest correlation is not a surprise as it happens between the two types of tomatoes (0.8349).

There are two main concerns that could potentially bias the results. First, since suppliers are risk averse, they might try to build a diverse portfolio in order to reduce risk. In this context, portfolio diversification means that if the supplier won an auction for a risky good, he or she might try to win another contract for which risk is negatively correlated with the good he/she won . Since I am not taking that into consideration in my empirical analysis, if this strategy is present it means that suppliers are more risk averse than what the estimates suggest. Therefore, if that is the case, the estimates I find could be interpreted as a lower bound for risk aversion. Second, it could be the case that suppliers prefer bundles rather than single items. Many of the auctions for fresh produce happen simultaneously, so cost synergies in the form of reduced transportation

[39] I excluded the negative estimates from this range. If the correlation of stock returns and consumption growth is constrained to be equal to 1, the estimates on relative risk aversion are smaller, ranging from 8.42 (Australia) to 49.32 (USA).

costs could play a role in suppliers' strategies.[40] In this case, the risk of the bundle is unchanged, but it could be that suppliers bid more aggressively to win more contracts. However, this effect would be partially captured by the fixed effects ϕ_{ij} since it affects the part of the cost that is fixed (transportation cost) and not the part that relates to the input price (expected price and variance). Moreover, changes in risk do not affect this preference.

4.3 Robustness checks

The main analysis presented so far argued that there is an intrinsic risk in the contracts that suppliers do not have much control over. This is because goods are perishable and cannot be stored for prolonged period of times, so suppliers are very exposed to price fluctuations. However, if there are certain types of goods that do not share these features, namely short durability and flexible storage requirements, would the estimates change? Intuitively, they should. Table 9 presents the same analysis done so far for five root vegetables: garlic, onions, potatoes (regular and clean) and yuca root. For those goods, I find that suppliers are not risk averse and therefore do not include a risk premium in their bids which is consistent with the far lower risk associated with supplying those contracts. This is in sharp contrast with the high risk aversion shown in the case of fruits.

Moreover, the main results presented in Table 5 and Table 7 use the winning bid and second-lowest bidder's traits in Equation (3). However, the equilibrium from the button auction also holds true for other lower ranked bidders: each supplier's cost is equal to the bid from the bidder ranked above. The only supplier in which it is not possible to infer the bidder's true cost is the winner. Table 10 presents the results when all bidders but the winner are included. There are 62 different suppliers (17 more than in the previous analysis) and they are less risk averse on average when we compare the results with the second-lowest bidder only. The same finding is present when I drop the restriction of including only suppliers that participated in more than 30 auctions, increasing the number of suppliers from 47 to 111 (Table 11).

[40] These complementarities among goods is another reason that hinder collusion in these auctions, since each supplier has incentives to break the collusive agreement in order to be able to win in a subset of goods rather than single items (Brusco and Lopomo (2002)).

5 Counterfactual Analysis

In this section, I use the estimation results to evaluate the government procurement costs in different schemes, most notably, schemes that reduce the contract risk for suppliers. The counterfactual mechanism I consider introduces risk sharing between the government and supplier. In principle, the government could completely eliminate the risk, but that would require knowledge of the fraction of the firms' cost that is due to the price of the good (γ_j in Equation (1)). However, this strategy would be impractical for many reasons: it would require a different type of contract for each good and an econometrician to estimate the model. Nonetheless, a simple contract in which the government is willing to take about 40% of the risk across all goods could translate into remarkable savings in public expenditures.

Providing suppliers more insurance or reducing contract risk is not unusual. For instance, in order to avoid contract uncertainty, US Forest Services indexes payments to timber prices at the time of the harvest, which can take place two to six years after the auction (Haile (2001)). I propose a different approach that introduces risk sharing between government and suppliers. Of course, this exercise is only applicable if we assume that the government is risk neutral or at least less risk averse than the suppliers. There are several reasons to argue that this might be the case. First, each government agency commissions several auctions per year, for many different goods, including other fresh produce not studied in this paper but also other types of goods, such as office supplies, furniture and clothing. Therefore, if there is any risk in these contracts from the agency perspective, it is much more diluted. Second, the State government as an entity is a far larger agent in the economy than the small suppliers that participate in the auction, and engage in much riskier projects than the purchase of fresh produce, such as highway construction, provision of public transportation and health care, to name a few. Finally, public employee wages are in the vast majority fixed and there are no incentive schemes to reward performance. That means that although the agency employee who manages the auction process has a budget to administer, his or her wage is not attached to the outcome of the auction.

Given that the government can be assumed to be risk neutral in the contracts for fresh produce, consider the following mechanism that changes the payment scheme to the auction winner: the contract specifies that the government will pay a fraction θ_j of the wholesale market price on the day the good is delivered and suppliers bid how much on top of that fraction that they are willing to sell the good for. The cost function of the firm, given by Equation (1), which I replicate below, is still the same. That is, suppliers still face uncertainty about their own cost since they do not know the price of the good $Z_{jt'}$ on the day they are supposed to deliver it:

$$c_{ijt'} = \phi_{ij} + \beta_1 d_{it} + \beta_2 X_t + \gamma_j Z_{jt'} + \varepsilon_{ijt}$$

However, if firm i wins the auction, the revenue is different with this new contract. Let $r_{ijt'}$ denote the revenue on the day the good is delivered. Then,

$$r_{ijt'} = \theta_j Z_{jt'} + l_{ijt}$$

where l_{ijt} is the lump sum amount on top of $\theta Z_{jt'}$ that the supplier bid on the auction day t. Note that in this new contract the revenue is also unknown on the day of the auction.

Therefore, the realized profit per unit a firm makes will be equal to

$$r_{ijt} - c_{ijt'} = l_{ijt} - \phi_{ij} - \beta_1 d_{it} - \beta_2 X_t + (\theta_j - \gamma_j) Z_{jt'} - \varepsilon_{ijt}$$

Following the same steps as in Section 2, from the utility function

$$U_{ijt}\left((r_{ijt'} - c_{ijt'}) q_{jt'}\right) = \frac{-e^{-\alpha\left((r_{ijt'} - c_{ijt'}) q_{jt'}\right)}}{\alpha}$$

supplier i submits a bid l_{ijt} as long as

$$l_{ijt} \geq \phi_{ij} + \beta_1 d_{it} + \beta_2 X_t - (\theta_j - \gamma_j) \mathbb{E}_t \left[Z_{jt'} | \mathcal{I}_t\right] + \frac{1}{2}\alpha (\theta_j - \gamma_j)^2 q_{jt'} V_t \left[Z_{jt'} | \mathcal{I}_t\right] + \varepsilon_{ijt} \quad (5)$$

Note that if we compare Equation (5) to (2), the terms that depend on i remain the same. That is, in this exercise, the ranking in the auction would not change with the new payment scheme and the equilibrium would be exactly the same. Therefore, from the button auction equilibrium, the winning bid will be the second-order statistic from the distribution of reservation price:

$$l^{(1)}_{ijt} = \phi^{(2)}_{ij} + \beta_1 d^{(2)}_{it} + \beta_2 X_t - (\theta_j - \gamma_j) \mathbb{E}_t \left[Z_{jt'} | \mathcal{I}_t\right] + \frac{\alpha}{2} (\theta_j - \gamma_j)^2 q_{jt'} V_t \left[Z_{jt'} | \mathcal{I}_t\right] + \varepsilon^{(2)}_{ijt} \quad (6)$$

Figures 9-13 plot the average risk premium associated with different values for θ_j. From Equation (6), it is clear that the risk premium will be zero when $\theta_j = \gamma_j$. Indeed, looking at the estimates for γ_j from Table 5, the plots show that the risk premium is at its minimum when θ_j is closer to those values. Figures 9-13 also included the case when $\theta_j = 0$ (equivalent to the actual contract) and, as it should, they are a perfect match with the ones computed in Table 7.

