Auction Performance and Bidding Behavior with a Strategic Auctioneer: Evidence from the Philippines

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Abstract

I examine the Treasury bond auction system in the Philippines by using actual bid data of at least 500 Treasury auctions from January 2010 to October 2017. The Philippines features a strategic auctioneer who uses both discriminatory and uniform price auctions. The auctioneer, or the government, adopts an active quantity management policy through frequent use of supply restrictions and full rejections. In this environment, the discriminatory price format generates superior outcomes in terms of lower borrowing costs but at the expense of concentrating awards amongst a few bidders. Empirical results also indicate: (i) the government's decision to restrict auction supply is driven by cost and strength of demand, (ii) bidders adjust for winner's curse, arising from heightened volatility and more competitors, by submitting bids with higher yield spreads, and (iii) bidder heterogeneity exists but average auction profits do not significantly differ across bidder "types".

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1 Introduction

Auctions are cost-effective, transparent and market-based alternatives to traditional underwriting and lending schemes which have dominated sovereign financing for many decades. For this reason, auctions have become the primary means of issuing debt for many emerging market economies Brenner et al. (2009). Despite its importance, there has been a dearth of academic work which systematically studies the performance of auction systems in developing countries. Data quality, and more importantly, researchers' lack of data access are the main reasons for this. Civil servants in emerging market economies are very reluctant to share bidder specific data, even in an anonymous format, to any third party group.

This state of affairs is unfortunate as both parties can benefit from sharing data and research results. Data would allow scholars to evaluate existing auction theory and potentially open up new avenues of research as many questions in the field cannot be conclusively answered by theory alone. Governments can also benefit from exposure to insights of auction theory. For instance, it is my view that the potential effects of winner's curse adjustments are not fully appreciated by policy makers. It is uncritically accepted that a higher number of auction participants will increase competitive pressures which will lead to lower borrowing costs. The last chain of reasoning is not necessarily true if winner's curse plays a significant role in bidder behavior. The results of this study indicate that higher auction participation might actually increase auction yield spreads.

This paper is an attempt to address the situation – I examine a dataset of more than 500 Philippine Treasury auctions from January 2010 to October 2017 through the lens of auction theory. I aim to study the following facets of Philippine Treasury auctions: (i) performance, (ii) auctioneer decision-making, and (iii) bidder behavior. Auction performance here refers to two things: auction yields relative to secondary market levels, and degree of award concentration. Efficiency is difficult to evaluate without a good methodology to extract bidders' value functions from bid submissions so this is not included in the analysis. Some of the most commonly used structural econometric methods rely upon the assumption that auction supply is fixed and can be taken as given by bidders. However, this is an assumption that cannot be plausibly made because the Philippine government is extremely active in its choice to restrict auction quantities.

Other countries, such as Mexico and Switzerland, also have the right to reduce the supply of bonds being issued but these countries do not exercise it as aggressively as the Philippines does. The government can even choose to reject all bids if it deems that the bids being submitted have unnacceptably high yields – what is "too high" is solely determined by the judgment of top Treasury officials. In addition to high yields, Treasury officials also say that quantity restrictions depend on the level of cash balances. However, I find that cash balances only matter for complete rejections, partial quantity restrictions are primarily driven by both cost considerations and the strength of auction demand.

McAdams (2007) has shown that having an auctioneer who can increase or decrease supply can reduce or even eliminate all collusive-seeming equilibria in uniform price auctions. If the auctioneer only has the right to reduce but not increase supply, as in the Philippine case, then some collusive-seeming equilibria will remain because bidders still have an incentive to submit demand curves that are as inelastic as possible (McAdams, 2007). In practice, such collusive outcomes do not materialize in the Philippine case because in addition to the aggressive use of supply restrictions, there are 34 potential auction participants that coordination, spontaneous or otherwise, is unlikely to occur.

For Treasury bond auctions, there is an unsettled debate on whether independent private values or common values are the best framework to analyze empirical data (Marszalec, 2017). The main argument for independent private values is that bidders are usually banks who participate primarily to satisfy client orders or regulatory requirements. Philippine government security dealers have also indicated that another motivation to participate in Treasury bills auctions is if they have excess liquidity that needs to be deployed. Hortaçsu and McAdams (2010) developed an econometric method to extract bidder values from bid submissions under the assumption of independent private values to perform a counterfactual comparison of discriminatory and uniform price auctions. They find that uniform price auctions do not significantly produce higher revenues than the discriminatory price format. My study finds a switch to uniform price format increases yield spreads by around 31 basis points.

On the other hand, the existence of a secondary trading market indicates that these debt instruments do have a common value shared by all bidders. To the extent that participation is motivated by amassing trading inventory or taking active "prop" positions then a common value framework might be more applicable. In this paper, I will adopt the empirical specifications of Bjønnes (2001) for Norway, Nyborg, et al. (2002) for Sweden, and Elsinger and Zulehner (2007) for Austria. These authors assume a common value framework and find that bidders adjust for winner's curse by increased bid shading, dispersion and reduced demand. In the Philippines, the average bidder adjusts for winner's curse by more aggressive bid shading.[1]

I study performance and bidder behavior separately because the average behavior of an individual bidder cannot be generalized to auction results in a straightforward manner. Wilson (1977), Reece (1978) and Milgrom (1979) show the winning bid increases in probability towards the good's "true" value as the number of participants increase, even though each individual bid declines (Bartolini and Cotarelli, 1994). The situation is more

[1] Bid shading refers to the practice of bidders submitting bids below what they think is the auctioned good's true value.

complicated in the Philippine setting as auction allocations are frequently dominated by as few as four bidders; the actions of a few bidders can be vastly more influential than that of the "average" participant.

The identities of individual bidders can be tracked so I also analyze whether the existence of bidder heterogeneity is important. Auction theory usually assumes symmetry amongst bidders but as Bikchandani and Huang (1993) point out – bidders, particularly large ones, might have a significant edge in terms of information pertaining to customer order flows. In this paper, I try to see if different bidder types differ systematically in their bidding behavior in terms of aggressiveness and their response to the prevailing economic and market environment. The general result of the analysis is while larger bidders exhibit lower degree of bid shading, higher bid dispersion and higher participation rates, average profits are roughly similar across bidder types.

2 Description of the Philippine Treasury Bond Auctions

Since 1995, Philippine treasury bonds and bills have been issued by the Department of Finance through its attached agency: the Bureau of the Treasury (BTr). Both discriminatory (DP) and uniform price (UPA) formats are used – all new treasury bond issuances are auctioned using UPA while all treasury bill auctions and bond re-issuance are sold through the DP format.[2] Ostensibly, the government found UPA to be more convenient in terms of setting the coupon rates of new bond issuances. While it is possible to set coupon rates using the weighted average of the winning bids in DP auctions, the "one yield for all" rule in UPA provides a simpler and more straightforward reference rate. Since UPA is used to set coupon rates, all UPA "revenues", defined as the cash proceeds from an auction, are the same for all auctions – the face value of the newly issued bonds. This is why I instead look at yield spreads to study performance.

Participation in the auctions is voluntary and limited to authorized primary dealers so other investors have to course their orders through these dealers. While the number can change, for the period I am studying (January 2010 to October 2017), there are 34 authorized primary dealers; no dealer participated in all the auctions in my dataset. To participate, each bidder must submit yield-quantity pairs through the electronic auction platform. For DP, a maximum of 7 competitive bids and 1 non-competitive bid is allowed while there is no such limit specified for UPA. There is no ceiling in the bid amount each

[2] Uniform price auctions are auctions where every winning bidder pays the same yield – the highest yield which equates demand with supply. Discriminatory price auctions, on the other hand requires winning bidders to pay what they bid for.

bidder can submit while the minimum amount is negligible (PHP10 Million or roughly USD200,000).

A very important feature of Philippine treasury auctions is the unusually large role that non-competitive bids can play in DP auctions – a maximum of 40% of announced auction supply can be allocated to non-competitive bids. Non-competitive bids only specify quantities with the price to be paid or the yield to be received equal to the weighted average of the winning bids. If the total non-competitive bid amount is more than the prescribed 40% maximum then allocation will be on a pro-rated basis. The existence of this provision alleviates the potential of winner's curse, but it also makes it easier for aggressive bidders to set the winning price. This is most evident in auctions with only one winning competitive bid – the remaining amount is allocated to non-competitive bids.

Table 1 shows the average demand composition in bonds and bills auctions. Bills auctions have signficantly more non-competitive bid submissions (as share of total bid amount). According to dealers this is partly because bills are more suitable outlets for excess cash holdings than bonds. Assuming not all competitive bids are rejected, submitting a non-competitive bid guarantees an allocation.

Table 1: Demand Composition in DP Auctions

	Bills	*Bonds*	*Total*
Non-Comp.	0.61 (0.60)	0.10 (0.13)	0.52 (0.58)
Comp.	1.87 (1.08)	1.97 (0.85)	1.89 (1.04)
Total	2.48 (1.56)	2.07 (0.92)	2.41 (1.48)

The table lists the average values with the standard deviation enclosed in parenthesis.

Philippine law prescribes a maximum of 25 years maturity for any commercial bond issuance. There is no minimum maturity length but the shortest instrument being issued is the 91-day Treasury bills. In addition to the 91-day bills, the BTr also issues 182 and 364-day bills; the auctions for these bills are held simultaneously but on different days than the bond auctions.

There is no fixed issuance frequency for either bonds or bills. While the BTr announces a tentative auction calendar at the start of every quarter, it is frequently revised. Moreover even if the announced schedule was strictly followed, the aggressive use of quantity restrictions means that the future supply of securities in the market can be very uncertain. How these things can potentially affect bidder strategies is beyond the scope of this study.

