

Testing for Market Efficiency with Transactions Costs: An Application to Convergence Bidding in Wholesale Electricity Markets

Akshaya Jha*

and

Frank A. Wolak†

April 30, 2015

Abstract

With risk neutral traders and zero transactions costs, the expected value of the difference between the current forward price and the spot price of a commodity at the delivery date of the forward contract should be zero. Accounting for the transactions costs associated with trading in these two markets invalidates this result. We develop statistical tests of the null hypothesis that profitable trading strategies exploiting systematic differences between spot and forward market prices exist in the presence of trading costs. We implement these tests using the day-ahead forward and real-time locational marginal prices from California's wholesale electricity market and use them to construct an estimate of the variable cost of trading in this market. During our sample period, we observe the introduction of convergence bidding, which was aimed at reducing the costs associated with exploiting differences between forward and spot prices. Our measures of trading costs are significantly smaller after the introduction of convergence bidding. Estimated trading costs are lower for generation nodes relative to non-generation nodes before explicit virtual bidding and trading costs fell more for non-generation nodes after explicit virtual bidding, eliminating any difference in trading costs across the two types of nodes. We also present evidence that the introduction of convergence bidding reduced the total amount of input fossil fuel energy required to generate the thermal-based electricity produced in California and the total variable of costs of producing this electrical energy. Taken together, these results demonstrate that purely financial forward market trading can improve the operating efficiency of short-term commodity markets.

*Department of Economics, Stanford University, 579 Serra Mall, Stanford, CA 94305. e-mail: akshayaj@stanford.edu

†Program on Energy and Sustainable Development and Department of Economics, Stanford University, 579 Serra Mall, Stanford, CA 94305-6072, e-mail: wolak@zia.stanford.edu

1 Introduction

Many commodities are traded in both forward and spot markets. With risk neutral arbitrageurs and zero transactions costs, market efficiency implies that the forward price at time t for delivery k periods in the future, F_{t+k} , is equal to the expected value of the spot price k periods in the future conditional on the information available to market participants at time t , $E_t[P_{t+k}]$. After accounting for transactions costs, the existence of a profitable trading strategy implies the $|E_t(F_{t+k} - P_{t+k})| > c$, where c is the dollar per unit cost associated with transacting in both the forward and spot markets. Specifically, the expected profits from exploiting the difference between the forward and spot price is greater than the trading costs. This paper develops tests of the null hypothesis that profitable trading opportunities exist in a commodity market with transaction costs, and applies this testing framework to data from the California wholesale electricity market to derive an estimate of the per unit trading cost, c .

Wholesale electricity markets with a day-ahead forward market and real-time market are ideally suited to test for the existence of profitable trading strategies because the same products—electrical energy delivered during each hour the following day—is sold in the day-ahead and real-time markets and the time lag between the purchase or sale in the forward market and subsequent sale or purchase in the real-time market is less than one day. Our tests of this hypothesis are complicated by the fact that each day there are 24 hourly trading opportunities between the day-ahead price and real-time price. Therefore, we derive tests of the null hypothesis of the existence of a profitable trading strategy with transactions costs for different portfolios of the 24 hourly price differences.

This analysis also has implications for the design of wholesale electricity markets because of the controversial role that purely financial traders play in these markets. Regulators have been reluctant to allow explicit financial transactions in day-ahead and real-time energy markets in spite of the fact that it is impossible to determine if the reason a market participant sells or buys more or less energy in the day-ahead market than their real-time production or consumption is because of new information about real-time demand or supply conditions after the close of the day-ahead market or because the market participant is attempting to profit from anticipated differences between prices in the day-ahead and real-time markets.

Exploiting anticipated differences between day-ahead and real-time prices typically involves costly actions by generation unit owners and load-serving entities that can have adverse system reliability consequently. For example, if a generation unit owner expects the real-time market price to be higher than the day-ahead price, the unit owner is likely to delay selling its output until the real-time market. If enough generation unit owners share these expectations, the system operator will find that the day-ahead market clears at a level of demand below expected real-time demand. The independent system operator (ISO) must therefore purchase a substantial amount of energy in the real-time market to meet actual demand, which can be extremely challenging for the ISO to manage and can increase the total cost of serving final demand. These concerns were ultimately realized in a number of United States (US) wholesale markets, which led to the introduction of convergence or

virtual bidding—a purely financial product that is designed to allow market participants to profit from expected price differences between the day-ahead and real-time markets without these reliability consequences or potential production cost increases.

Convergence bidding was implemented on February 1, 2011 in the California wholesale electricity market. It allows market participants to take purely financial positions in the day-ahead market that must be closed out in the real-time market. A trader that sells energy in the day-ahead market using an incremental or INC convergence bid has an obligation to buy back the same amount of energy as a price-taker in the real-time market. The net payoff from this transaction is the difference between the day-ahead and real-time prices for that hour times the number of megawatt-hours (MWhs) sold in the day-ahead market. Buying energy in the day-ahead market using a decremental or DEC convergence bid implies an obligation to sell that same amount of energy in the real-time market as a price-taker. This transaction has a net profit of the difference between the real-time price and the day-ahead price for that hour times the number of MWhs purchased.

Convergence bidding was introduced for two major reasons: (1) to reduce the cost to market participants of exploiting price differences between the day-ahead and real-time markets, and (2) reduce the total cost of serving demand at all locations in the transmission network in real time. We present evidence that convergence bidding achieved both of these goals. Specifically, our measures of the implied per unit cost of trading day-ahead versus real-time price differences fell for the three major pricing zones and at virtually all of the more than 4,000 nodes in the California ISO control area after the introduction of explicit virtual bidding. We also find that the total hourly input fossil fuel energy consumed fell by 2.8 percent and the total hourly variable cost of producing fossil fuel-fired electricity in California each fell by 2.6 percent after the introduction of convergence bidding. We also find that the variance of the difference between day-ahead and real-time prices declined and the variance of the real-time price declined after the introduction of convergence bidding.

The remainder of the paper proceeds as follows. The next section describes the mechanism used to set locational marginal prices and determine dispatch levels in the day-ahead and real-time markets in California and all other bid-based markets in the United States. This section also describes how the actions of generation unit owners and load serving entities influence locational marginal prices in the absence of convergence bidding as well as how convergence bids influence locational marginal prices in the day-ahead and real-time markets. Section 3 describes the data used to perform our hypothesis test and presents descriptive statistics on the behavior of the average hourly differences in the day-ahead and real-time price for the 24 hours of the day before versus after the implementation of convergence bidding. Section 4 derives our test of the null hypothesis of the existence of a profitable trading strategy with transactions costs. This is followed by a presentation of the distributions of the pre- and post-convergence bidding implied trading costs for our hypothesis test. This section also discuss our tests for a reduction in the variance of day-ahead minus real-time price difference and the variance of real-time prices pre- versus post-convergence bidding. Section 5 presents our analysis of the market efficiency consequences of implementing convergence bidding. Section 6 closes with a discussion of the implications of our results for the design of wholesale electricity markets.