It is worth noting that it would not be desirable for the government to apply a fraction θ_j that is too high. At first, this goes in the opposite direction of common sense since a higher θ_j means that the government is taking a higher share in the risk. However, a higher θ_j means less uncertainty about the cost but more uncertainty about the revenue. And because suppliers are risk averse, they do not like uncertainty, and the U-shaped curves in Figures 9-13 then seem very intuitive.

Although it would be impractical to implement $\theta_j = \gamma_j$ because it would require a different contract for each good and the estimation of the coefficients, which could make the procurement process less transparent in the eyes of the public, nevertheless the government could still apply a simple rule by choosing a uniform θ to all goods and reduce the risk premia. From Figures 9-13, if $\theta = 0.4$, the risk premium for each of the goods barely reaches 1% of the winning bid. For bananas, limes and oranges, this reduces the risk premia by half when compared to the actual contract (Table 7). For both types of tomatoes, the savings are quite substantial and it would mean a drop in the average risk premia from 38% and 26% to nearly zero for ripe and green tomatoes, respectively.

6 Conclusion and Future Work

This paper provides evidence that contract risk associated with market uncertainty can affect the procurement cost for the government. Using a parsimonious model to assess the cost and risk preference parameter of suppliers that bid in these type of contracts, suppliers are shown to be highly risk averse and, as a result, there is a significant risk premium built into their bids. However, when bidding for contracts that are far less sensitive to future market conditions, bidders' risk premium is vastly lower.

I propose an alternative type of contract that allows the government to share part of the risk with suppliers and which could substantially reduce the government's procurement cost. If the government offers to pay 30-50% of the market price and suppliers bid how much more they are willing to sell the good above that amount, the risk premium would be reduced to at most 1% of the winning bid. This contract would then significantly reduce the expenditure incurred by the government in exchange for them taking on some of the risk.

While jump bids and post-auction bargaining are largely absent from fresh produce procurement auctions, they are features in the data for other products and services sold through auction by the Sao Paulo State government. I intend to examine both jump bidding and post-auction bargaining in future research.

Jump bidding is a common phenomenon in English auctions that is not yet fully understood. Because of the richness of this dataset, I am able to describe which industries are more prone to jump bidding and when this behavior is more likely to happen during the auction. This exercise will shed light on a common practice in real world auctions that is not captured by standard models. Finally, for those goods in which the bargaining stage is an important part of the procurement process, the data includes chat transcripts of the negotiation between suppliers and government agency, which is very rare. Moreover, because the government may reject the offers made by the winning bidder and bargain with the second-lowest bidder, the value of the contract depends on a bidder's beliefs about the agency's bargaining power and how bargaining will eventually unfold. This limited commitment from the government will add new insights to the empirical auctions literature.

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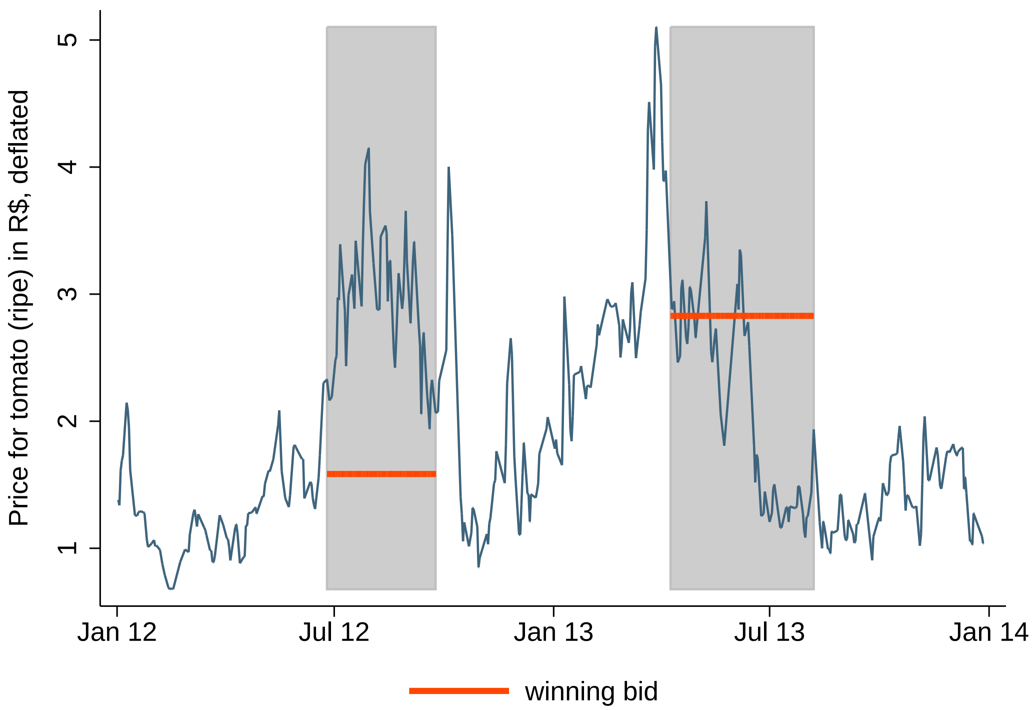

Figure 1: Contract Risk Example: This figure plots the series of wholesale prices for tomatoes (ripe) for 2012-2013. The shaded areas represent the duration of two different contracts and the horizontal lines are the winning bids for each of these contracts. Prices are per kilo (2.2 pounds) and showed in Brazilian currency (R$) deflated to 2005 prices using the National Consumer Price Index (IPCA).

Table 1: Summary Statistics for Wholesale prices, Winning Bid, and Contract Characteristics: 2008-2014

Good	Wholesale Price	Winning Bid	Quantity	Contract Length	# of auctions
Banana	0.7463	0.6112	8,792	106.34	1,742
	(0.1367)	(0.2882)	(5,957)	(23.03)	
Lime	1.3314	1.2335	671	105.07	519
	(0.8345)	(0.6659)	(1,038)	(22.81)	
Orange	0.8066	0.5689	9,625	106.14	1,023
	(0.1521)	(0.7309)	(7,892)	(24.25)	
Tomato (ripe)	1.7130	0.8264	4,186	107.96	1,053
	(0.6552)	(0.4482)	(2,068)	(21.03)	
Tomato (green)	1.7170	0.8564	5,923	106.76	1,652
	(0.6564)	(0.4600)	(3,139)	(22.79)	

Note: This table presents descriptive statistics for wholesale prices, winning bids and contract characteristics for the five most common produce goods that were purchased using electronic procurement auctions during 2008-2014. Table entries are sample means and standard deviations (in parentheses). The unit of analysis for average wholesale prices, winning bids and quantity is per kilo (2.2 pounds). Average contract length is in days. Prices are in Brazilian currency (R$) and deflated to 2005 prices using the National Consumer Price Index (IPCA). Sample includes auctions that had at least two suppliers.

Table 2: Summary Statistics for Prices Received By Farmers, Wholesale Prices and Winning Bid: 2008-2014

Good		Farmers' Prices	Winning Bid	Wholesale
Banana		0.45	0.61	0.74
Tomato	Industry	0.14	0.84	1.71
	Consumers	0.95		
Orange	Industry	0.16	0.56	0.80
	Consumers	0.22		

Note: This table presents descriptive statistics for the prices received by farmers, wholesale prices and winning bids during 2008-2014. Farmers' prices were collected from the Agricultural Economics Institute in the State of Sao Paulo and are sample means from the monthly average prices available. Winning bids and wholesale market prices for tomatoes are sample means from the entries in Table 1 for ripe and green tomatoes. The unit of analysis is per kilo (2.2 pounds). Prices are in Brazilian currency (R$) and deflated to 2005 prices using the National Consumer Price Index (IPCA).