3 Data

3.1 Auction Data

The BTr provided a dataset consisting of all the regular Treasury bill and bond auctions from January 2010 to 17 October 2017. Every participant in the auction can be identified and there is information on all the competitive and non-competitive bids they have submitted, as well how much each of their bids have been given allocation. There are 550 total auctions, of which 417 were for Treasury bills and 133 were for Treasury bonds. 90 bond auctions were DP while 43 were UPA. One bill auction had to be dropped because of various issues with data quality.

There were problems with the electronic data set for the 43 UPAs which I address using hard copies of the bid arrays.[3] Unfortunately, complete information were missing for UPAs held prior to 2013 so while I use 540 auctions for aggregate performance analysis, the data limitation only allows me to use 518 auctions for bidder-specific analysis.

Table 2: Auction Summary Statistics

	Bills	*Bonds*			*All*
		DP	UPA	Both	
Bid-Cover Ratio	2.48 (1.56)	2.08 (0.92)	2.89 (1.02)	2.30 (1.02)	2.44 (1.46)
Under-subscribed Auctions	40	9	2	11	51
Bidders	18.69 (3.37)	25.61 (3.02)	26.41 (3.10)	25.83 (3.05)	20.33 (4.46)
Winners	7.48 (4.26)	14.11 (7.44)	15.76 (5.25)	14.56 (6.93)	9.11 (5.82)
Total Auctions	416	90	34	124	540

3.2 Secondary Market Price Data

The Philippine market convention is to quote security prices in yield terms and in this paper I use the PDST-R2 rates provided by the Philippine Dealing and Exchange Corpo-

[3]The recording system of the BTr replaced the specific yields submitted by bidders with the actual award yields.

ration (PDEx). These rates are the end-day reference rates calculated from the weighted average yields of done trades. In situations where the volume of done trades are insufficient then bid rates posted by the banks would be used.[4] I use reference rates because actual prices or yields of specific securities are not available for the entire period of study. They are also important because the central bank requires these rates to be used for mark-to-market valuation of banks' government bond holdings.

Table 3 provides a snapshot of these PDST-R2 rates. For most re-issuances, the actual residual maturity is different from the specified maturity buckets so I round it to the nearest whole number. In cases where the rounded tenor of the auction security falls outside the listed maturities I interpolate the reference rates.[5]

Table 3: PDST-R2 rates (in pct.)

Tenor	04/30/2018	04/27/2018	04/26/2018	04/25/2018
1M	3.7547	3.7233	3.7500	3.7946
3M	3.4778	3.4941	3.4944	3.5302
6M	3.8326	3.8285	3.8575	3.8003
1Y	4.3661	3.8565	3.8926	3.8558
2Y	4.2550	4.2750	4.2994	4.2855
3Y	4.5656	4.5735	4.5960	5.1633
4Y	5.2720	5.4950	5.1300	5.5950
5Y	5.3987	5.3543	5.4228	5.4415
7Y	5.8000	5.8061	5.9000	5.9000
10Y	6.2033	6.2052	6.2932	6.6339
20Y	7.2179	7.2196	7.2964	7.2743
25Y	–	–	–	–

3.3 Macroeconomic/Other Data

In addition to the auction data, the BTr has also provided daily cash flow statements for 2010 – 2017. I use both the daily cash balances and the net cash flow requirements for the next three working days. Other macroeconomic and financial market data I include such as the US Dollar/Philippine Peso exchange rate, CBOE Volatility Index (VIX), 10-year US Treasury yields and the Philippine inflation rates are from Bloomberg and Reuters.

[4] If there are no bid rates then the rate will be interpolated from the yields of other benchmark securities.

[5] For more details, please refer to the official PDEx calculation guidelines found in their website: http://www.pds.com.ph.

4 Survey of Theory and Empirical Results

4.1 Revenue Performance

Unlike single-unit auctions, auction theory does not provide a general result on the revenue superiority of auction formats for multi-unit auctions. Even if the comparison is limited to the two-most commonly used formats, DP and UPA, Ausubel et al. (2014) show the best answer theory could provide is: it depends on the specific form of bidders' demand functions. Theoretical results are also sensitive to assumptions about the nature of the auction supply. Both McAdams (2007) and Back and Zender (2001) show many collusive-seeming and low revenue equilibria in UPAs are eliminated if the auctioneer can reduce quantities after seeing submitted bids. Pycia and Woodward (2017) prove revenue equivalence between the formats can hold under two assumptions: the auctioneer knows the bidders' values, and it can optimally set supply and reserve prices.

This difference between single and multi-unit auctions has to be emphasized – no less an economist as prominent as Milton Friedman (1991) argues for the revenue superiority of UPA over DP by treating the former as the multi-unit equivalent of the single-unit second-price auction and the latter as the first-price auction equivalent. Similar to second price auctions, he argues there is no incentive for auction participants to shade their bids in UPAs and this strategic honesty would increase treasury auction revenues. Binmore and Swierzbinski (2000) point out this argument is incorrect – UPAs do not eliminate bid shading incentives and truth-telling equilibria can only happen in pathological cases.

Empirical results are mixed depending on the method of comparison used. Studies using natural experiments, wherein countries switched from one format to another tend to conclude UPA produces higher revenues than DP. This is the case for Mexico (Umlauf, 1993) and the United States (Malvey and Archibald, 1997). If we consider non-Treasury bond auctions then Feldman and Reinhart (1996) and Tenorio (1993) find similar results for the International Monetary Fund's 1976-80 gold auctions and Zambia's 1985-87 foreign exchange auctions respectively.

On the other hand, counterfactual analyses using structural econometric methods tend to find evidence for DP's revenue superiority. Février et al. (2004) for French T-bills, Hortaçsu and McAdams (2010) for Turkish T-bills and Marszalec (2017) for Polish treasury auctions all conclude switching to UPA would at best generate similar revenues and at worst reduce revenues compared to DP.

4.2 Award Concentration

Similar to revenue performance, there are no unambiguous theoretical results for which format is expected to produce higher concentration outcomes (Bartolini and Cotarelli, 1997). Friedman (1991) argues the simplicity of UPAs could reduce costs of bid preparation, and encourage smaller players to be more aggressive by reducing the information advantage of big bidders. UPAs also reduce incentives to funnel bids through brokers, thus narrowing the scope for a small ring of brokers to collude and corner markets (Bartolini and Cotarelli, 1997).

The issue of concentration and non-competitive behavior prompted the US Treasury's experiment with UPAs (Bartolini and Cotarelli, 1997). Malvey and Archibald (1997) find in addition to generating higher revenues, the switch to UPAs also reduced the concentration of awards to the top primary dealers.

Brenner et al. (2009) surveys 48 countries about their choice of auction format. They find market-oriented economies and those practicing common law tend to use UPA while economies who are less market oriented and adopt civil law are likely to use DP. They also find low financial market development is a determinant for choosing DP. They conjecture these countries have financial sectors dominated by a few big banks who prefer DP because this format allows them to better leverage their information advantage to generate higher profits (Brenner et al., 2009).

4.3 Winner's Curse

In common-value auctions, the winner's curse is the idea that the winning bidder has paid more than the "true" value of the good being sold. It arises from the difference between the conditional and unconditional expectations of winning – the winning bidder must reduce his estimation of the true value relative to his unconditional expectation (Nyborg et al., 2002). Winning conveys information that the bidder's estimate was the highest, and in the absence of superior information then it is very likely he has over-estimated the true value of the auctioned good – in short, winning is bad news (Ausubel, 2004).

Ausubel (2004) points out the problem of winner's curse might be magnified in multi-unit auctions and terms it "champion's plague" – if winning one good is bad news then winning two is even worse news. More formally, "champion's plague" describes a situation where the bidder's expected value conditional on winning more objects is less than her expected value conditional on winning fewer objects (Ausubel, 2004). The existence of the champion's plague implies rational bidders will submit downward-sloping demand curves even under constant marginal values (Nyborg et al., 2002).

The rational bidder will submit bids which account for the winner's curse/champion's plague. Using data on Swedish T-bills auctions, Nyborg et al. (2002) studies bidders' winner's curse adjustments by looking at three facets of a bidder's strategy: (i) bid shading, (ii) price dispersion, and (iii) quantity demanded. The main source of winner's curse potential in the study is the daily volatility of bond returns – assuming markets are relatively efficient then higher volatility means each bidder signal is less reliable. They find in response to higher potential of winner's curse, bidders react by increased bid shading, higher dispersion, and lower quantity demanded.

Bjønnes (2001), using Norwegian T-Bills auctions data, extends Nyborg et al.'s (2002) empirical framework by also including the number of auction participants as a source for winner's curse. More participants will bias upwards the highest signals and this has to be adjusted for (Bjønnes, 2001). He finds evidence for winner's curse adjustments for both volatility and the number of competing participants – bidders shade more, disperse more, and demand less in response to both higher volatility and more competitors (Bjønnes, 2001). Elsinger and Zulehner (2007) also find similar results for Austrian T-bond auctions.

The three empirical studies mentioned above focus on countries which uses the DP format, Keloharju et al. (2005) on the other hand examine the Finnish T-bonds auctions which are carried out under the UPA format. They find bidders increase bid shading, reduce quantity demanded in response to higher volatility – all of which point to the importance of winner's curse adjustments as a driving force of bidder behavior (Keloharju et al., 2005).

4.4 Bidder Heterogeneity

Bjønnes (2001) examines the behavior of different bidder types – he classifies bidders into three types depending on the number of auctions they participated in and the size of their purchases. His results indicate the biggest bidders tend to make larger adjustments due to winner's curse, which is surprising because these bidder types should possess superior information (Bjønnes, 2001). One potential explanation he offers is, unlike smaller competitors, these bidders must be prepared for the possibility of winning every auctioned T-bills due to their size – the negative information implied in winning is worse when you are the only winner rather than one of many winners (Bjønnes, 2001).