2 Locational Marginal Pricing and Convergence Bidding in the California Market

This section first describes the important features of multi-settlement locational marginal pricing wholesale electricity markets that currently exist throughout the United States. In the process we describe how a market participant's actions are used to determine the prices received by generation unit owners and paid by load serving entities in the day-ahead and real-time markets. We then describe how suppliers and load-serving entities exploited expected price differences between the day-ahead and real-time markets before the introduction of explicit convergence bidding. We then explain the mechanics of convergence bidding, including how these purely financial transactions influence day-ahead and real-time locational marginal prices. Finally, the transactions costs associated with exploiting expected differences between day-ahead and real-time prices with and without convergence bidding are discussed.

2.1 Locational Marginal Pricing in Multi-Settlement Markets

Short-term wholesale electricity markets differ from markets for other products because the electricity produced by a generation unit at one location and sold to a customer at another location is not actually delivered to that location in the same sense that an automobile produced in Detroit is delivered to the customer that purchased it in San Francisco. Energy injected into the transmission network flows according to Kirchhoff's laws, rather than from the seller to the buyer of the energy. The capacity of the transmission network often limits the amount that generation units at certain locations can inject and the amount that consumers at certain locations can withdraw. This circumstance is referred to as transmission congestion and it can cause a wholesale electricity market to become segmented, meaning that some generation units cannot compete to sell energy at certain locations in the transmission network because the configuration of the transmission network, the locations and outputs of other generation units, and the locations and levels of final demand do not allow it. Under these circumstances, a market mechanism that assumes that all generation units in the geographic region covered by the wholesale market can compete to sell energy anywhere in that geographic region will likely produce an infeasible dispatch of the available generation units, because capacity constraints in the transmission network and other operating constraints prevent the suppliers that offer the lowest prices for their output from selling all of their available energy.

For this reason, spatial pricing mechanisms that explicitly account for the configuration of the transmission network and operating constraints on the transmission network and generation units have become the *de facto* standard in the United States. All wholesale markets currently operating in the United States—in New England, New York, the PJM Interconnection (in Pennsylvania, New Jersey, Maryland and a number other eastern states), the Midwest, Texas, and California—use variants of the locational marginal pricing (LMP) algorithm described by Bohn, Caramanis and Schweppe (1984). This pricing mechanism

sets potentially different prices at all locations or nodes in the transmission network. To compute these prices in the day-ahead market, suppliers submit generation unit-level offer curves giving their willingness to supply energy as a function of the price from each generation unit they own. These willingness-to-supply schedules have two parts: a start-up cost offer and energy supply curve. The start-up cost offer is a fixed dollar payment that must be paid to the generation unit owner if it is off-line at the start of the following day and the unit is accepted to produce a positive output during that day. The energy offer curve is a non-decreasing step function giving the willingness of the generation unit owner to supply additional energy as a function of the price it is paid for energy. All US markets allow generation units owners to submit multiple price and quantity pairs for each generation unit each hour of the day. For example, a supplier might be permitted to submit ten price and quantity pairs for each generation unit, with the offer price giving the minimum price at which the unit's owner is willing to supply the output in the quantity offer associated with that offer price. The sum of the quantity increments is restricted to be less than the capacity of the generation unit and offer prices are typically required to be greater than a price floor (which could be negative) and less than a price ceiling, both of which are approved by the Federal Energy Regulatory Commission (FERC), the US wholesale market regulator. In the day-ahead market, load-serving entities (LSEs) submit location-specific willingness-to-purchase functions that are decreasing functions of the price at that location. The functions are composed of price-quantity pairs ordered from highest to lowest price where each quantity increment gives the amount the LSE is willing to increase its demand if the price is at or below that price level.

All US markets simultaneously operate ancillary services markets along with the energy market. Generation unit owners submit non-decreasing step functions giving their willingness-to-supply each ancillary service. These offer curves are generation unit-specific and unit owners are only allowed to submit offers to supply an ancillary service from their generation unit that the ISO has certified that their unit is able to provide. All US ISOs operate markets for spinning reserve, non-spinning reserves and regulation reserve (automatic generation control). In the day-ahead market, the amounts of each operating reserve accepted from each generation unit and the price paid for that operating reserve is determined simultaneously with the generation schedules and LMPs for energy.

To compute the locational marginal prices or LMPs at each node in the transmission network and prices for each ancillary service for every hour of the following day, the independent system operator (ISO) minimizes the as-offered total cost (based on the generation-unit level hourly offer curves and location-specific hourly demand curves submitted for each hour of the following day) of serving the demand for energy and ancillary services at all locations in the transmission network during all 24 hours of the following day subject to all relevant transmission network and other relevant operating constraints. Although the locational demands for energy are determined by the offer curves submitted by the LSEs, the locational demand for each ancillary service is determined by the ISO. The network constraints used to solve for the day-ahead hourly market outcomes are the ISO's best estimate of real-time configuration of the transmission network during each hour of the following day. The solution to this as-bid cost minimization problem determines firm financial commitments for generation unit owners and load-serving entities for all 24 hours of the following day. The

day-ahead generation unit and locational load schedules and ancillary service schedules that solve this optimization problem are forward market sales and purchases for each hour of the following day.

For example, if a generation unit owner sells 50 MWh in the day-ahead market at a price of \$40/MWh during one hour of the following day, then this supplier is guaranteed to be paid, $\$2,000 = 50 \text{ MWh} \times \$40/\text{MWh}$, regardless of the actual production of energy from its generation unit during that hour of following day. Similarly, if a load-serving entity purchases 100 MWh in the day-ahead market during an hour of the following day at a price of \$75/MWh, then this entity must pay $\$7,500 = 100 \text{ MWh} \times \$75/\text{MWh}$, regardless of how much energy it withdraws from the network during that hour. The LMP at each node in the transmission network is equal to the increase in the minimized value of the objective function from this optimization problem as a result of increasing the amount of energy withdrawn at that location by 1 MWh. This property of the LMPs gives them their name. For ancillary services, the locational marginal price is also the increase in the minimized value of the objective function associated with increasing the locational demand for that ancillary service by 1 MW. These LMPs and ancillary services prices for all 24 hours of the following day are computed during the afternoon of the day before the energy is scheduled to be delivered. All market participants are notified of these prices and their day-ahead generation unit-level energy and ancillary services schedules and location-specific load schedules in the afternoon of the day-ahead before they are valid.

Starting with midnight the following day, a real-time market determines the actual output of all generation units necessary to serve demand at all nodes in the transmission network. The real-time generation output and load-serving entity withdrawal levels are determined by minimizing the as-offered cost of serving the actual demand for energy and ancillary services at all locations in the transmission network subject to all relevant constraints in the transmission network and on generation units in the real-time market. Suppliers are allowed to change their hourly generation unit-level offer curves between the day-ahead and real-time markets.