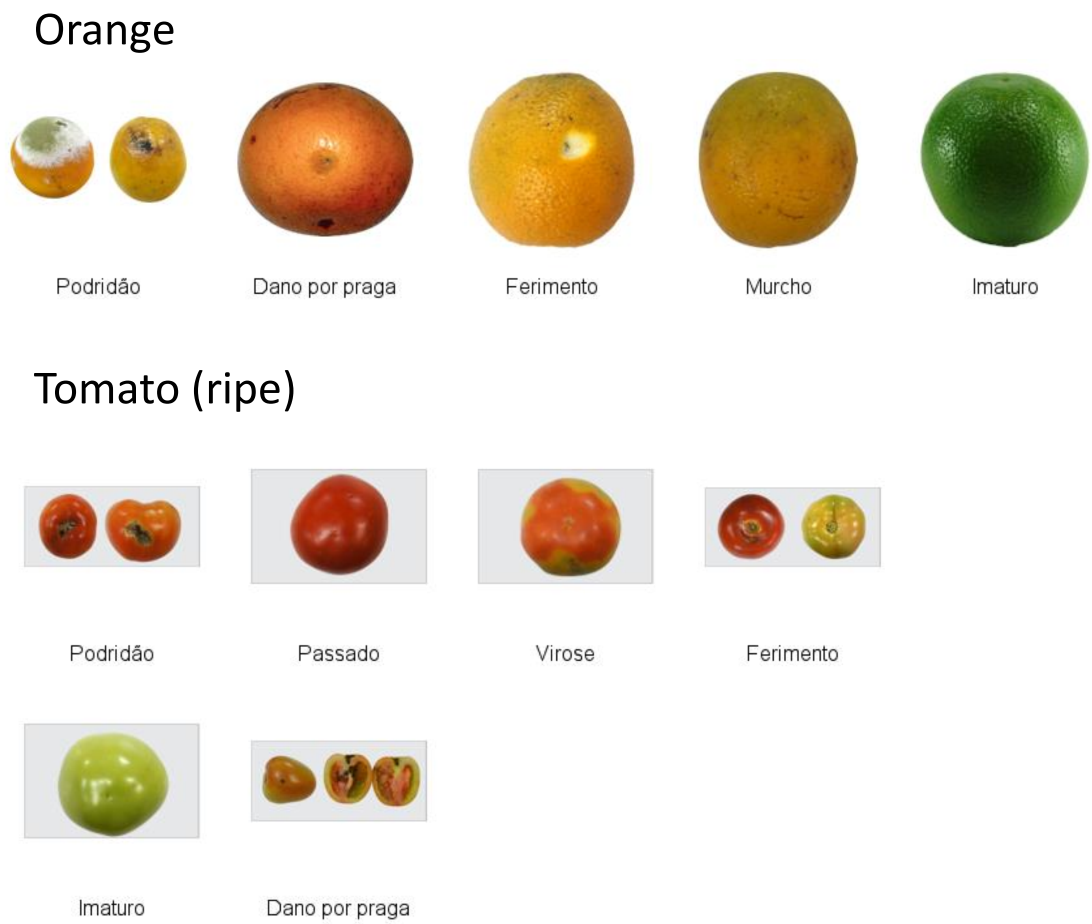

Figure 2: Goods that Cannot be Accepted Example: This figure shows the pictures of poor-quality oranges and ripe tomatoes that should not be accepted by government agencies. Those pictures are provided to government agency staff from Ceagesp (Program Hortiescolha) as part of their training to help agencies get high-quality goods. All pictures can be easily accessed from the Hortiescolha website.

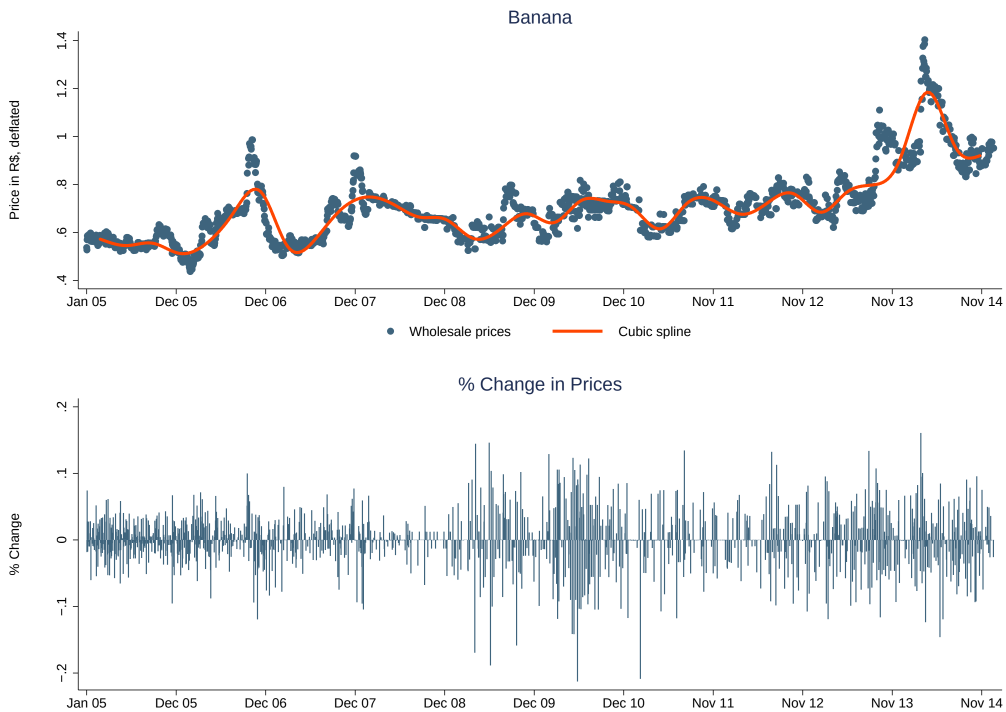

Figure 3: Banana Wholesale Prices Volatility: 2005-2014. The figure on top plots the complete series of wholesale prices for bananas. Prices are per kilo (2.2 pounds) and showed in Brazilian currency (R$) deflated to 2005 prices using the National Consumer Price Index (IPCA). The orange line is a cubic spline fit for better visualization of the main changes of the series. The bottom figure plots the daily percentual change in prices.