The likeliest source of heterogeneity is access to superior information, specifically customer order flow, which allows bidders to get a more accurate estimate of the true value. Hortaçsu and Kastl (2012) uses detailed data from Canadian Treasury auctions, where dealers observe customer bids while preparing their own bids. These customer bids potentially contain information about the distribution of competing bids and the post-auction value of the security. They find no evidence bidders are learning about fundamentals or the true value but they estimate the "information about competition" contained in customer bids accounts for 13–27% of bidders' expected profits (Hortaçsu and Kastl, 2012).

5 Empirical Framework

In this section, I discuss the estimation framework and the variables I use for the analysis.

5.1 Auction Performance

Revenues

In this paper, I use the spread between the full or maximum-award (FoM) auction yields and the secondary market rates as the measure for auction revenues.[6] Using the traditional measure of revenues, price per cent of face value, all UPAs will generate total revenues equal to the face value of the bonds sold because the auction format is used to set coupon rates as well. This measure is also problematic for DPs because of the massive yield compression that happened during the period under study; yields, across the term structure, were halved from 2010 to 2017.

To see this clearly, let us consider the case of two very similar bonds. They have the same residual maturity, and same cashflow structure, but they have different coupon rates because they were issued in different economic/market environments. If the two bonds were auctioned then the bond with the higher coupon or premium will always generate superior revenues under the traditional measure simply because of how prices are computed from yields. The problem is still present even for zero-coupon bills. Securities which were issued in 2010 will always have steeper discounts, and therefore, lower revenues than those issued in latter periods because of the higher interest rate environment.

I use yield spreads rather than yield levels in order to adjust for the term premia – securities with longer maturities have higher yields under normal market conditions. Furthermore, yields, as with many financial time series, are non-stationary so inferences on yield behavior are problematic unless the variables are properly transformed. Yield spreads are also easier to interpret than price differentials; what the auctioneer or the government truly cares about is the borrowing costs implied by the auction results and these are directly measured by yields rather than prices.

There is also an issue on which secondary market rate ought to be used as the reference point. BTr officials, indicate they always compare the auction results on past levels of the secondary market yields. Specifically they look at the previous week's trend and check if the auction yields are "reasonable" given the trend. Another potential reference point is the end of auction day yield levels because many papers use the difference between end-day secondary market prices and auction prices as the relevant measure of bidder profits. Auctioneer revenues can also be interpreted as the negative of bidder profits. In

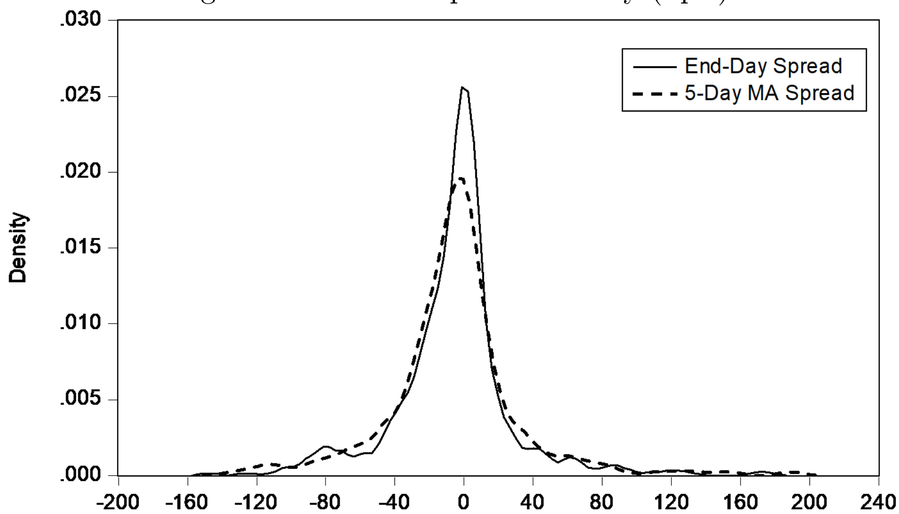
[6]For DPs, FoM yield is a quantity-weighted average while it is a single yield number for UPAs.

this study, I will be using both reference points: (i) previous 5-day moving average, and (ii) end of auction day yields.

Lastly, I do not use the actual auction yield spreads because of endogeneity issues – the BTr aggressively restricts quantity in response to the submitted bids and other potential explanatory variables. The FoM yields are the yields which will fully allocate all the offered supply or satisfy all the submitted bids if the auction is undersubscribed. The FoM spread cannot be changed by the BTr's decisions and addresses many concerns about endogeneity.

Figure 1 plots a kernel density for both measures of revenues, both are expressed in terms of basis points (bps) or 1% of a percentage point (0.01%). While the end-day spread has a higher mean, both measures still have negative mean values. On average the auctions generate lower yields compared to secondary market levels. However, just looking at the average might be misleading considering the high kurtosis in the data.

Figure 1: Revenue Spread Density (bps.)



Award Concentration

The measure of award concentration I use in this study is the share of total allocation received by the top four bidders. The analysis focuses on the auctions in which announced supply was fully allocated because the allocation rules for ties specify randomization. Because of this randomization, it is difficult to construct the counterfactual full award distributions for auctions with partial awards and full rejections. Table 4 provides summary statistics on the degree of award concentration across auction formats and instrument types. Awards are extremely concentrated among a few bidders – the top four bidders are expected to get around 84% of the supply with the lion's share going to just one bidder.

Table 4: Award Concentration (in pct.)

	Top 4				Top 1
	UPA	*DP*		*All*	*All*
		Bonds	*Bills*		
Mean	72.70	74.58	88.06	84.57	50.11
Standard Deviation	14.96	15.41	11.14	13.68	21.65
Maximum	100.00	100.00	100.00	100.00	100.00
Minimum	45.57	44.44	46.98	44.44	11.63
Obs.	32	59	278	369	369

Independent Variables

I use the same set of independent variables for both revenues and concentration. The covariates can be classified into three: (i) auction characteristics, (ii) government fiscal situation, and (iii) market environment. For auction characteristics, I will be looking at (i) non-competitive demand, (ii) competitive demand, (iii) instrument type (bills or bonds), (iv) auction format, (v) security's residual maturity, (vi) auction participants, (vii) auction size, and (viii) non-competitive shortfall.

Both competitive and non-competitive demand are measured as multiples of auction size – total bids divided by auction size. Instrument type and auction format are dummy variables which both take the value of 1 if the auction was selling T-bonds using the UPA format. Residual maturity is the remaining years left before the security has to be redeemed. The auction participants is the number of bidders in an auction who have submitted at least one competitive or non-competitive bid. Auction size is the total face value of the bonds being sold – note that this is the announced value and not the amount of actual awards. The last variable, non-competitive shortfall is calculated as: $max(0, \frac{40\% - Non\ Competitive\ Demand}{40\%})$ and it measures by how much non-competitive bid submissions fall short of the maximum amount that could be accepted (40% of auction size).

Table 5: Non-Competitive Shortfall

	Bills	*Bonds*	*All*
Mean	27.37	55.04	33.72
Standard Deviation	36.10	41.43	39.13
Auctions w/Shortfall	186	87	273
Total Auctions	416	124	540

Figure 2: Auction Size Histogram (PHP Bil.)

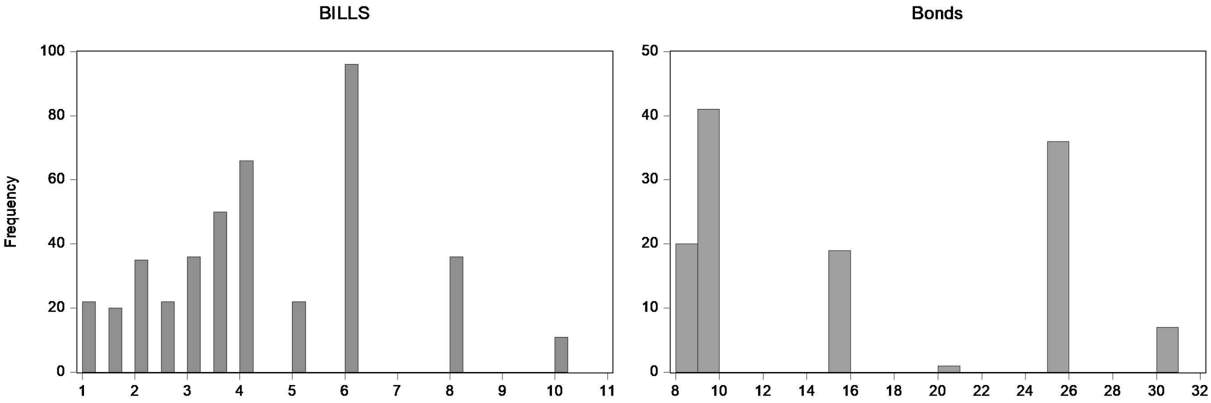
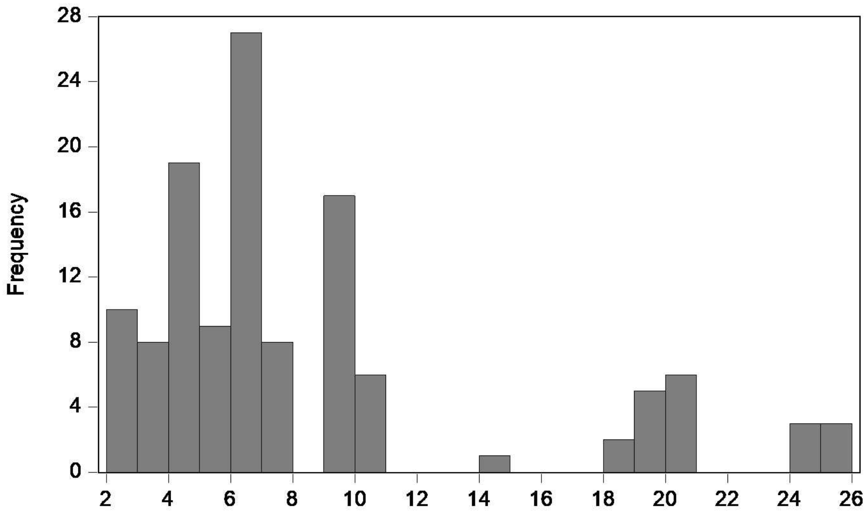


Figure 3: Residual Maturity of Auctioned Bonds (Years)



The rest of the covariates only serve as controls. For measures of the government's fiscal situation, I use both the cash balances (measured in PHP billions) as of the auction date and the 3-day rolling net-cash flow requirements. The reason for using the 3-day window is auctions are mostly used for cash management purposes (for bills) or to repay maturing obligations (for bonds). I include the cash balance variable because auction participants could attempt to secure higher yields from the government in times of cash shortfalls.