In all US ISOs, the real-time market is run every 5 minutes to determine the level of output of all generation units in the control area necessary to serve demand at all nodes in the transmission network. The solution to this optimization problem produces real-time locational marginal prices for each 5-minute interval within the hour. Hourly real-time prices are determined as the time average of the twelve 5-minute real-time prices during that hour. Generation unit owners that do not receive dispatch instructions within the hour receive this hourly real-time price for energy produced beyond their day-ahead forward market sales during that hour. Alternatively, they must purchase any energy sold in the day-ahead market during that hour that their unit does not produce at the hourly real-time price. Load-serving entities also only purchase or sell real-time deviations from their day-ahead schedules at the real-time price at their node in the transmission network. This combination of a day-ahead forward market and real-time spot market is called a multi-settlement market because of the property that only hourly real-time deviations from hourly day-ahead schedules are settled at the hourly real-time price.

Returning to the above example of the generator that sold 50 MWhs of energy in the

day-ahead market at a price \$40/MWWhs, if that generation unit only produced 40 MWWhs of energy, the owner would have to purchase the remaining 10 MWWhs at the real-time price to meet its forward market commitment. If the unit owner produced 55 MWWhs, then the additional 5 MWWhs beyond the unit's 50 MWWhs day-ahead schedule is sold at the real-time price.

2.2 Implicit Virtual Bidding in Multi-Settlement Markets

A supplier or load serving entity that expects the real-time LMP at their node to be different from the day-ahead LMP at their node could exploit this price difference by selling or buying more or less energy than it expected to produce or consume in real-time. For example, suppose that a generation unit owner expected to ultimately produce 100 MWWhs of energy from its unit and forecast a \$60/MWh real-time price that it expected to be higher than the day-ahead price. The unit owner would simply submit price offers into the day-ahead market at or above \$60/MWh, which could cause it to sell no energy in the day-ahead market. The supplier could then offer 100 MWWhs of energy into the real-time market as a price taker to ensure that it produces its expected output of 100 MWh. This is accomplished by offering to supply this energy into the real-time market at an offer price equal to the offer price floor.

These actions by the generation unit owner are likely to cause the day-ahead price to rise because less supply at or below the price of \$60/MWh has been offered into this market and the real-time price is likely to fall because more supply has been offered into this market. The net impact of the supplier's actions is to increase the likelihood that the day-ahead and real-time prices are closer together than would be the case if the supplier did not submit a high offer price into the day-ahead market. For this reason, these actions by generation unit owners have been called "implicit convergence or virtual bidding" because the supplier is using forward market sales from its generation unit as mechanism for exploiting expected price differences between the day-ahead and real-time markets.

Load-serving entities can also engage in implicit convergence bidding. Suppose that a load serving entity with a 100 MWh real-time demand expects the day-ahead price to be higher than the real-time price, which it expects to be \$100/MWh. This load-serving entity would then submit a demand bid into the day-ahead market with zero quantity demanded at prices above \$100/MWh. The load-serving entity would very likely not make any purchase in the day-ahead market and instead its demand would be entered as a price-taker in the real-time market. These actions by the load-serving entity would reduce the difference between the day-ahead and real-time price, because demand is lower in the day-ahead market and higher in the real-time market as a result of these actions.

Implicit convergence bidding can have severe system reliability consequences and increase the cost of serving system demand. The combination of the example of a supplier that submits high offer prices in the day-ahead market because of a desire to sell at a higher price in the real-time market and the desire of a load-serving entity to purchase at a lower price in the real-time market can result in aggregate day-ahead forward market generation and load

schedules that are below actual real-time demand levels. This can make it necessary for the system operator to have to find large amounts of additional energy between the close of the day-ahead market to ensure that actual demand is met. Wolak (2003) notes that during the summer of 2000 in the California electricity market this is precisely what happened in part because the offer cap on the day-ahead market was substantially higher than the offer cap on the real-time market. Load-serving entities submitted demand bids into the day-ahead with zero quantity demanded at offer prices above the offer cap on the real-time market. Suppliers submitted offer prices into the day-ahead market at or above the offer cap on the real-time market for much of their anticipated real-time output, which resulted in the day-ahead market clearing at quantity far below the anticipated real-time demand. This left the California ISO scrambling to find additional energy, often over 1/4 of the anticipated real-time demand, to ensure that real-time system demand would be met.

Besides the reliability consequences of implicit virtual bidding, there are also total variable cost consequences of these actions. All wholesale electricity markets have generation units that take a number of hours to start, but once started they are able to produce at a low variable cost. The implicit virtual bidding by both generation unit owners and load-serving entities can result in long-start, low-operating-cost units to be excluded from producing. Although it may be unilateral profit-maximizing for the owner of a portfolio of long-start, low-cost units and short-start, high-cost units to allow implicit virtual demand bids to cause some of these low-cost units not to operate, these actions increase the total cost of serving system demand.

2.3 Explicit Convergence Bidding versus Implicit Convergence Bidding

The two major motivations for introducing explicit convergence bidding are: (1) to eliminate the adverse reliability consequences of market participants attempting to exploit expected price differences between the day-ahead and real-time markets and (2) to reduce the total cost of serving final demand because market participants have lower cost options besides withholding long-start, low variable cost generation units to exploit differences between day-ahead and real-time prices. Convergence bidding introduces a purely financial instrument that allows generation unit owners, load-serving entities and energy traders to exploit LMP differences between the day-ahead and real-time markets so that generation unit owners and load-serving entities do not need to distort their bidding and offer behavior in the day-ahead market in ways that increase their costs and potentially harm system reliability.

Convergence or virtual bids are classified as either decremental (DEC) or incremental (INC) bids and are explicitly identified as such to the system operator. Market participants can submit either type of bid at any node in the transmission network. An INC bid at a node is treated just like a generation bid at the node. It is a step-function offer curve to supply additional energy in the day-ahead market. The only difference between an accepted convergence bid and an accepted bid from a generation unit owner is that the ISO knows that the energy sold in the day-ahead market from a convergence bid will be purchased in

the real-time market as a price-taker. A DEC convergence bid is treated just like a physical demand bid in the day-ahead market. It is a step function bid curve to purchase additional energy in the day-ahead market. An accepted DEC convergence bid implies an obligation to sell this energy in the real-time market as a price-taker.

As should be clear from the above description, an INC convergence bid has a revenue stream equal to the difference between the day-ahead and real-time LMPs at that node times the amount of MWhs sold in the day-ahead market and a DEC convergence bid has a revenue stream equal to the difference between the real-time and day-ahead LMPs at that node times the amount of MWhs purchased in the day-ahead market. An INC convergence bid earns positive revenues if the day-ahead price is higher than the real-time price, but the actions of INC convergence bidders made earning these profits less likely because the supply is higher in the day-ahead market and demand is higher in the real-time market as a result of the INC bids. A DEC convergence bid earns positive revenues if the real-time price is higher than the day-ahead price. The actions of DEC convergence bidders make this outcome less likely because demand in the day-ahead market is higher and supply in the real-time market is higher as a result of the DEC bids.