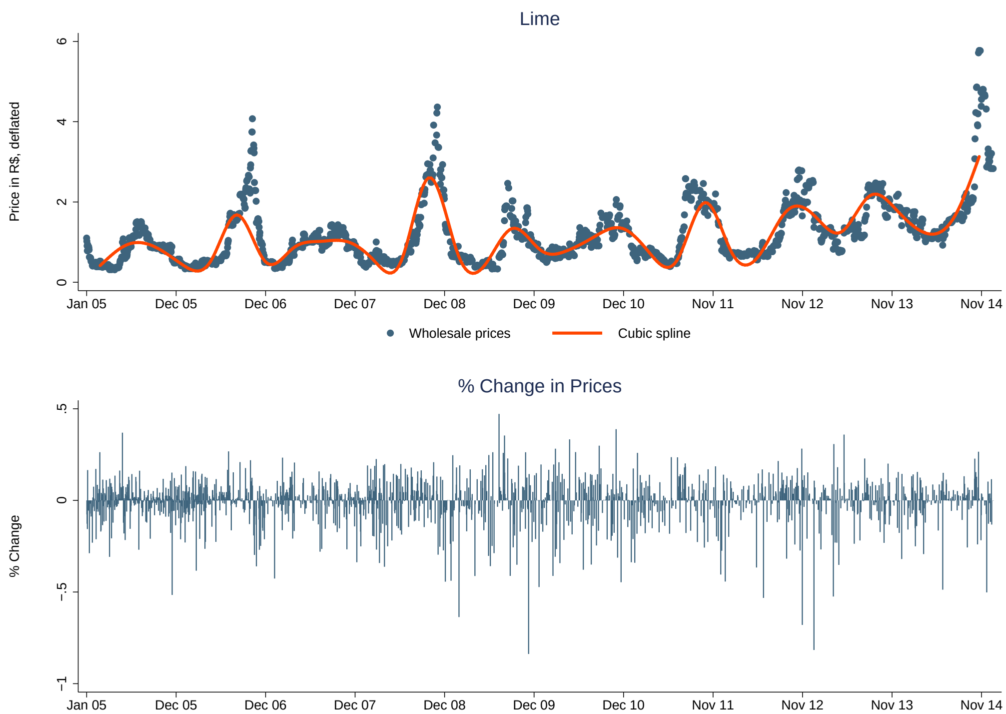

Figure 4: Lime Wholesale Prices Volatility: 2005-2014. The figure on top plots the complete series of wholesale prices for limes. Prices are per kilo (2.2 pounds) and showed in Brazilian currency (R$) deflated to 2005 prices using the National Consumer Price Index (IPCA). The solid line is a cubic spline fit for better visualization of the main changes of the series. The bottom figure plots the daily percentual change in prices.

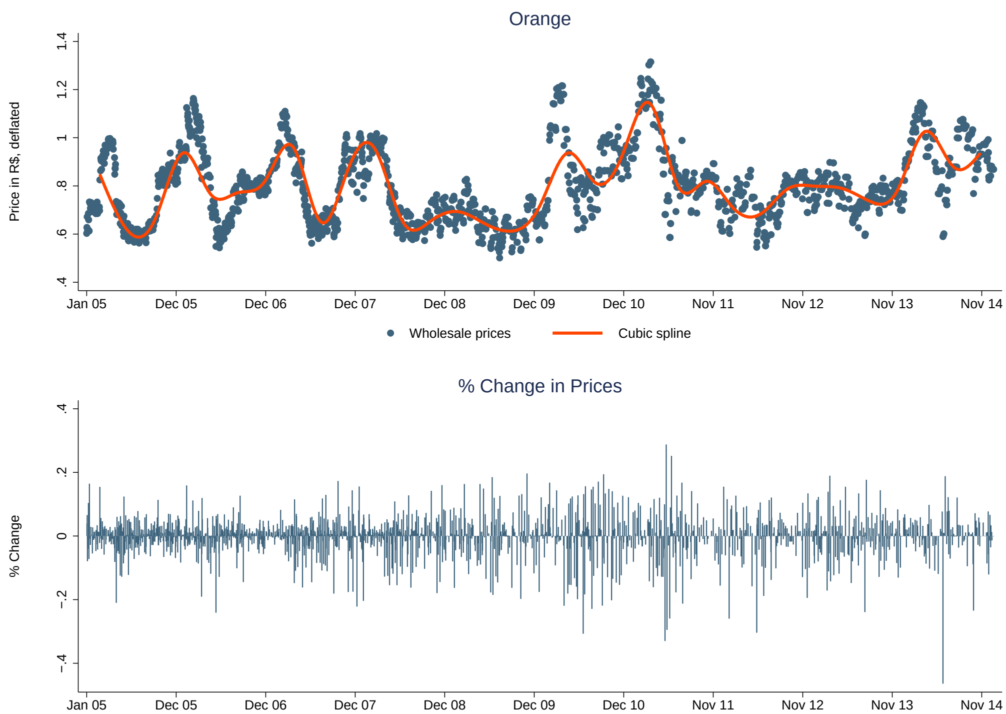

Figure 5: Orange Wholesale Prices Volatility: 2005-2014. The figure on top plots the complete series of wholesale prices for oranges. Prices are per kilo (2.2 pounds) and showed in Brazilian currency (R$) deflated to 2005 prices using the National Consumer Price Index (IPCA). The solid line is a cubic spline fit for better visualization of the main changes of the series. The bottom figure plots the daily percentual change in prices.

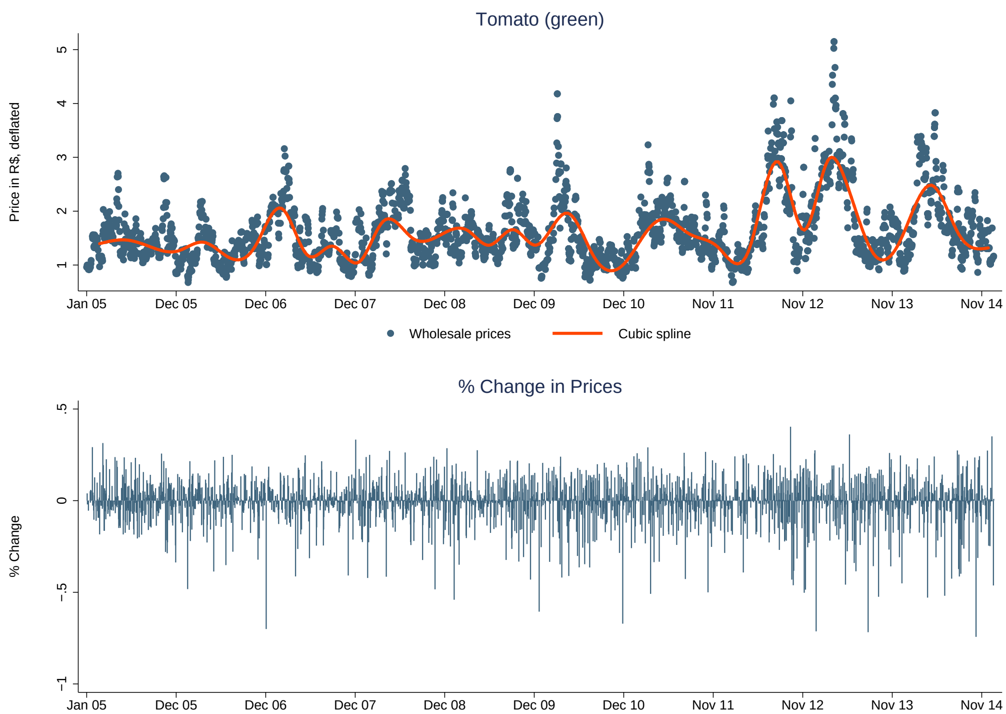

Figure 6: Tomato (green) Wholesale Prices Volatility: 2005-2014. The figure on top plots the complete series of wholesale prices for green tomatoes. Prices are per kilo (2.2 pounds) and showed in Brazilian currency (R$) deflated to 2005 prices using the National Consumer Price Index (IPCA). The solid line is a cubic spline fit for better visualization of the main changes of the series. The bottom figure plots the daily percentual change in prices.