For financial market variables, I use: (i) expected inflation, (ii) 10 Year US Treasury rates, (iii) foreign exchange momentum, and (iv) volatility of bond yields. Expected inflation is proxied by the actual year-on-year inflation rate for the succeeding month after the auction day (if auction was held on February, then I use the March inflation rate). The 10 year US Treasury yields are self-explanatory and I include it to control any effects that the levels of global risk free interest rates might exert on the yields demanded by bidders. Foreign exchange momentum is calculated as the difference between the weighted daily average of USDPHP exchange rate on auction day minus 5-day moving average of the currency pair. Positive values means there is either an existing or beginning short-term PHP depreciation trend while negative values indicate currency appreciation trend. Foreign exchange is potentially an important factor because many investors submit orders for bills and bonds to facilitate currency speculation. Lastly, to control for the level of uncertainty in the bond markets I estimate the one-day ahead conditional standard deviation of 10-year bond yields, for bond auctions, and 6-month T-bill yields, for bill auctions using an AR(1) - GARCH(1,1) model. More details on the exact model specification are found on Appendix A.

Estimation

I estimate the following equation using ordinary least-squares:

$$\begin{aligned} PERFORMANCE_i = \alpha_0 + \beta_1 NCD_i + \beta_2 CD_i + \beta_3 UPA_i + \beta_4 BONDS_i + \beta_5 MAT_i \\ + \beta_6 BIDDERS_i + \beta_7 SIZE_i + \beta_8 SHORTFALL_i + \delta_1 Z_i + \tau_i + \varepsilon_i \end{aligned}$$

where:
$PERFORMANCE$ = Revenue or award concentration for auction i
NCD = Non-competitive Demand for auction i,
CD = Competitive Demand for auction i,
UPA = 1 if auction i uses UPA, 0 if DP,
$BONDS$ = 1 if auction i is selling T-Bonds, 0 if T-Bills,
MAT = Residual Maturity,
$BIDDERS$ = Number of bidders in auction i,
$SIZE$ = Announced supply for auction i,
$SHORTFALL$ = Non-competitive shortfall in auction i,
Z = Vector of control variables,
τ = Year when auction i was held,

The coefficient on UPA provides answers regarding which auction format generates better outcomes in terms of borrowing costs and concentration of awards. The sign of the coefficient on BIDDERS tells us whether individual adjustments for winner's curse translate to aggregate auction results.

In Table 3, bill auctions are more concentrated than bond auctions and since bonds are issued using both DP and UPA, I include the BONDS variable to remove any confounding influence of the instrument type on the inference. I incorporate MAT because bidders and their clients value absolute yield levels and would be happy to trade lower spread for higher yields – 10% absolute yield with 2bps spread is preferable to 2% yield with

100bps spread. Upward-sloping yield curves imply yields are increasing in tenor length so MAT will control for these term premia effects on performance. Auction size is intended to capture the effects of potential capacity constraint on performance. Furthermore, risk aversion models of bidding behavior like those of Wang and Zender (2002) imply higher auction sizes lead to less aggressive bidding because the probability of getting allocations is higher for any bid submission.

Aggregate bidder demand is an important factor for performance and I break it down into NCD and CD. A higher CD can have no effect on auction performance if the increase is mostly coming from bids which will not be given allocation. NCD directly affects both performance measures because it effectively reduces available auction supply and guarantees the non-competitive bidder an allocation – but only until the prescribed 40% maximum. This 40% maximum requirement means the DP format under study is different from the standard DP being theoretically studied and applied in other countries. This feature also reduces the winner's curse potential of Philippine DP auctions. The SHORTFALL variable controls for the portion of NCD which directly affects performance measures – it adjusts for the decreased winner's curse potential and it facilitates comparson with UPA which do not allow non-competitive bids.

I also include year fixed effects to control all economic shocks and market trends prevailing every year. Fixed effects at the year level are suitable because almost all the significant trends affecting the auctions I am examining occured over a span of years. The yield compression, its normalization and the corresponding changes in secondary market trading took years to play out. The continuous improvement in the Philippine macroeconomic environment and its credit status were always being cited as important considerations for increased investor participation and interests in the country year-in and year-out. Global shocks, such as the Federal Reserve's announcement to start tapering its Quantitative Easing program, the oil price collapse and Brexit exerted influence on financial markets and auction behavior far longer than the month, quarter or semester when they occured.

5.2 Quantity Restriction

The BTr's decision to reduce auction quantities can take the form of full auction rejection or partial quantity awards. As the name implies, rejection means that all auction bids are rejected and no security has been sold. It is a right that the BTr has exercised with remarkable frequency – out of the 540 auctions being studied, 11% were full rejections. These 60 auctions include over and under-subscribed auctions.

To study partial awards, I only look at the set of auctions which were fully or over-subscribed and for which at least 1 bid has been accepted. I do not include rejected auctions even if they were over-subscribed because the decision-making process for full rejections is different from partial awards. Rejections are significantly more drastic actions in terms of market impact and disruption to cash management operations than partial awards. The number of auctions in this analysis is 460, of which 91, or nearly one-fifth, had partial awards.

Table 6: Quantity Restrictions – Incidence

	All Auctions			***Full Subscription***		
	Award	*Reject*	*Total*	*Full Award*	*Partial Award*	*Total*
Bills	367	49	416	278	75	353
Bonds	113	11	124	91	16	107
All	480	60	540	369	91	460

To undertand the decision-making process of the auctioneer, I estimate the following logit models:

$$
\begin{aligned}
Logit(REJECT_i) = \alpha_0 + \beta_1 SPREAD_i + \beta_2 NCD_i + \beta_3 CD_i + \beta_4 CASH_i + \\
+ \beta_5 SHORTFALL_i + \delta_1 Z_i
\end{aligned}
$$

$$
\begin{aligned}
Logit(PARTIAL_i) = \alpha_0 + \beta_1 SPREAD_i + \beta_2 NCD_i + \beta_3 CD_i + \beta_4 CASH_i \\
+ \beta_5 SHORTFALL_i + \delta_1 Z_i
\end{aligned}
$$

The variables REJECT and PARTIAL take a value of 1 if bids in the auction were fully rejected and partially awarded respectively. I use nearly the same set of covariates as the performance regressions except: (i) I use the 5-day Moving Average Spread as an important explanatory variable, (ii) I am now interested in the coefficient of both CASH variables (cash balance and cash flow) and (iii) I use VIX as a measure for perception of global financial market risk. Since there is no satisfying theory for how an auctioneer should exercise its ability to restrict auction supply, I use what the BTr officials deem to be important considerations – expensiveness relative to past secondary market yields and the level of cash balances.

I retain the vectors of control variables for economic and market environment because prior to every auction, decision makers take stock of the variables I include: (i) inflation (both current and future), (ii) the US interest rate levels (proxied by US Treasury rates), (iii) USDPHP exchange rate trend, (iv) and general perception of market risk (VIX). There is no formal theory how each of these variables affect the decision to restrict quantities, but since they are an explicit part of the auctioneer's information set, I include them to control for any confounding effects on the variables of interest.

5.3 Bidder Behavior

Following Nyborg et al. (2002), I consider three bidding variables: discount, bid dispersion and demand. Discount is the difference between the end-day secondary market price and the quantity weighted average price submitted by the bidder.[7] I measure bid dispersion by both the number of competitive bids submitted and the quantity weighted standard deviation of the submitted prices. Demand is the face value of the competitive tenders submitted by a bidder divided by the total value of competitive bids in the auction. Table 7 provides summary statistics of these bidding variables.

Table 7: Bidding Variables

	Mean	*Standard Deviation*	*Observations*
Discount	0.2429	1.004	10029
Spread	22.49	52.47	10029
Price Disp.	0.091	0.250	10029
Yield Disp.	3.49	6.28	10029
Comp. Bids	2.60	2.15	10029
Comp.Demand	0.09	0.16	10404

DISCOUNT and PRICE DISP. are denominated per 100 PHP. SPREAD and YIELD DISP. is measured in bps. COMP. BIDS is the number of co–mpetitive submitted. COMP. DEMAND is the bid volume submitted over–auction supply. The different observation is because COMP. DEMAND in–cludes observations where bidders only submitted non-competitive bids. C–OMP. BIDS is treated as a dispersion variable to be paired with PRICE DI–SP and YIELD DISP, hence I only look at observations where at least one–competitive bid was submitted.

Dealers submit yields rather than prices and while there is a one-to-one correspondence between the two, bond convexity means that the choice is important for the analysis. Bond convexity measures the non-linear relationship of bond prices to changes in interest rates – when bonds are trading at significant premium or discount then small changes in yields imply large changes in prices. Prices are what bidders ultimately pay and if cash constraints are binding then this is the relevant measure for both discount and price dispersion. On the other hand, market transactions and discussions revolve around interest rates to such an extent that it is equally plausible to argue bidders make decision based on yields and the conversion is mostly thought of as a settlement detail.