There are a number of reasons to believe that the introduction of explicit convergence bidding will lead to smaller realized nodal price differences between the day-ahead and real-time markets. First, submitting a convergence bid is a lower cost way for a market participant to take a financial position designed to profit from expected price differences between the day-ahead and real-time markets. By submitting an INC convergence bid with an offer price below the price it expects in the real-time market, a market participant can earn the difference between day-ahead and real-time market prices. The availability of this financial instrument makes it unnecessary for a supplier or load-serving entity to employ more costly distortions in their day-ahead energy purchases or sales in order to exploit expected day-ahead versus real-time price differences. Instead the supplier can offer their generation unit into the day-ahead market at its variable cost and submit decremental convergence bids with offer prices equal to the generation unit owner's expected real-time market price. In this way, the generation unit owner does not distort its offer prices for its generation units in order to exploit expected price differences between the day-ahead and real-time markets.

A second reason that nodal-level day-ahead versus real-time price differences are likely to be smaller is because of the introduction of explicit convergence bidding gives market participants greater flexibility to exploit locational price differences. A generation unit owner can only implicitly convergence bid total MWhs less than or equal to the capacity of their generation unit at a given node. An implicit convergence bidding supplier has no recourse if withholding this generation unit from the day-ahead market cannot increase the day-ahead price enough to cause it to equal the expected real-time price at that location. However, with (explicit) convergence bidding, the supplier can submit an almost unlimited quantity of DEC bids at that location to raise the price at that node in the day-ahead market. The same logic goes for a load-serving entity engaging in implicit virtual bidding. The actual demand of a load-serving entity limits the amount of demand it can bid into the day-ahead market. For example, without explicit convergence bidding, if bidding no demand into the day-ahead market still does not reduce the LMP at that node to the level the load-serving

entity expects in the real-time market, that supplier has no other way to reduce the day-ahead price at that node. However, with a sufficient volume of INC bids, the load-serving entity can reduce the price at that node to any level it expects to prevail in the real-time market.

Before nodal-level convergence bidding was introduced in California, the opportunities to implicit virtual bid at the nodal level was limited to locations with generation units. Implicit virtual bidding at nodes with no generation units was not possible. The California market requires the three large load-serving entities—Southern California Edison (SCE), Pacific Gas and Electric (PG&E), and San Diego Gas and Electric (SDG&E)—to bid their service area-level demand into the day-ahead market and the California ISO allocates this demand to all nodes in the load-serving entity’s service territory using load-distribution factors (LDFs) that the ISO produces. For example, if a load-serving entity has 100 MWhs of load and the ISO computes equal LDFs for the ten nodes in its service area, then the load-serving entity’s LDFs are equal to 1/10 for each node. This implies that it is very costly for a load-serving entity to implicitly virtual bid 1 MWh at one node, because this would effectively require 1 MWh of implicit virtual bids at all nodes. With the introduction of explicit nodal-level virtual bidding, load-serving entities and generation unit owners can exploit day-ahead and real-time price differences at any node, even those with no generation units, by submitting a virtual bid at that node.

A final market efficiency benefit of introducing explicit virtual bidding is that it makes it much easier for market monitors and regulatory authorities to identify implicit virtual bidding. Before the introduction of explicit virtual bidding a generation unit owner or load-serving entity could always claim that the reason their day-ahead sales or purchases was substantially less than their real-time production or consumption is because of the expectation of more favorable prices in the real-time versus day-ahead market. With the introduction of explicit virtual bidding, regulators can argue that suppliers and load-serving entities should sell and purchase their best estimate of their expected real-time production and consumption in the day-ahead market, because they can use convergence bidding to exploit any expected differences between day-ahead and real-time prices. The existence of this additional product to exploit expected price differences allows the regulator to be tougher on actions that might be unilaterally profit-maximizing for suppliers and load-serving entities but also reduce system reliability and overall market efficiency.

3 Descriptive Statistics for California Market

This section summarizes our evidence on hourly price convergence between the day-ahead and real-time markets for the three large load-serving entities in California before and after the implementation of convergence bidding. We also present the results of a test of the null hypothesis that the mean price difference vector for the 24 day-ahead and real-time hourly prices is equal to zero for these three load-serving entities and find that we overwhelmingly reject this null hypothesis in all cases. However, these naive tests do not account for the

transactions costs associated trading to exploit these mean price differences, motivating the development of our testing procedure, which does account for transactions costs.

These hypothesis tests are implemented using price data from April 1, 2009 when nodal pricing was implemented in California, to December 31, 2012 for the 24 hourly real time and day-ahead wholesale electricity prices. These prices are set at the node level and there are over 5,000 nodes, all with potentially different prices. However, each of the three large load-serving entities faces a single load aggregation point (LAP) price each hour of the day which is computed as a nodal quantity-weighted average price for that load-serving entity summed over all nodes in the load-serving entity's service area with positive amount of energy withdrawn from the transmission network during that hour. Each of the three large load-serving entities has its own day-ahead and real-time LAP price determined by the California ISO. For each of these LAPs, we compute the hour-of-day average price difference for all hours of the day.

Figure 1 presents a comparison by hour of day of the average difference between the day-ahead and real-time prices for the PG&E, SCE, and SDG&E LAPs both before and after the introduction of convergence bidding. This figure provides descriptive evidence that the day-ahead/real-time price spread is more pronounced prior to the introduction of virtual bidding than afterwards for each of the load-serving entities. For example, for PG&E, the average day-ahead price is much lower than the average real-time price during the hours of 8PM–12AM. These results immediately raise the question of whether these mean price differences reflect the existence of profitable trading strategies or are simply due to the existence of non-zero trading costs that allow non-zero mean price differences.

[Figure 1 about here.]

To further motivate our subsequent analysis, we present a zero transaction cost version of an arbitrage test for the PG&E, SCE, and SDG&E LAPs after the introduction of explicit virtual bidding in Figure 2. Namely, we plot the average day-ahead/real-time spread along with pointwise 95% confidence intervals around these means. For all three load-serving entities for some hours of the day, we can reject at a 5% significance level that the price spread is zero. Along these same lines, we can also simply perform a joint test that the daily mean of the vector of day-ahead and real-time price differences is zero for all hours of the day. We use the Newey and West (1987) autocorrelation consistent asymptotic covariance matrix estimate, $\hat{\Sigma} = \hat{\Lambda}_0 + \sum_{j=1}^m w(j, m)[\hat{\Lambda}_j + \hat{\Lambda}_j']$, where $\hat{\Lambda}_j = \sum_{t=j+1}^T (X_t - \bar{X})(X_{t-j} - \bar{X})'/T$, $\bar{X} = \sum_{t=1}^T X_t/T$, $w(j, m) = 1 - [j/(m + 1)]$ for $m = 14$ to construct the chi-squared test statistics. These test statistics are presented for each LAP before and after the introduction of explicit virtual bidding in Table 1. Note that these test statistics are quite large. We would reject the null hypothesis that the mean of the price difference vector is zero in all cases.¹ However, these two tests fail to account for the potentially sizable transaction costs present in nearly every commodities market. In the next section, we present a hypothesis test for the existence of the profitable trading strategy that accounts for the fact that the day-ahead/real-time price spread can differ from zero simply due to positive transaction costs.

¹The upper $\alpha = 0.05$ critical value for the $\chi^2(24)$ distribution is 36.415.

[Figure 2 about here.]

[Table 1 about here.]