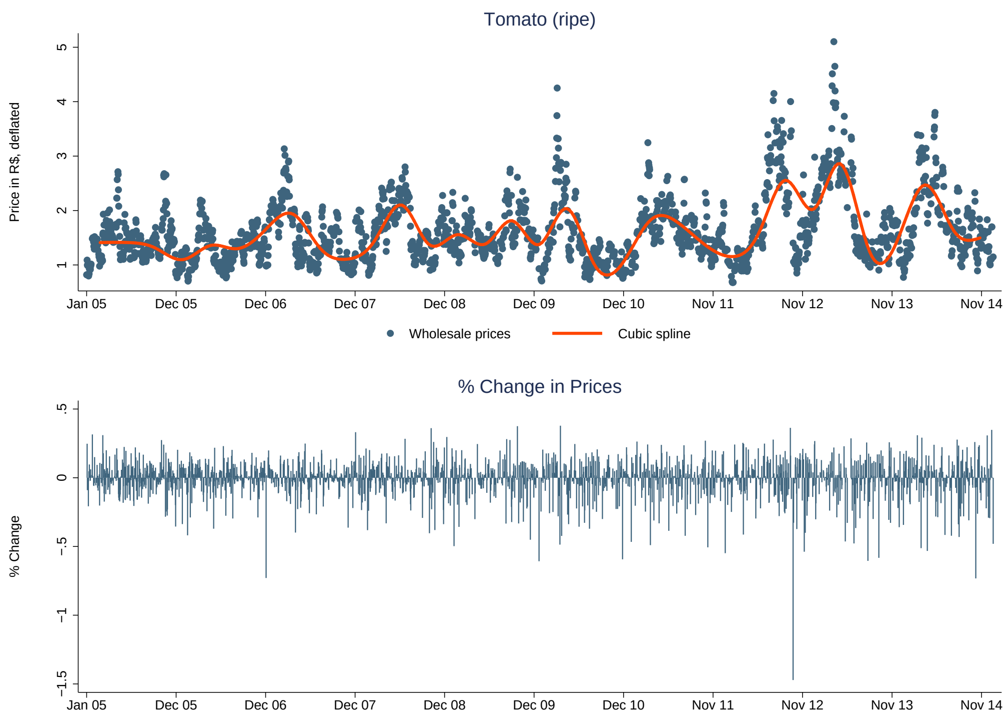

Figure 7: Tomato (ripe) Wholesale Prices Volatility: 2005-2014. The figure on top plots the complete series of wholesale prices for ripe tomatoes. Prices are per kilo (2.2 pounds) and showed in Brazilian currency (R$) deflated to 2005 prices using the National Consumer Price Index (IPCA). The solid line is a cubic spline fit for better visualization of the main changes of the series. The bottom figure plots the daily percentual change in prices.

Table 3: ARMA-GARCH Models for the Wholesale Prices Series

Good	ARMA(p, q)	Trend
Banana	(11,0)	yes
Lime	(13,2)	yes
Orange	(24,2)	no
Tomato (ripe)	(18,2)	yes
Tomato (green)	(20,1)	yes

Note: This table presents the best ARMA model fit for each of the goods using the complete wholesale price series (2005-2014). The models were chosen using the Akaike and Schwarz information criteria.

Table 4: Correlation Between Forecasts and Actual Series

Good	$\text{corr}(Z_{jt'}, \mathbb{E}_t[Z_{jt'}\mid\mathcal{I}_t])$	$\text{corr}(Z_{jt'}, V_t[Z_{jt'}\mid\mathcal{I}_t])$
Banana	0.9775	0.7816
Lime	0.8552	0.7835
Orange	0.9211	0.7727
Tomato (ripe)	0.9144	0.6684
Tomato (green)	0.8791	0.7089

Note: This table presents the correlation between the actual wholesale price series and the forecasts for the mean and variance from the ARMA-GARCH model for each good. I computed the forecasts for each day of the length of the contract, starting at the day the auction took place and then calculated the mean for that period. The forecasts were computed dynamically and only considered information up until the day of the auction, that is, it did not include the complete series. To compute the variance of the series, I used a 15-day window.

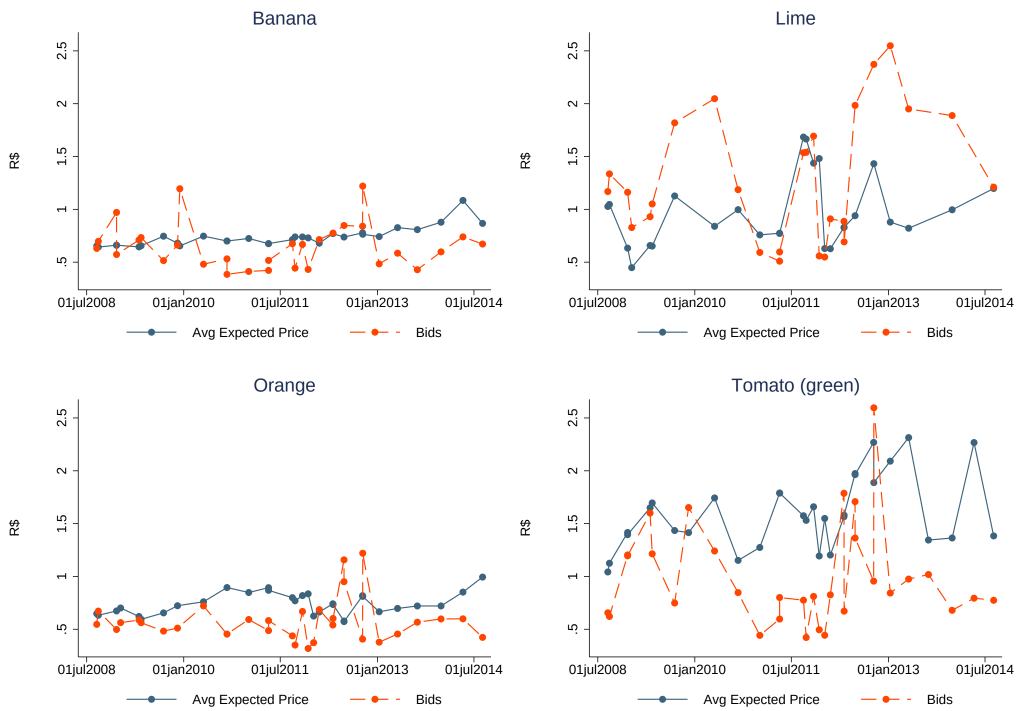

Figure 8: Mean Expected Prices and Bids: 2008-2014. This figure plots mean expected prices for the duration of the contract and winning bids for auctions commissioned by Prof Ataliba Nogueira Penitentiary in Campinas for bananas, limes, oranges and green tomatoes. The expected prices were computed using ARMA-GARCH model with the series of past prices and weather information. From the daily forecasts for each day of the contract length, the figure shows the mean value. Prices are per kilo (2.2 pounds) and showed in Brazilian currency (R$) deflated to 2005 prices using the National Consumer Price Index (IPCA).

Table 5: Estimated Risk Aversion - Fruits

		Coefficient	Standard error
Risk aversion		0.0174***	0.0037
Banana	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.6678***	0.0943
	Quantity	-9.09e-06***	1.48e-06
	# of bidders	-0.0633***	0.0079
Lime	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.2811***	0.0305
	Quantity	-0.00006***	0.00001
	# of bidders	-0.16379***	0.0205
Orange	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.3382***	0.1145
	Quantity	-6.85e-06***	1.64e-06
	# of bidders	-0.0745***	0.01278
Tomato (ripe)	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.4586***	0.0379
	Quantity	-0.00008***	0.00001
	# of bidders	-0.0718***	0.0144
Tomato (green)	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.3581***	0.0230
	Quantity	-0.00005***	6.01e-06
	# of bidders	-0.0631***	0.0108
Distance		-9.87e-08**	4.198e-08
N		5,983	
Adj R^2		0.1380	

Note: This table presents the estimate on coefficient of absolute risk aversion when suppliers have CARA utility and their costs are normally distributed. The dependent variable is the winning bid. The mean expected variance is multiplying the total quantity commissioned. All variables were demeaned by suppliers-goods' average to account for fixed effects. Winning bids and quantity unit is per kilo (2.2 pounds). Distance is from the agency to the second-lowest bidder location to represent the button auction equilibrium and it is showed in meters (3.28 feet). Significance levels 5%, and 1% are denoted by **, and ***, respectively.