[7] Discount is the formal measurement of bid shading.

Unlike aggregate auction performance, there is no clear reason to prefer one measure or the other so I will include them both. For the yield measure, the equivalent of the discount is the bid spread – defined as the difference between quantity weighted average yield and the end-day secondary market yields. The equivalent of the price dispersion is the yield dispersion which is the quantity-weighted standard deviation of yields submitted.

I estimate the bidder-level regression below using ordinary least-squares:

$$\begin{aligned} BID_{it} = \alpha_0 + \beta_1 DP_t + \beta_2 SIZE_t + \beta_3 VOL_t + \beta_4 BIDDERS_t + \beta_5 \Delta PRICE_{t+1} \\ + \beta_6 \Delta FX_t + \tau_t + \gamma_i + \kappa_i + \varepsilon_{it} \end{aligned}$$

BID refers to the bidding variables under study and it is indexed at both the individual and auction level. DP is a dummy variable that takes the value of 1 if the auction format is DP. Optimal bidding strategies differ depending on the auction format but the expected coefficient sign is theoretically ambiguous because of the potential for numerous equilibria and sensitivity to assumptions on bidder demand. SIZE, VOL and BIDDERS and ΔFX are the same covariates used in the peformance regressions.

Higher levels of volatility and more auction participants increase the potential for winner's curse so these variables are expected to have a positive impact on discount and dispersion but a negative relationship with demand. Auction size would be relevant if capacity constraints are binding or if bidding behavior can be explained by a risk aversion model similar to Wang and Zender (2002). Bidders are expected to submit more conservative bids, higher discounts or spreads and lower volume, in response to foreign exchange depreciation because it reduces client flows driven by currency speculation and forces bidders to assume more interest rate risk. $\Delta PRICE$ is the one day percentage change in prices after the auction, when using price measures, or the one-day yield change from auction day. It measures potential profits, and is meant to proxy the unconditional expectation of the security's common value. A higher common value is expected to encourage aggressive bidding through reduced bid shading and higher participation rates, although its effects on bid dispersion is unclear.

Bidder-specific fixed effects (γ_i) are included to account for systematic differences in bidding strategies across dealers. I also use year fixed effects (τ_t) to control for economic and global shocks. The last fixed effect dummy controls for security-specific impact on the variables of interest. In the Philippine bond market, not all securities are equal, some 10 year bonds see more trading activity than other 10 year securities. κ is meant to capture all such idiosyncratic effects on bidding behavior. All specific bond ID numbers are included while the bills are grouped by tenor length. Bills only get re-issued if their remaining maturity is equal to any of the three tenor groups (91, 182, and 364 days).

5.4 Heterogeneity

The same framework in the preceding section can be used to analyze bidder heterogeneity in the Philippine context. I classify bidders into three groups based on the number of times they received allocations worth at least 15% of auction supply. Type 1 bidders received 15% or more allocations in more than 80 auctions, Type 2 are those bidders who received that much allocation in more than 10 but less than 80 auctions and the rest are Type 3 bidders. The criteria captures the aggressiveness of the bidders and is also positively correlated with size, measured in terms of assets and market value. Relevant summary statistics are included in Table 8 below.

The most striking part of the table are the negative signs on the profit column – if profits are negative then bidders participation must be explained. First, these are not "realized profits", the definition of profits here is the difference between end-day price and the weighted award price each bidder has to pay after winning. These losses are not necessarily actualized if bidders do not sell the securities at end-day prices. This is an important point because if bidders are simply taking client orders then their profits would likely come from the bid-offer spread.

Even if the awarded securities are for trading, many bidders can and do wait for market prices to be favorable to get out of their positions – sometimes they wait for at least a month before they close losing positions. Some bidders also participate just to secure interest income so secondary market prices are not very important considerations. Nonetheless, since these prices are available, it means some winners do realize losses after each auction but how many is something that cannot be answered with available data.

A cursory look at Table 8 indicates that Type 1 bidders are the most aggressive in terms of discount submissions and participation while booking higher average profits. I perform a pair-wise test to see if the observed means for both the bidding variables and profits are statistically different across bidder types. The difference of the profit between bidder types is more important than the absolute levels. We can change the minuend from end-day prices to one-day after, two-days after, or even one-week after prices and for as long as this is consistently applied across bidder types then any statistical comparisons of means will still yield the same results.[8]

I estimate the same set of equations in 5.3 but I explicitly include interaction terms for Type 2 and Type 3 bidders. Statistically significant coefficients indicate heterogeneity in bidder adjustments to winner's curse potential and market environment. Given the consistency in the concentration of the awards present in Philippine auctions, it is

[8] Admittedly, this would not address the issue of realized trading profits and losses but such an analysis is beyond the scope of this paper. These mark-to-market profit calculations are still informative because systematically higher unrealized gains confer significant advantage to any bidder type in terms of booking realized profits.

Table 8: Bidder Heterogeneity

Type 1 Bidders (N = 5)	*Auctions*	*Discount*	*Price Disp.*	*Spread*	*Yield Disp.*	*Comp. Bids*	*Comp. Demand*	*Profit*	*Allocation*
Average	432.20	0.1077	0.1146	8.288	5.010	3.646	0.1779	-0.1783	16.96
Standard Deviation	69.70	0.8612	0.2920	39.56	7.415	2.469	0.2122	0.8190	20.64
Obs.	5	2019	2019	2019	2019	2019	2161	1467	1467
Type 2 Bidders (N = 8)									
Average	419.88	0.1939	0.0947	19.52	3.806	2.692	0.1180	-0.1944	9.986
Standard Deviation	118.36	0.8477	0.2570	50.94	5.975	2.203	0.1880	0.9257	15.09
Obs.	8	3265	3265	3265	3265	3265	3359	1569	1569
Type 3 Bidders (N = 21)									
Average	232.57	0.3341	0.0773	30.57	2.624	2.087	0.0420	-0.2360	3.38
Standard Deviation	159.93	1.1421	0.2226	56.67	5.788	1.761	0.0643	1.128	4.75
Obs.	21	4745	4745	4745	4745	4745	4884	1554	1554

The unit of PROFIT is per 100 PHP, similar to DISCOUNT and PRICE DISP. ALLOCATION is denominated in percentages.

reasonable to think the most aggressive bidders do have superior information and thus make less adjustments for winner's curse.

6 Results

6.1 Auction Performance

Table 9: Auction Performance – Regression Results

	Revenues		***Concentration***
	5-Day MA	*End-Day*	
Constant	-25.034 (21.18)	-7.71 (21.81)	107.62*** (9.48)
Non-Comp. Demand	1.21 (4.97)	0.98 (4.52)	-11.05*** (1.58)
Comp. Demand	-9.53*** (1.86)	-3.01* (1.66)	2.80*** (0.75)
N.C. Shortfall (pct.)	0.45*** (0.07)	0.34*** (0.06)	-0.17*** (0.03)
Bonds	-24.00*** (7.76)	-16.23** (7.77)	-6.95 (4.73)
Uniform	31.15*** (7.07)	14.14** (6.87)	-17.40*** (3.63)
Residual Maturity (Years)	-0.83** (0.37)	-0.51 (0.33)	0.04 (0.26)
Bidders	0.93** (0.46)	0.15 (0.48)	-1.14*** (0.21)
Auction Size (PHP Billions)	0.28 (0.47)	0.98** (0.47)	0.32 (0.23)
Fiscal Variables	Not significant	Not significant	Not significant
Market Variables	Significant***	Not significant	Not significant
Year-Fixed effects	Significant***	Significant***	Significant***
Observations	540	540	369
Adjusted R^2	0.45	0.29	0.42

*, **, *** - significant at 10%, 5% and 1% respectively.
Standard errors in parenthesis. Both of these conventions apply for all the results in this paper.

Table 9 provides the results of the performance regressions. The most significant result here is the clear trade-off that the UPA format presents – it reduces concentration but at the cost of higher spreads. The size of the effects are substantial, UPAs reduce concentration by around 17% but is expected to increase spreads by about 14 bps over end-day levels and 31 bps over previous week levels.

More competitive demand reduce spreads but increase concentration. This gives us an indication that the degree of competitive demand from auction to auction is largely driven by the behavior of the most aggressive bidders. These dealers submit high bid volumes at yield levels which are likely to win allocations.

Only the portion of non-competitive bids which form part of the 40% maximum requirement has any explanatory or predictive power on the resulting yield spreads. Non-competitive bids lead to lower spreads by effectively reducing auction supply and giving the most aggressive bidders more influence on setting the auction price or yield. The effect of non-competitive demand on concentration is a bit more nuanced. If more bidders submit non-competitive bids then allocation will be more diffused because everyone will get some allocation. This is reflected by the significant negative impact of both non-competitive demand and number of bidders on concentration.

It is also possible for non-competitive bids to increase concentration – a few bidders can submit extraordinarily high bid volumes and the pro-rationing rule will allow them to win nearly all supply. Highly aggressive bidders do submit both large amounts of competitive and non-competitive bids, so they are likely to win a disproportionally larger share of both allocations. The negative and significant coefficient of shortfall on concentration reflects this channel. Higher shortfalls indicate the most aggressive bidders are submitting lower non-competitive bids than usual. This allows other participants to win more securities by increased competitive bid awards and higher share of non-competitive allocations.

Bonds and residual maturity are associated with lower spread outcomes which is consistent with expectations – bidders are willing to trade lower spreads for higher bond yields. It is however surprising that bond auctions are not expected to reduce concentration given the summary statistics in Table 4. The difference in concentration is accounted by the different auction formats and not the instrument type.