4 Tests for the Existence of a Profitable Trading Strategy

4.1 Introduction

In this section, we first develop our test of the null hypothesis that a profitable trading strategy exists. For simplicity, we restrict attention to trading strategies that only condition on the value of the (24x1) vector of hour-of-day day-ahead minus real-time mean price differences. Our null hypothesis is that a profitable trading strategy exists. Rejection of this null hypothesis implies that the data provides evidence against the existence of a profitable trading strategy based on, μ , the unconditional mean of the (24 x 1) vector of daily price differences. We then present empirical evidence that strategies that condition on past realizations of the vector of daily price differences are unlikely to be of practical importance, because we find no evidence against the null hypothesis that all autocorrelations in the daily price differences vector beyond the first lag are jointly zero. The timing of the day-ahead and real-time markets precludes trading strategies that condition on the first lag of the price difference vector because the all real-time prices for the current day are not known when market participants submit their offers into the day-ahead market for the following day.²

It is often the case when analyzing the performance of a new drug relative to an existing drug that the researcher would like to conclude the two drugs are bioequivalent in terms of their efficacy. In this general case, the researcher formulates the null hypothesis as some nonlinear function $g(\theta)$ of the parameter vector of interest lies outside of the set (a,b) , versus the alternative that it lies in the set (a,b) . If the interval (a,b) contains zero, then rejection of the null hypothesis implies the two drug are bioequivalent, because the difference in their efficacy does not lie outside the interval (a,b) . For this reason, this class of hypotheses are called equivalence hypotheses. See Romano (2005) for a discussion of optimal equivalence tests.³ Note than the typical approach to testing market efficiency as the null hypothesis is to find no evidence against market efficiency by failing to reject the null hypothesis. By formulating the test as an equivalence hypothesis, failing to reject the null hypothesis says that we have no evidence against the null hypothesis that a profitable trading strategy exists. On the other hand, rejection of the hypothesis implies that the data is inconsistent with the existence of a profitable trading strategy based on the unconditional mean of the price differences.

²Offers to the day-ahead market must be submitted by noon the day before actual system operation, so it is not possible to base a daily trading strategy on knowledge of the first-order autocorrelation of the price differences vector.

³Testing equivalence hypotheses has a rich tradition in the statistics literature. See Berger and Hsu (1996), Perlman and Wu (1999), and Munk and Pflüger (1999).

We motivate our statistical test by considering the problem facing a market participant attempting to maximize expected profits from exploiting day-ahead versus real-time price differences. The hypothesis test is derived from expected profit-maximizing trading strategy involving a portfolio of the 24 (one for each hour of the day) price differences. Because the explicit costs of buying and selling these assets is only one component of the cost of exploiting these price differences, we use the hypothesis tests to recover an implied trading cost and a distribution of this implied trading cost. We do this both at the LAP and nodal level, for before and after the introduction of convergence bidding. Using a hypothesis testing procedure for directionally differentiable functions of a regular parameter estimate developed by Fang and Santos (2014), we apply a bootstrap procedure developed by Hong and Li (2015) to compute an estimate of the distribution of the trading cost estimate. Comparing these estimated trading cost distributions before versus after the introduction of convergence bidding allows us to assess whether the point estimates of our implied trading costs are statistically significantly different before versus after the introduction of convergence bidding. We also perform a test of the null hypothesis that the profits traders expected to earn from buying and selling differences between the 24 day-ahead and real-time prices fell after the implementation of convergence bidding using the multivariate inequality constraints testing procedure of Wolak (1989).

4.2 The Trader's Problem

Consider a trader with access to 24 assets, where asset X_h for $h \in \{1, \dots, 24\}$ is equal the difference between the day-ahead and real-time price for hour h of the day. This implies $X_h = P_h^{DA} - P_h^{RT}$, where P_h^{DA} is the day-ahead price for hour h and P_h^{RT} is the real-time price for hour h . Purchasing this security requires the trader to sell 1 MWh more energy in the day-ahead market than it produces in real-time. Selling this security requires that the trader buy 1 MWh more energy in the day-ahead market than it consumes in real-time. Let $\mu_h = E(X_h) = E(P_h^{DA}) - E(P_h^{RT})$ for $h = 1, 2, \dots, 24$. Define μ as the 24×1 vector composed of $(\mu_1, \mu_2, \dots, \mu_{24})'$ and X_d equal the 24×1 vector composed of $(X_{1d}, X_{2d}, \dots, X_{24d})'$ for day d . Let Λ_0 equal the 24×24 contemporaneous covariance matrix of X_d . Suppose the per-unit trading cost of buying or selling this security is c . The expected profit-maximization problem of a trader holding the portfolio with weights vector, $a = (a_1, a_2, \dots, a_{24})'$, where each a_i can be positive or negative, and paying a per unit trading cost c is:

$$\max_{a \in R^{24}} a' \mu - c \sum_{i=1}^{24} |a_i| \text{ subject to } \sum_{i=1}^{24} |a_i| = 1. \quad (1)$$

Our null hypothesis is that this optimization problem results in a sufficiently positive expected profit for the vector-valued function of μ , $a(\mu)^* \in R^{24}$, that solves this problem. Our equivalence null hypothesis is that $a(\mu)^* \mu - c > 0$. Note the trader pays the same dollar per MWh charge for sales and purchases of the hourly price difference, which is why the trading charge is assessed on the sum of the absolute values of the individual portfolio weights, a_i , which satisfy the constraint $\sum_{i=1}^{24} |a_i| = 1$. The optimized value of the objective function

reduces to

$$a(\mu)^* \mu = \max_{i \in \{1, \dots, 24\}} |\mu_i| \quad (2)$$

Our procedure fits the framework developed by Fang and Santos (2014) for testing hypotheses involving directionally differentiable functions of a regular parameter estimate. The function $\phi(\mu) \equiv a(\mu)^* \mu$ is a directionally differentiable function of the parameter vector, μ , and $\bar{X} = \frac{1}{N} \sum_{d=1}^N X_d$ where N is the number of days in the sample. Because $\sqrt{N}(\bar{X} - \mu)$ possesses an asymptotic normal distribution, the sample mean of the X_d is regular estimate of μ .

4.3 Test for the Existence of a Profitable Trading Strategy

To implement the hypothesis test, we compute $\phi(\bar{X})$, which also equals the element of \bar{X} that is the largest in absolute value. The difference between $\phi(\bar{X})$ and c , the trading cost is our test statistic. Fang and Santos (2014) present a modified bootstrap procedure for computing an estimate of the asymptotic distribution of a directionally differentiable function of \bar{X} , this case $\sqrt{N}(\phi(\bar{X}) - \phi(\mu))$. Hong and Li (2015) develop a numerical derivative-based procedure for simulating the distribution of $\phi(\bar{X})$ that proceeds as follows. Compute a moving blocks bootstrap re-sample of \bar{X} , say \bar{X}^b , with block size equal to the largest integer less than or equal to $N^{1/3}$. Using these two magnitudes compute:

$$Z^b = \frac{\phi(\bar{X} + \sqrt{N}(\bar{X}^b - \bar{X})\epsilon) - \phi(\bar{X})}{\epsilon}, \quad (3)$$

for $b = 1, 2, \dots, B$. Hong and Li (2015) demonstrate that the asymptotic distribution of $\sqrt{N}(\phi(\bar{X}) - \phi(\mu))$ can be approximated by the bootstrap distribution of Z^b as T go to infinity and ϵ tends to zero sufficiently slow so that $\epsilon\sqrt{T}$ tends to infinity. We use $\epsilon = T^{-1/3}$, the value recommended by Hong and Li (2015).