Table 6: Contract Value and Implied Coefficient on Relative Risk Aversion

	Contract Value		Relative Risk Aversion	
	Mean	Std Dev	Median	Mean
Banana	4984.76	3,904.45	71.59	86.93
Lime	787.48	1507.38	6.23	13.73
Orange	4720.34	4223.28	66.05	82.32
Tomato (ripe)	3329.20	2381.27	49.86	58.06
Tomato (green)	4780.11	3439.04	70.64	83.36

Note: This table presents the mean and standard deviation of contract values for each good and the implied median and mean of relative risk aversion. The contract value is computed by multiplying the winning bid by the the total quantity commissioned in the contract. The relative risk aversion is computed by multiplying the estimate on the absolute risk aversion by the contract value.

Table 7: Implied Risk Premium: Percentage of Winning Bid

	Banana	Lime	Orange	Tomato (ripe)	Tomato (green)
25th percentile	1.0	0.2	0.6	21.3	13.6
Median	2.1	0.6	2.2	38.3	26.5
Mean	2.5	2.4	3.1	39.9	26.8
75th percentile	3.4	1.7	4.1	55.5	36.8

Note: This table presents statistics for the implied risk premium for each good. It is computed as the percentage of the winning bid attributed to the mean expected variance.

Table 8: Bidder-Good Estimated Fixed Effects Correlation

	Banana	Lime	Orange	Tomato (ripe)	Tomato (green)
Banana	1				
Lime	0.6409	1			
Orange	0.7461	0.5873	1		
Tomato (ripe)	0.5653	0.2186	0.3089	1	
Tomato (green)	0.5244	0.2890	0.2351	0.8349	1

Note: This table presents the correlations between suppliers' estimated fixed effects per good from the non linear regression.

Table 9: Estimated Risk Aversion - Root Vegetables

		Coefficient	Standard error
Risk aversion		3.11e-09	5.14e-09
Garlic	$\mathbb{E}_t\left[Z_{jt'} \middle\| \mathcal{I}_t\right]$	0.7845***	0.0162
	Quantity	-0.0001***	0.00002
	# of bidders	-0.2545***	0.0193
Onion	$\mathbb{E}_t\left[Z_{jt'} \middle\| \mathcal{I}_t\right]$	0.7892***	0.1096
	Quantity	-6.70e-06	5.51e-06
	# of bidders	-0.0590***	0.0164
Potato	$\mathbb{E}_t\left[Z_{jt'} \middle\| \mathcal{I}_t\right]$	0.5110*	0.2820
	Quantity	-0.00001*	6.18e-06
	# of bidders	-0.0442	0.0309
Potato (washed)	$\mathbb{E}_t\left[Z_{jt'} \middle\| \mathcal{I}_t\right]$	0.6425**	0.2645
	Quantity	-4.96e-06	4.29e-06
	# of bidders	-0.0649*	0.0252
Yuca	$\mathbb{E}_t\left[Z_{jt'} \middle\| \mathcal{I}_t\right]$	0.0981	0.3714
	Quantity	-0.00001	0.00001
	# of bidders	-0.0945	0.0407
Distance		5.94e-07***	9.23e-08
N		4,026	
Adj R^2		0.4113	

Note: This table presents the estimate on coefficient of absolute risk aversion when suppliers have CARA utility and their costs are normally distributed. The dependent variable is the winning bid. The mean expected variance is multiplying the total quantity commissioned. All variables were demeaned by suppliers-goods' average to account for fixed effects. Winning bids and quantity unit is per kilo (2.2 pounds). Distance is from the agency to the second-lowest bidder location to represent the button auction equilibrium and it is showed in meters (3.28 feet). Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table 10: Estimated Risk Aversion: All Suppliers Except Winners

		Coefficient	Standard error
Risk aversion		0.0076***	0.0014
Banana	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.6781***	0.0588
	Quantity	-6.03e-06***	8.81e-07
	# of bidders	-0.0241***	0.0046
Lime	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.4213***	0.0274
	Quantity	-0.00006***	9.99e-06
	# of bidders	-0.1115***	0.0119
Orange	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.2552***	0.0755
	Quantity	-3.80e-06***	8.77e-07
	# of bidders	-0.0745***	0.01278
Tomato (ripe)	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.5466***	0.0301
	Quantity	-0.00004***	7.10e-06
	# of bidders	-0.0409***	0.0075
Tomato (green)	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.3705***	0.0162
	Quantity	-0.00003***	3.29e-06
	# of bidders	-0.0309***	0.0069
Distance		3.33e-08	2.88e-08
N		11,457	
Adj R^2		0.1245	

Note: This table presents the estimate on coefficient of absolute risk aversion when suppliers have CARA utility and their costs are normally distributed. The dependent variable is the bid from the bidder ranked one position above. This results follow the button auction equilibrium and includes all bidders except the winner, for which it is not possible to recover the cost. The mean expected variance is multiplying the total quantity commissioned. All variables were demeaned by suppliers-goods' average to account for fixed effects. Bids and quantity unit is per kilo (2.2 pounds). Distance is showed in meters (3.28 feet). Significance levels 5%, and 1% are denoted by **, and ***, respectively.

Table 11: ESTIMATED RISK AVERSION: ALL SUPPLIERS

		Coefficient	Standard error
Risk aversion		0.0124***	0.0026
Banana	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.6542***	0.0941
	Quantity	-8.40e-06***	1.37e-06
	# of bidders	-0.0643***	0.0075
Lime	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.3298***	0.0324
	Quantity	-0.00007***	0.00001
	# of bidders	-0.1726***	0.0196
Orange	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.3550***	0.1099
	Quantity	-6.16e-06***	1.47e-07
	# of bidders	-0.0759***	0.0121
Tomato (ripe)	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.4974***	0.0383
	Quantity	-0.00007***	0.00001
	# of bidders	-0.0745***	0.0137
Tomato (green)	$\mathbb{E}_t\left[Z_{jt'} \middle\vert \mathcal{I}_t\right]$	0.3787***	0.0222
	Quantity	-0.00004***	5.43e-06
	# of bidders	-0.0626***	0.0104
Distance		-9.25e-08*	4.11e-08
N		6,553	
Adj R^2		0.1415	

Note: This table presents the estimate on coefficient of absolute risk aversion when suppliers have CARA utility and their costs are normally distributed. The dependent variable is the bid from the bidder ranked one position above. This results follow the button auction equilibrium and includes all bidders except the winner, for which it is not possible to recover the cost. The mean expected variance is multiplying the total quantity commissioned. All variables were demeaned by suppliers-goods' average to account for fixed effects. Bids and quantity unit is per kilo (2.2 pounds). Distance is showed in meters (3.28 feet). Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