Depending on the measure of revenues, there is mixed evidence on the impact of the number of bidders and auction size. Using the 5-day MA spread, more participants lead to higher spread outcomes which is suprising because it implies that winner's curse adjustments might be overwhelming whatever cost benefits increased competition is supposed to bring. Looking at the end-day spread measure, there is some support for the view that capacity constraints might be important – to sell more securities, the BTr must be prepared to pay higher spreads.

6.2 Quantity Restrictions

Table 10: Quantity Restriction – Regression Results

Logit	***Reject***			***Partial Award***
	All Auctions	*Fully Subscribed*	*Under-Subscribed*	
Constant	-7.75*** (2.27)	-6.44** (2.53)	-18.58 (15.68)	-0.61 (1.88)
Cash Balance (PHP Billion)	0.011*** (0.004)	0.008** (0.004)	0.040* (0.022)	0.003 (0.002)
3-Day Net Cashflow (PHP Billion)	-0.007 (0.013)	-0.012 (0.016)	0.02 (0.05)	-0.001 (0.007)
5-Day MA Spread (bps)	0.015** (0.007)	0.022** (0.010)	-0.04 (0.03)	0.037*** (0.009)
Non-Comp. Demand	-0.15 (1.18)	0.30 (1.17)		-1.38 (0.92)
Comp. Demand	-1.18** (0.52)	-0.74 (0.51)	-5.46 (6.99)	-3.22*** (0.51)
N.C. Shortfall (pct.)	0.0257** (0.010)	0.032*** (0.012)	0.004 (0.043)	0.011 (0.007)
Under-subscribed	1.45** (0.62)			
Other Auction Variables	Not Significant	Not Significant	Not Significant	Significant**
Market Variables	Significant**	Significant*	Not Significant	Significant*
Observations	540	489	51	460
Obs. = 1	60	29	31	91
Obs. = 0	480	460	20	369
McFadden R^2	0.49	0.37	0.69	0.47

Prior to every auction, the BTr reviews its cash position and future cash requirements but the results show that only in the decision to reject does available cash balances play a role. More cash makes full rejections likelier because the consequences are not as costly – day-to-day operations of the whole government are unlikely to be crippled or compromised. This same logic should also hold for partial awards but while the coefficient has the correct sign, it is statistically insignificant.[9]

The regressions cannot detect the influence of future cash requirements in the decision

[9] The regression in the third column does not use non-competitive demand because all undersubscribed auctions have non-zero shortfall. These two variables convey the same information.

to restrict quantities. A longer time horizon than three days might be warranted but it is difficult to disentangle the effects of the cash *flow* with the cash *balance* because cash levels have always been sufficient to cover months of expenditure requirements. Outflows were unlikely to be sufficiently binding to force the BTr to accept any auction result.

While spreads are significant in both regressions, the coefficient value is higher for partial awards. Logit coefficients cannot be directly interpreted but the difference in magnitude here is an indication partial award decisions are more cost sensitive compared to full rejections. The same thing could be said for the effect of competitive demand, except one should be careful in comparing the value of its coefficients with the other covariates – demand is measured in terms of auction size multiples so a one unit increase can be substantial.

By itself, non-competitive demand has little explanatory or predictive power but shortfalls are important in explaining the decision to reject. In over-subscribed auctions, extremely high levels of shortfall can persuade the BTr to opt for full rejection rather than accept a small fraction of the bids. This point is further emphasized in Table 11: average non-competitive shortfall for rejected auctions are significantly higher compared to partial and full award auctions.

Table 11: Quantity Restriction – N.C. Shortfall (pct.)

Oversubscribed Auctions	***Award*** *Partial*	*Full*	***Reject***
Mean	50.66	19.85	69.42
Standard Deviation	36.34	32.71	32.78
Observations	91	369	29
Test of Equality			
Hypothesis	*Mean Diff.*	*t-stat.*	*p-value*
H_0: Reject=Partial H_1: Reject≠Partial	18.76	2.61	0.011
H_0: Reject=Full H_1: Reject≠Full	49.57	7.84	0.000

6.3 Bidder Behavior

Table 12 provides the results of the bidder-level regressions. DP auctions see higher discounts or spreads, slightly more bid submissions and lower price and yield dispersion. If DP is supposed to have more winner's curse potential then bidders should adjust by submitting more dispersed bids. What the results do indicate is bidders are more conservative or careful with their bidding strategy under the DP format simply because if they win then they will pay with full certainty what they bid for. The coefficients on DP for the discount and spread regressions give an indication of how much room for aggressiveness bidders believe that UPAs grant.[10]

The negative impact of auction size on competitive demand points to the importance of budget constraints in bidder behavior; it is consistent with the idea that dealers do have a fixed budget which they can use to participate in auctions. Client orders might provide additional resources on top of this cash constraint but it is not sufficient to absorb additional auction supply. Higher auction sizes prompt higher bid dispersion and this complements the budget constraint hypothesis – having satisfied their requirements, bidders will only purchase extra securities if they can get it at a cheaper price.

Volatility increases discount or spread submitted by dealers and there is some evidence that they disperse their bids more. These are consistent with winner's curse adjustments because volatile bond markets make every bidder signals less reliable, hence the need to shade and disperse more. However, higher demand in response to more volatility cannot be explained by bidder concerns about winner's curse, in fact it should discourage participation. A potential explanation is that some of the dealers have indicated a preference for higher volatility because of increased profits opportunities and this motive seems to be more dominant.

Bidders adjust for more competitors by shading and dispersing their bids more and this is further support for the winner's curse hypothesis. More bidders bias upwards the highest common value which has to be compensated for by more aggressive discounts or spreads. Higher dispersion allows bidders to take advantage of higher than expected demand while simultaneously reducing their potential losses if demand is weaker than expected.

The unconditional expected profits as measured by the one-day return for discount and one-day yield change for spread have the expected coefficient signs. Higher expected returns can encourage less bid shading because participants believe they can easily recoup the prices they have paid. The positive coefficient on spread by the one-day yield change conveys the same information. Higher yields in the next day means lower prices, and therefore losses, so bidders tend to compensate by charging higher spreads. There is indication dealers disperse bids more as expected profits get higher but this adjustment is not necessarily due to winner's curse. Higher dispersion gives a higher chance of getting *some* allocation at the cost paying higher prices – optimism about future returns make this trade-off worthwhile.

Foreign exchange also plays a role in bidding behavior, a PHP depreciation trend

[10]These regressions were only able to use 12 UPAs for a total 404 observations.

Table 12: Bidder Behavior – Regression Results

	Discount (per 100 PHP)	*Price Disp. (per 100 PHP)*	*Spread (bps)*	*Yield Disp. (bps)*	*Comp. Bid Count*	*Comp. Demand*
Constant	-0.6326***	0.2850***	-33.22***	2.4395***	-1.8327***	0.0594**
	(0.1697)	(0.0350)	(7.18)	(0.9275)	(0.2205)	(0.0279)
Discriminatory	0.6523***	-0.2062***	18.44***	-3.4805***	0.8971***	-0.0135
	(0.1074)	(0.0282)	(2.20)	(0.4725)	(0.1611)	(0.0100)
Auction Size (PHP Billions)	-0.0041	0.0057***	0.1564	0.1001***	0.0891***	-0.0142***
	(0.0109)	(0.0020)	(0.3862)	(0.0591)	(0.0042)	(0.0015)
Volatility (bps)	0.0063***	0.00015	0.5572***	0.0276***	-0.0012	0.0009***
	(0.0006)	(0.00010)	(0.0546)	(0.0074)	(0.0015)	(0.0002)
Bidders	0.0119***	-0.0006	1.192***	0.0946***	0.1092***	0.0011
	(0.0023)	(0.0006)	(0.188)	(0.0255)	(0.0056)	(0.0007)
One-Day Return (pct.)	-0.5689***	0.0506***			0.0451	0.0058
	(0.0592)	(0.0182)			(0.0490)	(0.0042)
ΔYields (bps)			0.5937***	0.0007		
			(0.0189)	(0.0026)		
FX Momentum (100 pips)	0.0012***	0.00002	0.0746***	-0.0005	-0.0021***	-0.00017**
	(0.0004)	(0.00005)	(0.0237)	(0.0029)	(0.0008)	(0.00008)
Bidder Fixed Effects	Significant	Significant	Significant	Significant	Significant	Significant
Year Fixed Effects	Significant	Significant	Significant	Significant	Significant	Significant
Security Fixed Effects	Significant	Significant	Significant	Significant	Significant	Significant
Observations	10029	10029	10029	10029	10029	10404
Adjusted R^2	0.42	0.45	0.44	0.15	0.36	0.21

A pip is the smallest unit in which currency pair prices are quoted. In this context, 100 pips is 0.01 PHP and a positive value means PHP depreciation against the USD. Bid Count and Demand regressions give similar results if I use yield change as a measure of the unconditional expectation of the common value. Observations for demand include situations where bidders only submitted non-competitive bids. All fixed effects are significant at the 5% level at least.

against the USD prompts bidders to submit higher discounts and spreads. Depreciation means the bidders cannot count on foreign speculators to buy the securities they were awarded – lower demand in the secondary markets means lower prices profits. Depreciation also means client orders from these speculators dry up so quantity demanded should go down as borne out in the results.

Winner's curse adjustment, particularly for volatility and number of bidders, is most evident in the bid shading variables. Dispersion also shows winner's curse adjustment but only for the yield measure of dispersion. Since bidders submit yield-quantity pairs one can argue the quantity-weighted standard deviation of submitted yields is a more "natural" measure of dispersion in the sense that it underwent fewer manipulations and transformations compared to the equivalent price measure. It is competitive demand for which winner's curse does not have good explanatory power – volatility and number of bidders have positive coefficients when winner's curse adjustments should entail the opposite.