Although we can compute the cost of purchasing or selling elements of X_d in the California ISO market, this is just one component of the trading cost. Setting the trading cost, c , equal to this magnitude and performing our hypothesis test implies that there is no opportunity cost of the time of the individual undertaking the trades, no up-front costs of participating in the ISO markets, and no other cost associated with preparing or updating a strategy for trading day-ahead and real-time price differences. For this reason, we use our hypothesis testing results to compute implied trading costs. These implied trading costs can be compared to the actual cost of purchasing and selling the 24 elements of X in the ISO market, including conservative estimates of other transaction costs.

We use the bootstrap distribution of Z^b to compute an estimate of the distribution of $\phi(\bar{X})$. We compute each bootstrap re-sample of $\phi(\bar{X})$ as:

$$\phi(\bar{X})^b = \phi(\bar{X}) + \frac{Z^b}{\sqrt{T}}. \quad (4)$$

We then use this distribution to compute two values of c : (1) the smallest value of c that causes rejection of the $\alpha = 0.05$ size test of null hypothesis $a(\mu)^* \mu - c > 0$ and (2) the largest

value of c that causes rejection of the $\alpha = 0.05$ test of the null hypothesis $a(\mu)^* \mu - c < 0$. The first value of c is the smallest value of the dollar per MWh trading cost that would cause rejection of the null hypothesis that a profitable trading strategy exists. It is computed as the lower 5th percentile of the distribution of $\phi(\bar{X})$. For this reason, we denote it c_{lower} . The second value of c is the largest value of the trading charge that causes rejection of the null hypothesis that no profitable trading charge exists. It is computed as the 95th percentile of the distribution of $\phi(\bar{X})$. For this reason, we denote it c_{upper} .

4.4 Test for Difference in Absolute Value of Means Before and After Virtual Bidding

We also test whether expected trading profits fell after the introduction of convergence bidding using a multivariate inequality constraints test. If we let the trading costs prior to explicit virtual bidding be c^{pre} and the trading costs after explicit virtual bidding be c^{post} , then a test of the null hypothesis that trading profits fell after the introduction of explicit virtual bidding can be formulated as $|\mu_{pre}| - \mathbf{1}c^{pre} > |\mu_{post}| - \mathbf{1}c^{post}$, where $|\mu_J|$ is the vector composed of the absolute value of the individual elements of the vector μ_J for $J = pre, post$, and $\mathbf{1}$ is 24 x 1 vector of 1's. The difference $|\mu_{pre}| - \mathbf{1}c^{pre}$ is the expected profits associated with buying one unit of μ_h if it is positive and selling one unit μ_h if it is negative for $h = 1, 2, \dots, 24$. Consequently, re-arranging this inequality we see that it implies $|\mu_{pre}| - |\mu_{post}| > \mathbf{1}(c^{pre} - c^{post})$. If we assume that $c^{pre} > c^{post}$, which is consistent with the results presented in Section 5, then the null hypothesis that expected trading profits fell after the introduction of convergence bidding is that $|\mu_{pre}| - |\mu_{post}| > 0$. Therefore, testing $|\mu_{pre}| - |\mu_{post}| > 0$ is a test of that null hypothesis. Conversely, by rejecting the null hypothesis $|\mu_{post}| > |\mu_{pre}|$, we can conclude that the null hypothesis that trading profits were higher after the introduction of convergence bidding can be rejected. If we fail to reject the null hypothesis that $|\mu_{pre}| > |\mu_{post}|$ but reject the null hypothesis that $|\mu_{post}| > |\mu_{pre}|$, then we have evidence that trading profits fell after the introduction of convergence bidding.

We implement these two multivariate nonlinear inequality constraints tests using the methodology derived in Wolak (1989). We present the procedure for $|\mu_{pre}| > |\mu_{post}|$ below:

Proposition 1 Direct Test of Null Hypothesis that $|\mu_{pre}| > |\mu_{post}|$

Let $\hat{V} = diag[SIGN(\bar{X}^{pre})]' \frac{\hat{\Sigma}^{pre}}{N^{pre}} diag[SIGN(\bar{X}^{pre})] + diag[SIGN(\bar{X}^{post})]' \frac{\hat{\Sigma}^{post}}{N^{post}} diag[SIGN(\bar{X}^{post})]$ and calculate the test statistic:

$$TS = \min_{\theta \geq 0} (|\bar{X}^{pre}| - |\bar{X}^{post}| - \theta)' \hat{V}^{-1} (|\bar{X}^{pre}| - |\bar{X}^{post}| - \theta)$$

We reject the Null hypothesis that $|\mu_{pre}| > |\mu_{post}|$ if and only if $\sum_{h=1}^{24} w(24, 24-h, \hat{V}) Pr[\chi^2_{(h)} > TS] < \alpha$, where χ^2_h is a chi-squared random variable with h degrees of freedom and $w(24, 24-h, \hat{V})$ are the weights defined in Wolak (1989) and α ia the size of the hypothesis test.

Cataloging notation, the $diag[Z]$ operator takes a vector Z , and returns a diagonal matrix with elements of Z on the diagonal. $\hat{\Sigma}^{pre}$ is the estimated autocorrelation consistent

asymptotic covariance matrix with $m = 14$ lags of the vector of hour-of-day price difference means prior to the introduction of explicit virtual bidding and N^{pre} is the number of days in the sample prior to the start of explicit virtual bidding. $\hat{\Sigma}^{post}$ is the estimated autocorrelation consistent covariance matrix with $m = 14$ of the vector of means after to the introduction of explicit virtual bidding and N^{post} is the number of days in the sample after explicit virtual bidding. These are the same estimates used in the prior subsection describing the trading costs-based approach. Note that we calculate $w(24, 24 - h, \hat{V})$ using the simulation method described in Wolak (1989).

4.5 Test for Difference Between Variance Matrices Before versus After Virtual Bidding

We also expect that the introduction of explicit virtual bidding to reduce the day-ahead uncertainty about real time prices. We would therefore expect that the variance of the day-ahead/real-time price difference and the variance of real-time prices to fall after the introduction of explicit convergence bidding.

With nodal-level convergence bidding, market participants can profit from their ability to forecast real-time system conditions at any location in the transmission network. A market participant that believes the real-time price will be higher than the day-ahead price because of a higher real-time demand for energy at a location will submit a DEC bid to purchase energy in the day-ahead market that is subsequently sold at the real-time price. If this market participant is correct, she will be rewarded with positive trading profits. However, these actions will also cause the day-ahead price to rise (because of the higher day-ahead demand implicit in the DEC bid) and the real-time price to fall (because of the higher real-time demand due to the sale of the accepted DEC bid in the real-time market), which will reduce this market participant's trading profits. These profits will not go to zero unless the total (across all market participants) amount of day-ahead DEC bids at that location is large enough to close this price gap. Conversely, market participants that incorrectly believe the real-time price will be lower than the day-ahead price because they believe the real-time demand at that location will be lower will submit INC bids and subsequently purchase the energy sold in the day-ahead market from the real-time market. They will lose money from these actions.