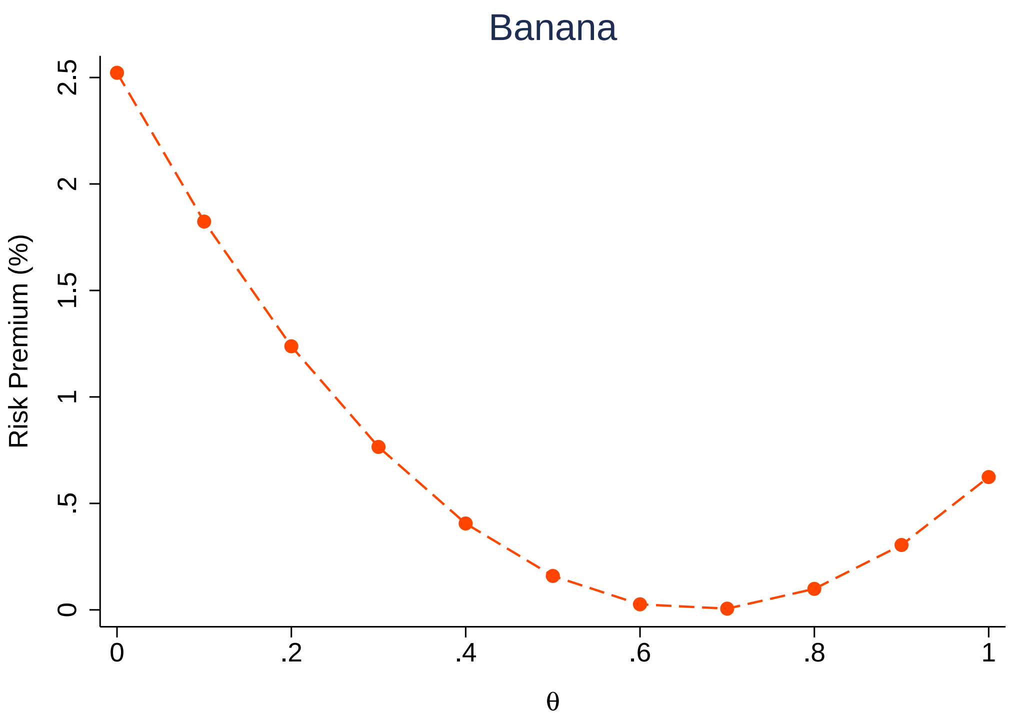

Figure 9: Risk Premium for Different Fractions of Risk Sharing: Banana. This figure plots the average risk premium associated with different contracts in which the government offers to pay a percentage θ of the wholesale market price. The risk premium is the percentage of the winning bid attributed to the mean expected variance. The risk premium associated with $\theta = 0$ is the same as in the current contract format. For θ close to the estimated coefficient on the mean expected price (0.66), the risk premium is at its minimum.

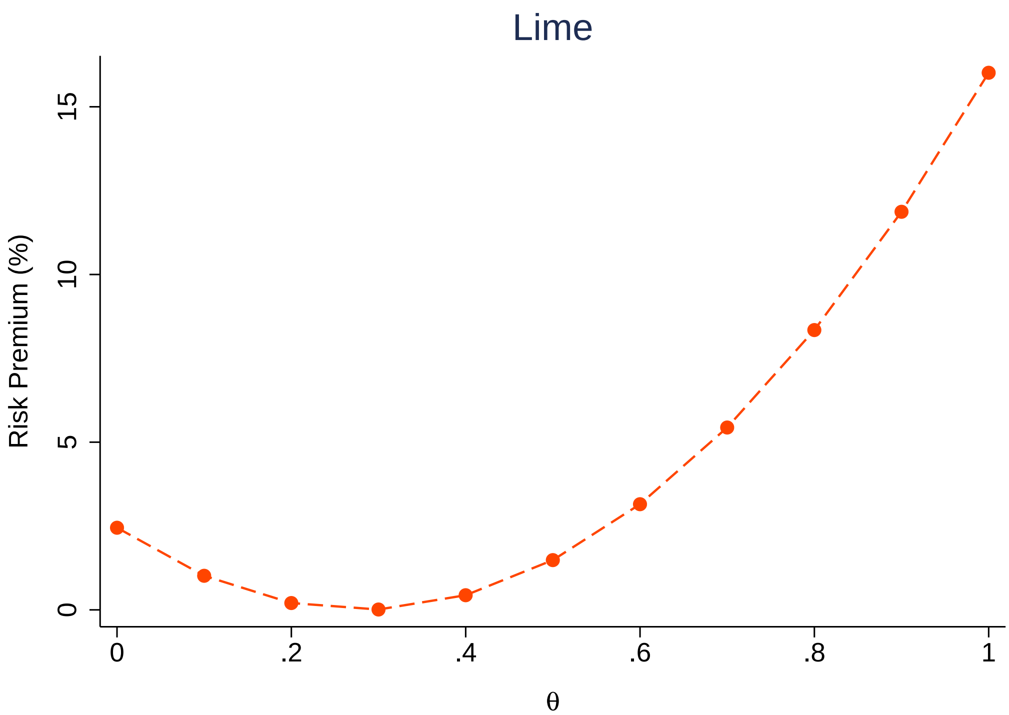

Figure 10: Risk Premium for Different Fractions of Risk Sharing: Lime. This figure plots the average risk premium associated with different contracts in which the government offers to pay a percentage θ of the wholesale market price. The risk premium is the percentage of the winning bid attributed to the mean expected variance. The risk premium associated with $\theta = 0$ is the same as in the current contract format. For θ close to the estimated coefficient on the mean expected price (0.30), the risk premium is at its minimum.

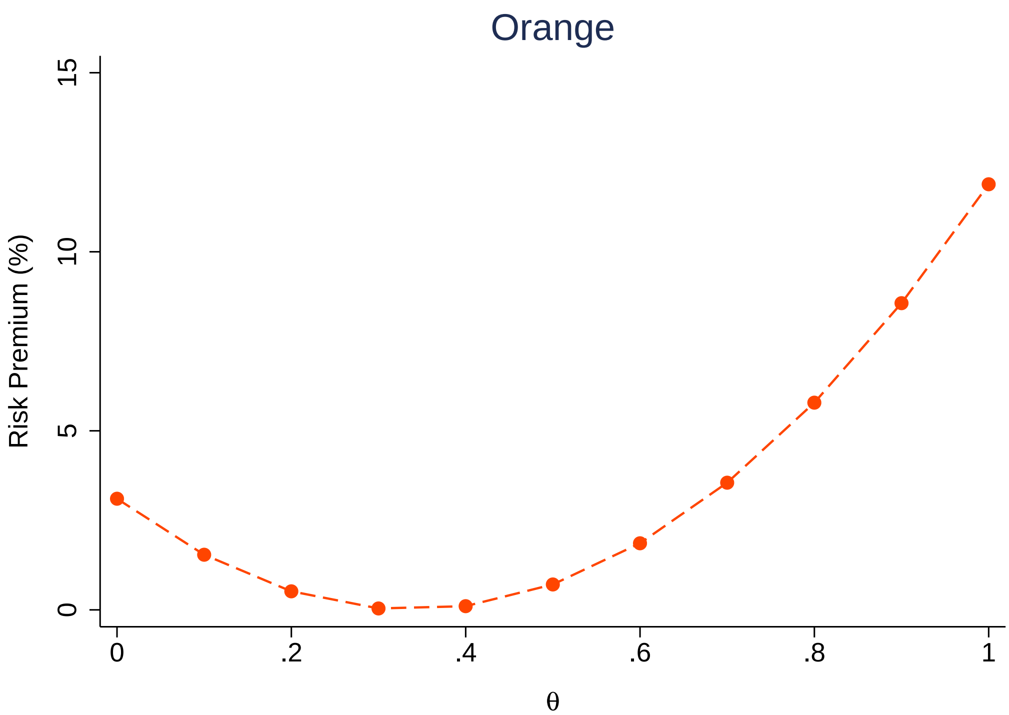

Figure 11: Risk Premium for Different Fractions of Risk Sharing: Orange. This figure plots the average risk premium associated with different contracts in which the government offers to pay a percentage θ of the wholesale market price. The risk premium is the percentage of the winning bid attributed to the mean expected variance. The risk premium associated with $\theta = 0$ is the same as in the current contract format. For θ close to the estimated coefficient on the mean expected price (0.33), the risk premium is at its minimum.