6.4 Heterogeneity

Table 13: Heterogeneity – Test of Equality

	Type 1=Type 2	*Type 1=Type 3*	*Type 2=Type 3*
Discount	-3.56 (0.0004)	-8.93 (0.0000)	-6.30 (0.0000)
Spread	-8.97 (0.0000)	-18.49 (0.0000)	-9.12 (0.0000)
Price Disp.	2.52 (0.0117)	5.14 (0.0000)	3.13 (0.0017)
Yield Disp.	6.16 (0.0000)	12.88 (0.0000)	8.81 (0.0000)
Comp. Bids	14.21 (0.0000)	25.73 (0.0000)	13.07 (0.0000)
Comp. Demand	10.69 (0.0000)	29.17 (0.0000)	22.52 (0.0000)
Profit	0.51 (0.6105)	1.61 (0.1066)	1.12 (0.2610)

Values in the table are t-statistics, p-values are enclosed in parenthesis.

In terms of aggressiveness of bidding behavior: Type 1 > Type 2 > Type 3 and this is true for all the bidding dimensions. Type 1 bidders shade less, submit more bids, demand more volume and disperse their bids more in order to increase the probability of securing at least some portion of the auction supply. Such aggressiveness is not being penalized by lower profits relative the other bidder types. The mean of Type 1 profits in the dataset is in fact higher compared to the other bidder types but the test could not detect the difference because of the large variance in the data.

For other bidder types it does not make sense to try and beat Type 1 bidders. If they cannot match the profit performance of Type 1's with their more conservative approach then adopting a more aggressive strategy will lead to worse relative performance. One reason for this result is Type 1 bidder's access to superior information – larger client base confers significant advantage. Unfortunately, this hypothesis cannot be tested on the available data.

The variables in Table 14 are interaction terms and should be interpreted as strength or degree of response compared to Type 1 bidders. Regressions using yield measures for shading and dispersion is better equipped to detect any behavioral differences across bidder types. This could be attributed to all the issues surrounding yield-to-price conversions discussed before. Bond convexity could potentially magnify the price impact of small yield differentials depending on how far from par value the specific security is. All the potential noise in the price measure mean that results for the yield measures should receive more weight especially when one is contradicted by the other.

Compared to Type 1's, other bidders display significantly less aggressive behavior in DPs relative to UPAs in terms of the spreads they submit and the degree of dispersion contained in their bids. All bidders types submit lower prices or higher yields in DPs compared to UPAs but Type 2's and Type 3's submit spreads which are 12.28 bps and 22.88 bps higher than Type 1's respectively. Type 2's and Type 3's also submit lower bid counts and smaller yield dispersion compared to their Type 1 peers. The bid count adjustment differential is economically significant given that the average number of bids per bidder in the data set is around 2.58. One tentative conclusion here is UPAs do encourage smaller bidders to behave more aggressively. Their bids are unlikely to be price setting, so submitting more dispersed bids and higher prices to increase their chances of getting allocations do not necessarily entail prohibitively high costs.

Higher auction sizes induce larger spread reductions from Type 2 and Type 3 bidders relative to Type 1's. Bjønnes (2001) argues bigger auctions reduce winner's curse potential; an increase in supply means a bidder is less likely to win a larger fraction of the total amount being sold. Winning, therefore, conveys less bad news than it would have under an smaller auction size scenario. This result is consistent with the idea that smaller and informationally disadvantaged participant tend to adjust more for winner's curse potential.

The economic content of the negative and significant coefficient of SIZE for both types with respect to competitive demand is hard to detect. If all bidder types do not do

Table 14: Heterogeneity – Regression Results

	Discount	*Price Disp.*	*Spread*	*Yield Disp.*	*Comp. Bid*	*Comp. Demand*
Type 2 x DP	-0.0028	-0.0492	12.2794***	-2.0639**	-1.7104***	-0.0483*
	(0.0957)	(0.0339)	(4.0364)	(0.8023)	(0.2713)	(0.0259)
Type 2 x Size	0.0006	-0.00007	-0.6344***	0.0711*	0.0227	0.0038***
	(0.0060)	(0.0014)	(0.1921)	(0.0398)	(0.0138)	(0.0010)
Type 2 x Vol.	-0.0025 *	0.0003	-0.1467	-0.0282*	0.0085*	0.0003
	(0.0013)	(0.0005)	(0.0919)	(0.0168)	(0.0050)	(0.0006)
Type 2 x Bid.	0.0058	0.0013	0.2774	0.0422	0.0220	-0.0020
	(0.0052)	(0.0018)	(0.2494)	(0.0496)	(0.0158)	(0.0015)
Type 2 x Ret.	0.0776	0.0375	-0.0392	0.0001	-0.0245	-0.0181
	(0.0785)	(0.0551)	(0.0477)	(0.0086)	(0.1444)	(0.0170)
Type 2 x FX	0.1009	-0.0312	12.4766**	-2.1134**	-0.1275	-0.0462
	(0.0879)	(0.0218)	(5.3010)	(0.9558)	(0.2552)	(0.0285)
Type 3 x DP	-0.0271	0.0048	22.8806***	-1.7821**	-1.3680***	-0.0569***
	(0.1104)	(0.0319)	(4.0490)	(0.7710)	(0.2414)	(0.0211)
Type 3 x Size	0.0105*	-0.0058***	-0.7120***	0.0028	-0.0484***	0.0040***
	(0.0058)	(0.0014)	(0.1763)	(0.0377)	(0.0124)	(0.0008)
Type 3 x Vol.	-0.0017	0.0018***	0.1122	-0.0321**	0.0102**	-0.0004
	(0.0014)	(0.0004)	(0.0902)	(0.0151)	(0.0046)	(0.0004)
Type 3 x Bid.	0.0089	-0.0020	0.1881	-0.0116	-0.0078	-0.0046***
	(0.0057)	(0.0016)	(0.2393)	(0.0475)	(0.0140)	(0.0012)
Type 3 x Ret.	0.1066	-0.0179	-0.0821*	-0.0012	-0.0551	-0.0266**
	(0.0799)	(0.0453)	(0.0473)	(0.0078)	(0.1278)	(0.0128)
Type 3 x FX	0.0731	-0.0373	3.5251	-1.7122*	0.1218	-0.0116
	(0.0916)	(0.0217)	(5.1718)	(0.9205)	(0.2395)	(0.0235)

To save space, I omit the constant and the coefficients of the un-interacted covariates and include these in Appendix B. DP refers to Discriminatory, SIZE refers to Auction size, VOL refers to yield volatility, BID refers to number of bidders in the auction, RET stands for return, and FX is FX momentum. For the spread and yield dispersion regressions I use the one day yield change to measure return, all the other regressions uses the one day percentage change in prices.

anything in response to an increase in auction size then the measured competitive demand will go down for all – the denominator increases but the numerator stays constant. But the rate of decrease is higher for Type 1 bidders because they submit also higher bid volumes in the first place. In short, the result might be an artifact of the measurement choice for competitive demand.

In response to more volatile bond markets, Type 1 yield dispersion adjustments are larger compared to other bidder types.[11] More dispersion is a possible response to increased winner's curse potential but another interpretation for higher dispersion is increased appetite for risk-taking – some bidders prefer volatile environments because of the availability of profit opportunities. Following the second interpretation then the results show higher volatility induces the most aggressive bidders to increase dispersion, which will increase their chances of getting some allocations at the cost of higher prices. If volatile market indeed offers more opportunities for profits, then the trade-off might be worthwhile.

Unless the response for a specific variable is statistically different for both bidder types, it is prudent to discount the statistical significance of some results – the sheer number of variables in the regression means some statistically significant coefficients may appear by chance alone. The Type 2 spread response to FX momentum is an exception because foreign banks do constitute a sizable portion of Type 2 classification. Most foreign clients likely course their orders through these institutions hence the statistically and economically significant results. The negative coefficient on the impact of FX momentum on yield dispersion, like volatility adjustments, is better explained by reduced risk appetite rather than increased winner's curse potential.

7 Conclusion and Implications

There is a trade-off between cost outcomes and concentration of awards. DPs generate lower spreads but more concentrated security allocations – it is when a few bidders monopolize awards that we see low spreads. An important reason why the DP format is associated with lower cost outcomes is that it allows the most aggressive bidders to exert a large influence on the setting of prices or yields. This is facilitated by the significant role of non-competitive bids which reduce available auction supply – in some auctions only one competitive bid was enough to fully allocate all the offered securities.

Concentration of awards might be relevant if the BTr also cares about the smooth operation of secondary markets – a bond market dominated by a few dealers is not

[11] The omitted coefficient on the un-interacted volatility variable indicates that Type 1 bidders increase yield dispersion in response to high volatility environments

optimal. Monopolizing supply will generate trading profits far in excess to what was paid for in the auctions and this motive could also explain the aggressiveness of some bidders.

Theoretical results by McAdams (2007) and Back and Zender (2001) show the important role that supply restrictions can play in keeping bidders "honest", especially in UPAs. BTr decision-making is sensitive to prices and they have demonstrated the willingness to restrict supply and even reject all the offered bids. The credible threat to restrict auction supply should have eliminated many collusive-seeming equilibria yet UPAs still show substantially higher spread outcomes than DPs. This finding is in agreement with Pycia and Woodward (2017) – when the auctioneer does not know bidders' values, optimally designed DP weakly dominates UPA. All of these highlight the important role that country and institutional context have in making these performance comparisons.

Lastly, one relevant variable which increases winner's curse potential and is within the control of BTr is the number of auction participants. At 34 auction participants, the results indicate that at the aggregate level, the cost reduction benefits of increased competition is outweighed by the individual bidder adjustments for winner's curse. Currently, becoming a primary dealer does not entail stringent requirements, so the number might further increase in the future. If the rationale for accepting such applications is to encourage competition to reduce costs then this might be misguided. In fact, the findings would support reducing the number of dealers or, at the very least, imposing more obligations to compensate for the higher cost outcomes caused by the large number of auction participants.