These market outcomes for the two types of convergence bidders create the incentive for final day-ahead generation schedules to be closer to the real-time output of these generation units, leading to the prediction that we should see a decrease in the volatility in day-ahead/real-time price spread as well as the volatility in real-time prices themselves after the introduction of convergence bidding. In short, the actions of expected profit-maximizing convergence bidder causes day-ahead generation schedules to resemble more closely real-time electricity production. This should lead to less volatility in real-time prices and the difference between day-ahead and real-time LMPs because the ISO will be less likely to have to make substantial purchases or sales in the real-time market at any location in the transmission network.

Formally, we consider the Null hypothesis that $H_1 : \Lambda_{pre} - \Lambda_{post}$ is a positive semi-definite matrix, where Λ_J is the 24×24 contemporaneous covariance matrix for time period $J \in \{pre\ EVB, post\ EVB\}$. In order to implement this test, we find the eigenvalues $\hat{\omega}_j$, $j = 1, 2, \dots, 24$ of $\hat{\Omega} \equiv \hat{\Lambda}_{pre} - \hat{\Lambda}_{post}$ and test the joint null hypothesis that all of these eigenvalues are greater than or equal to zero. We use the multivariate inequality constraints test employed in the previous section, where we obtain the covariance matrix for our estimated eigenvalues $\hat{\omega}_j$, $j = 1, 2, \dots, 24$ using a moving-block bootstrap procedure. Briefly, this moving block procedure accounts for fact that the variable of interest (X_d) may be autocorrelated across days. Let $\hat{\Lambda}_c$ equal the (24×1) vector of eigenvalues of Ω . We employ a moving-blocks bootstrap to compute an estimate of asymptotic covariance matrix $\hat{\Lambda}_c$. First we re-sample contiguous blocks of length $B = N^{1/3}$ (where N is the sample size) from the time series of daily price difference vectors. We repeat this process L times and to yield a $\hat{\Lambda}_c^b$ for each re-sample $b \in \{1, 2, \dots, L\}$. We then take the sample covariance of these $\hat{\Lambda}_c^b$ over L re-samples in order to get an estimate of the covariance matrix of $\hat{\Lambda}_c$, which we call $Var(\hat{\Lambda}_b)$. Our statistic $TS = \min_{z \geq 0} N(\hat{\Lambda}_c - z)'[Var(\hat{\Lambda}_c)]^{-1}(\hat{\Lambda}_c - z)$ is asymptotically distributed as the weighted sum of chi-squared random variables given in the previous section under the null hypothesis.

We can also perform this test for $H_2 : \Lambda_{post} - \Lambda_{pre}$ is a positive semi-definite matrix. Failing to reject H_1 and rejecting H_2 (for both the vector of price differences and the vector of real time prices) would give us strong evidence consistent with our prediction that the introduction of convergence bidding reduced the variance in the day-ahead/ real-time price spread and the variance of real-time prices.

4.6 Why not condition on past values of X_d ?

Because all of the values of the (24×1) vector real-time prices for day $d - 1$ are not known before offers are submitted to the day-ahead market for day d , there can be first-order autocorrelation between realizations of X_d that cannot be exploited through a feasible trading strategy. Specifically, any trading strategies involving portfolios of the (24×1) price differences that condition on X_{d-k} , for $k > 0$, would have to condition on values from at least $k = 2$ days ago, because those are the only realizations of X_{d-k} that are known when a market participant submits bids or offers into the day-ahead market for day d . This logic implies that X_d following a vector MA(1) process is consistent with the lack of a profitable trading strategy that conditions on past values of X_d . To investigate this hypothesis, we would like to estimate a vector MA(1) process for X_d and then test null hypothesis that the errors from this model are multivariate white noise. However, estimating the (24×1) vector MA(1) model necessary to test this hypothesis has proven extremely difficult to compute in finite time.

As a result, we formulate a different approach that does not rely on estimate a vector MA(1) model for the daily price difference vector. Consider the following 24×24 autocorrelation matrix: $\Gamma(\tau) = E(X_t - \mu)(X_{t-\tau} - \mu)'$. Based on the above discussion, the lack of a profitable trading strategy that conditions on past values of X_d corresponds to X_t having a non-zero value of $\Gamma(1)$, but $\Gamma(\tau) = 0$ for all $\tau > 1$. We consider the Null

hypothesis:

$$H : \Gamma(2) = 0, \Gamma(3) = 0, \dots, \Gamma(R) = 0$$

for a fixed value of R . For our application, we test using $R = 10$. This hypothesis test is implemented by first defining $\xi \equiv \text{vec}(\Gamma(2), \Gamma(3), \dots, \Gamma(L))$, where the $\text{vec}(\cdot)$ operator takes a (24 x 24) matrix and stacks it columnwise to create a (576 x 1) vector. Therefore, ξ has $5760 = 576 * 10$ elements, which all must equal zero under the Null hypothesis. We create a simple Wald Statistic, using the moving block bootstrap (described more fully in the previous subsection) in order to estimate the 5760 x 5760 covariance matrix associated with $\hat{\xi}$. Our Wald statistic $N\hat{\xi}'\hat{\Sigma}_{\xi,\text{boot}}^{-1}\hat{\xi}$ is asymptotically distributed as a chi-squared with $24^2 * (R - 1)$ degrees of freedom under the null hypothesis.

5 Empirical Results

This section presents our estimation of c_{lower} and c_{upper} and our tests that expected trading profits fell after the introduction explicit virtual bidding. Before we present these results, we provide some evidence that more complex trading strategies based on lagged values of price differences may not yield significant profit improvements relative to a strategy that just conditions on the elements of μ .

5.1 Is there autocorrelation in daily price differences beyond the first lag?

We now describe our test of the null hypothesis that the second through tenth autocorrelation matrices for X_d are zero: $\Gamma(2) = \Gamma(3) = \dots = \Gamma(10) = 0$. We test separately for each LAP, both before and after the introduction of explicit virtual bidding. The test statistics are recorded in Table 2. The upper $\alpha = 0.05$ critical value for these test statistics is $\chi^2(5184) = 5352.6$.

[Table 2 about here.]

For this critical value, we fail to reject the null hypothesis that the second through tenth autocorrelation matrices are zero for any LAP, either before or after the introduction of convergence bidding. This lends strong evidence in favor of our assertion that daily price differences follow an MA(1) process. As traders cannot condition on the previous day's price realizations when submitting into the day-ahead market, we only consider trading strategies that depend on, μ , the unconditional mean of X_d .