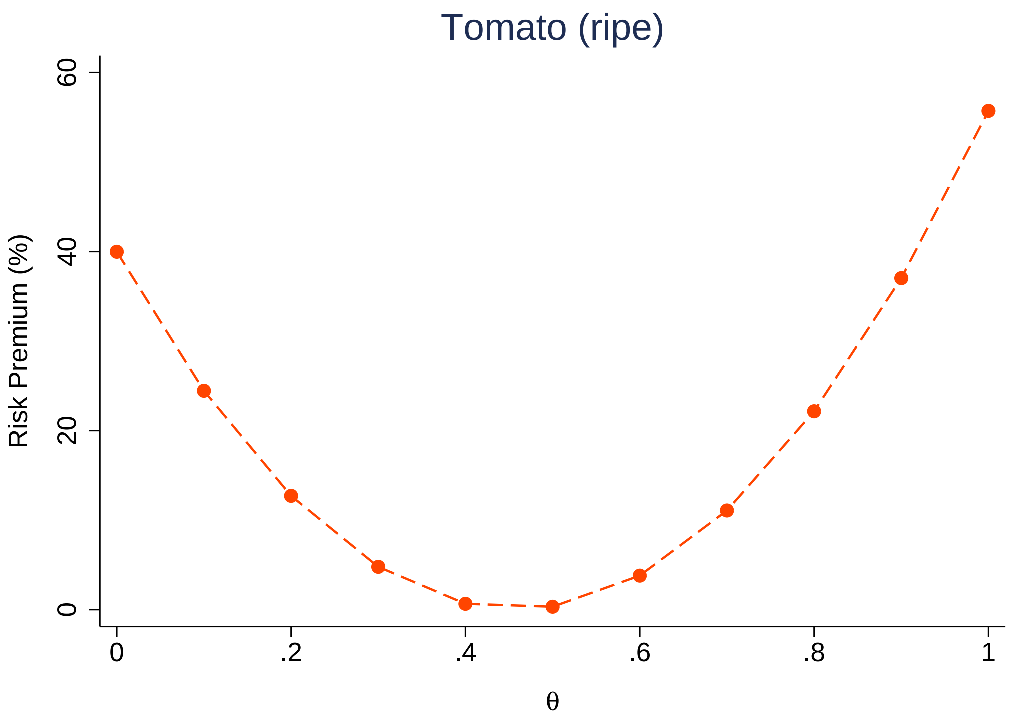

Figure 12: Risk Premium for Different Fractions of Risk Sharing: Tomato (ripe). This figure plots the average risk premium associated with different contracts in which the government offers to pay a percentage θ of the wholesale market price. The risk premium is the percentage of the winning bid attributed to the mean expected variance. The risk premium associated with $\theta = 0$ is the same as in the current contract format. For θ close to the estimated coefficient on the mean expected price (0.46), the risk premium is at its minimum.

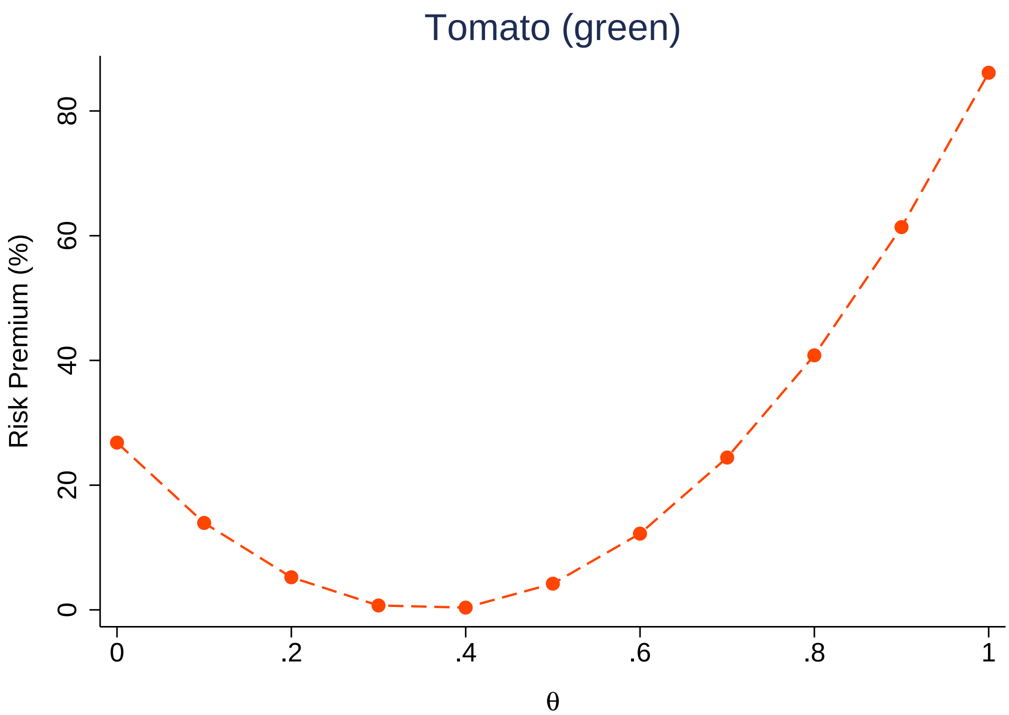

Figure 13: Risk Premium for Different Fractions of Risk Sharing: Tomato (green). This figure plots the average risk premium associated with different contracts in which the government offers to pay a percentage θ of the wholesale market price. The risk premium is the percentage of the winning bid attributed to the mean expected variance. The risk premium associated with $\theta = 0$ is the same as in the current contract format. For θ close to the estimated coefficient on the mean expected price (0.36), the risk premium is at its minimum.

Appendix

Derivation of CARA expected utility with Gaussian distribution

Let X be normally distributed with mean μ and variance σ^2. We want to know the expected value of e^{mX} where m is a constant.

$$\begin{aligned}
\mathbb{E}\left[e^{mX}\right] &= \int\limits_{-\infty}^{+\infty} e^{mx}\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x-\mu)^2}{2\sigma^2}}dx \\
&= \int\limits_{-\infty}^{+\infty} e^{mx}\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{\left(x^2-2x\mu+\mu^2\right)}{2\sigma^2}}dx \\
&= \int\limits_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{\left(x^2-\left(2\mu+2\sigma^2m\right)x+\mu^2\right)}{2\sigma^2}}dx
\end{aligned}$$

Adding and subtracting $\int_{-\infty}^{+\infty}\frac{1}{\sqrt{2\pi\sigma^2}}e^{\frac{2\sigma^2\mu m+\sigma^4m^2}{2\sigma^2}}dx$ to the above expression, we get:

$$\begin{aligned}
\mathbb{E}\left[e^{mX}\right] &= e^{\frac{2\sigma^2\mu m+\sigma^4m^2}{2\sigma^2}}\int\limits_{-\infty}^{+\infty}\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{\left(x-\left(\mu+\sigma^2m\right)\right)^2}{2\sigma^2}}dx \\
&= e^{\mu m+\frac{\sigma^2}{2}m^2}
\end{aligned}$$