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A Appendix: Volatility Estimation

I estimate the conditional volatility by using an AR(2)-GARCH(1,1) model. Inputs for the T-bill and T-bond volatility are the daily 6-month and 10-year yields respectively. Figure 4 illustrates the reason for this choice – the yields of bonds and bills behave differently. Bond yields for other maturities exhibit the same pattern as the 10 year yields, and the same is true for the 3-month and 12-month yields with respect to the 6-month yields. The model below is estimated by maximum likelihood:

$$\Delta y_t = \mu + \rho_1 \Delta y_{t-1} + \rho_2 \Delta y_{t-2} + \varepsilon_t \tag{1}$$

$$\varepsilon_t = v_t \sigma_t,\ v_t \sim N(0,1) \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{3}$$

Yield levels, like many financial time series, are nonstationary so working with first-differenced data is necessary. The two lag terms account for the serial correlation structure of daily yield changes and (3) is the equation generating the conditional volatility estimates. Table 15 reports the estimation results for both bonds and bills while Figure 5 provides the conditional volatility time series graph.

Table 15: AR(2) - GARCH(1,1) Estimation Results

Mean Equation	Constant	AR(1)	AR(2)
Δ6M Yields	-0.29 (0.35)	-0.35*** (0.03)	-0.14*** (0.03)
Δ10Y Yields	-0.39** (0.17)	-0.28*** (0.02)	-0.05** (0.02)

Variance Equation	Constant	ε_{t-1}^2	σ_{t-1}^2
6M σ_t^2	6.88*** (0.22)	0.097*** (0.004)	0.909*** (0.003)
10Y σ_t^2	0.33*** (0.06)	0.055*** (0.002)	0.951*** (0.001)

Figure 4: 6M vs. 10Y Yields (in pct.)

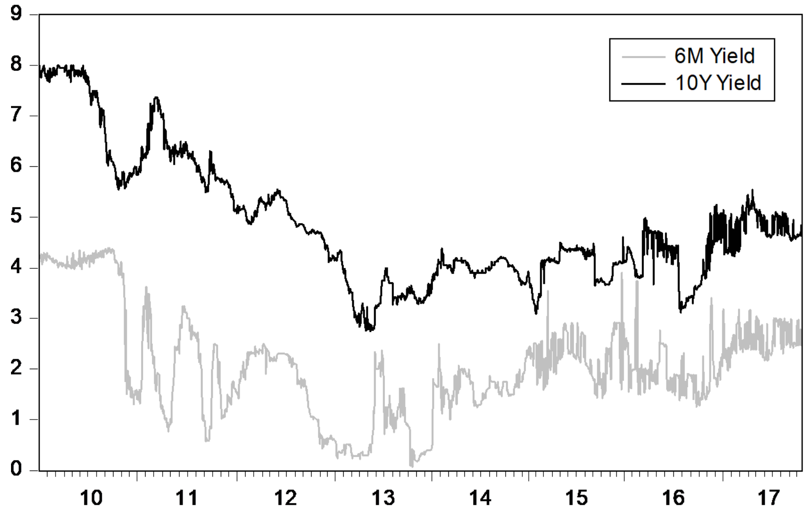
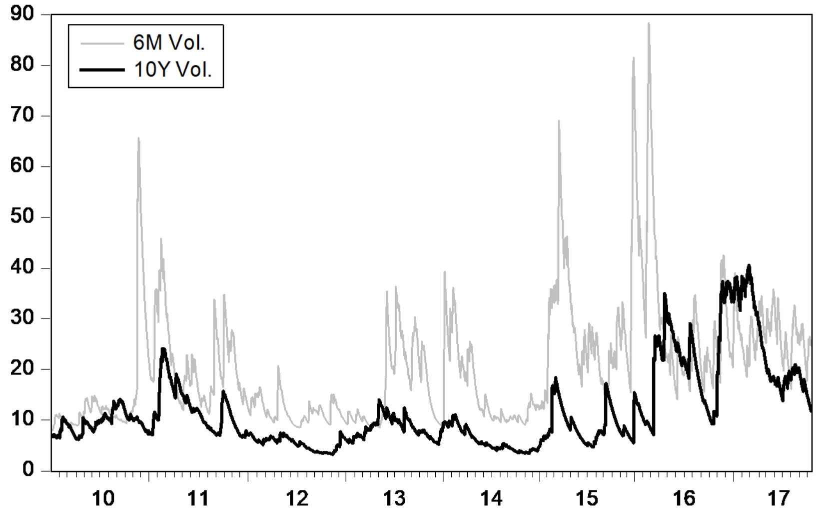


Figure 5: Conditional Volatility (in bps.)



B Appendix: Heterogeneity Regression cont'd

Table 16 includes the coefficients of the un-interacted variables omitted from the main Heterogeneity regression table. These values represent how Type 1 bidders react to auction structure and the financial market environment.

Table 16: Heterogeneity – Type 1 Coefficients

	Discount	*Price Disp.*	*Spread*	*Yield Disp.*	*Bid Count*	*Demand*
Discriminatory	0.6447***	-0.1975***	1.7489	-1.9690***	2.3013***	0.0303
	(0.1149)	(0.0350)	(3.3820)	(0.7334)	(0.2628)	(0.0228)
Auction Size	-0.0109	0.0085***	0.5769	0.0857	0.0175	-0.0176
	(0.0116)	(0.0022)	(0.4154)	(0.0680)	(0.0182)	(0.0016)
Volatility	0.0076***	-0.0008**	0.5363***	0.0543***	-0.0088**	0.0011
	(0.0010)	(0.00034)	(0.0791)	(0.0149)	(0.0044)	(0.0005)
Bidders	0.0084*	-0.0009	1.1256***	0.0560	0.0566***	0.0040***
	(0.0043)	(0.0014)	(0.2491)	(0.0479)	(0.0133)	(0.0013)
Return	-0.6559***	0.0519	0.6481***	0.0014	0.1665	0.0252**
	(0.0661)	(0.0407)	(0.0381)	(0.0073)	(0.1194)	(0.0128)
FX Momentum	0.0624	0.0291*	2.7529	1.3210	-0.2600	0.0024
	(0.0692)	(0.0169)	(3.9918)	(0.8873)	(0.2220)	(0.0234)
Year Fixed Effects	Significant	Significant	Significant	Significant	Significant	Significant
Security Fixed Effects	Significant	Significant	Significant	Significant	Significant	Significant
Observations	10029	10029	10029	10029	10029	10404
Adjusted R^2	0.39	0.46	0.39	0.10	0.34	0.16

C Appendix: Financial Market Variables

This section provides time series graphs for financial market variables used in the analysis.

Figure 6: USDPHP Exchange Rate (1USD:PHP)

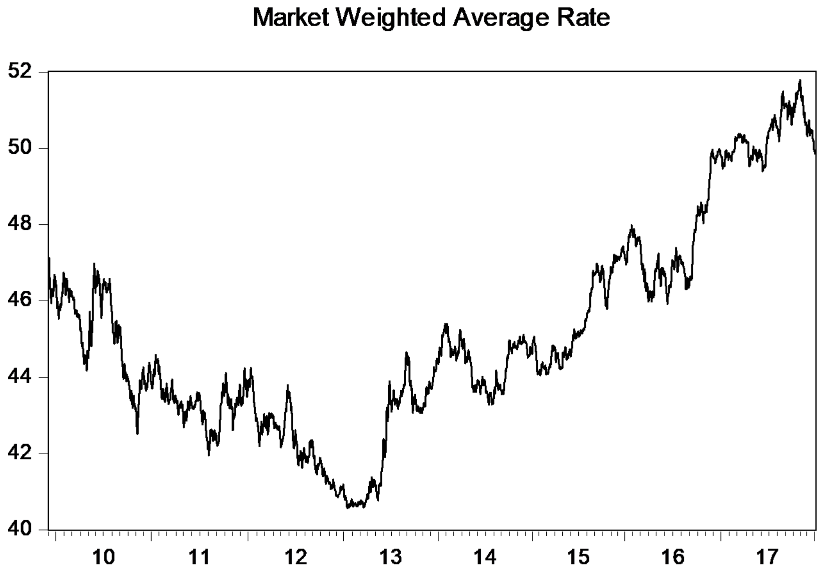


Figure 7: Philippine Monthly Inflation Rate (y-o-y in pct.)

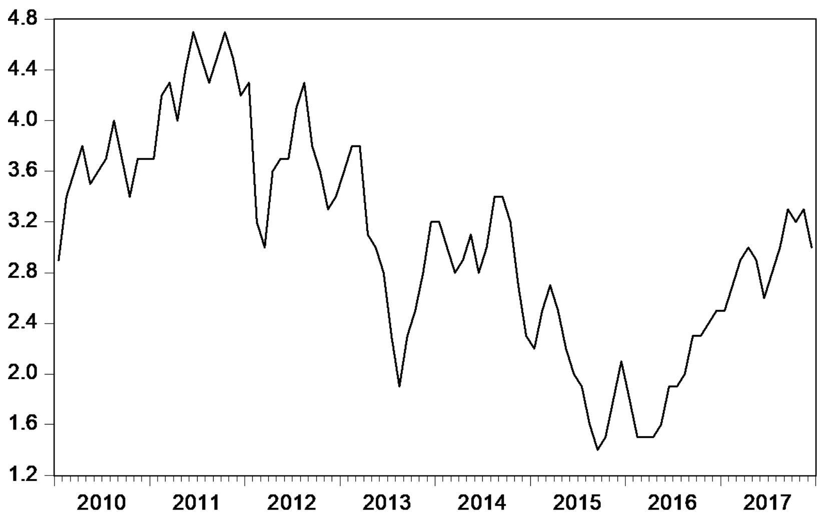


Figure 8: 10 Year US Treasury Rates (in pct.)

Figure 9: CBOE Volatility Index (VIX)