We repeated these same autocorrelation tests at the nodal level and found that before the implementation of convergence bidding, particularly at non-generation nodes, the null hypothesis that $\Gamma(2) = \Gamma(3) = \dots = \Gamma(10) = 0$ could be rejected at approximately 70 percent of the nodes. However, after the implementation of convergence bidding this null hypothesis was rejected at approximately five percent of the generation and non-generation nodes which

is consistent with this null hypothesis being true for all nodes after the implementation of convergence bidding, because the size of each individual nodal-level test was $\alpha = 0.05$.

5.2 Results from Trading Costs Hypothesis Tests

We first implement our trading cost hypothesis tests at the load aggregation point (LAP) level. These results are presented in Table 3. For each LAP we report the value of c_{lower} and c_{upper} both before and after the introduction of explicit convergence bidding. Recall that c_{lower} is the smallest value of c such that the null hypothesis of the existence of an expected profit-maximizing trading strategy can be rejected and that c_{upper} is the largest value of c such that the null hypothesis that no profitable trading strategy exists can be rejected. First note from Table 3 that for all LAPs, the values of both c_{lower} and c_{upper} fall after the introduction of explicit virtual bidding. This is consistent with logic outlined in Section 2 that the costs of trading day-ahead versus real-time price differences decreases after the introduction of explicit virtual bidding. Figure 3 plot the bootstrap distributions of $\phi(\bar{X})$ for the pre-EVB and post-EVB sample period for each of the three LAPs. The solid vertical lines on each graph are the values of c_{lower} and c_{upper} for the pre-EVB sample period and the dotted vertical lines on each graph are the values of c_{lower} and c_{upper} for the post-EVB sample.

[Figure 3 about here.]

[Table 3 about here.]

To obtain a more formal comparison of the implied trading costs before versus after the introduction of explicit virtual bidding, we compute the bootstrap distribution of the difference in implied trading costs for each LAP before versus after the implementation of explicit virtual bidding. Figure 5 plots the bootstrap distribution of the difference in trading costs for each of the three LAPs. The lower vertical line on the graph is the 5th percentile of the distribution of $c_{pre} - c_{post}$ and the upper vertical line is the 95th percentile of this distribution. If 5th percentile of the distribution of $c_{pre} - c_{post}$ is greater than zero, then this implies that the $\alpha = 0.05$ test of the the null hypothesis that $c_{pre}^{true} \leq c_{post}^{true}$ can be rejected. If 95th percentile of the distribution of $c_{pre} - c_{post}$ is less than zero, then this implies that the $\alpha = 0.05$ test of the the null hypothesis that $c_{pre} \geq c_{post}$ can be rejected. For both SCE and SDG&E the null hypothesis that the difference in trading costs pre- versus post-EVB is less than or equal to zero can be rejected and the null hypothesis that the trading charges pre-versus post-EVB is greater than zero cannot be rejected. For PG&E the null hypotheses cannot be rejected for both tests.

We can also compute the values of c_{lower} and c_{upper} for each node in the California ISO control area. Figure 4 plots the values of c_{lower} and c_{upper} for each node before and after the introduction of EVB.⁴ We plot the across-node distributions of c_{lower} and c_{upper} separately

⁴Note that the box portion of box and whiskers plot corresponds to the 25% through 75% of the distribution of trading costs over nodes. The upper (lower) whisker corresponds to data points within 1.5(IQR) of the 75% (25%) quantile point, where IQR is the inter-quartile range defined by the distance between the 25% and 75% quartiles. Finally, the remaining points are outliers outside of the aforementioned range.

for nodes associated with generation units and nodes not associated with generation units. Note that the inter-quartile range of the distribution these two measures of implied trading costs across nodes markedly decreases when we calculate it using data after the introduction of explicit virtual bidding. Recall that we reject the null hypothesis that a profitable trading strategy exists for actual trading costs larger than than the values plotted for c_{lower} . Therefore, for any value of actual trading costs, we would reject our null hypothesis of the existence of a profitable trading strategy at more nodes after the introduction of explicit virtual bidding.

We repeat the bootstrap estimation of the distribution of $c_{pre} - c_{post}$ for each of the more than 4,000 nodes in the California ISO control area. The first line of Table 4 reports the fraction of nodes that the null hypothesis that $c_{pre}^{true} \leq c_{post}^{true}$ can be rejected for generation nodes (Gen Node) and for non-generation nodes (Non-Gen Node). The second line of Table 4 reports fraction of nodes that the null hypothesis that $c_{pre}^{true} \geq c_{post}^{true}$ can be rejected for generation nodes (Gen Node) and for non-generation nodes (Non-Gen Node). For more than 70 percent of the nodes the null hypothesis that the implicit trading charge increased after the introduction of EVB can be rejected. The percentage of rejections at non-generation nodes is slightly higher than at generation nodes. For less than 5 percent of the nodes, the null hypothesis that the trading charge fell after the introduction of EVB can be rejected. This rejection frequency is consistent with this null hypothesis being true for all nodes, because of the size of each hypothesis test is 0.05.

[Table 4 about here.]

[Figure 4 about here.]

From the logic discussed in sections 2.2 and 2.3, we expect the following two relationships to hold between the true values of the implied trading costs across generation versus non-generation nodes before versus after the introduction explicit convergence bidding. First, because suppliers can implicitly convergence bid at the nodal level before the implementation of the explicit convergence bidding through how they operate their generation units and load-serving entities can only bid in at the LAP level before explicit convergence bidding, we expect the implied trading costs to be higher at non-generation nodes before the implementation of explicit convergence bidding. Second, because the introduction of explicit convergence bidding allows, for the first time, convergence bidding at non-generation nodes, we expect the the mean reduction in implied trading costs for non-generation nodes to be larger than for generation nodes. To test these two hypotheses, we regressed the value of c_{lower} and c_{upper} at each node both before and after explicit convergence bidding on a constant, an indicator variable for whether the node was a generation node, an indicator variable for whether the implied trading cost was from the post-explicit convergence bidding period, and an indicator variable for whether the observation was from a generation node during the post-explicit convergence bidding period (the interaction term between “generation node” and “post explicit virtual bidding”).

Table 5 reports the results of estimating these difference-in-differences style regressions for c_{lower} and c_{upper} . For both percentiles of the distribution of nodal-level implicit trading costs, we find strong evidence consistent with both of our hypotheses. The best linear

prediction of both c_{lower} and c_{upper} before the introduction of explicit virtual bidding is significantly lower for generation nodes and this difference is essentially eliminated after the introduction of virtual bidding. Specifically, for both c_{lower} and c_{upper} , we find that the null hypothesis that the sum of the coefficient on "Generation Node Indicator" and the coefficient on "Interaction Between Generation Node and Post EVB Indicator" is zero cannot be rejected. Combining this result with the very large predicted reduction in implied trading costs for all nodes after the introduction of explicit virtual bidding, implies that the difference in implied trading cost before versus after explicit virtual bidding fell more for non-generation nodes than for generation nodes.

[Figure 5 about here.]

Figure 6 contains monthly average hourly virtual supply offered and cleared and virtual demand offered and cleared for October 2011 to December 2012 taken from the California ISO Department of Market Monitoring's Q4 Report on Market Issues and Performance of February 13, 2013. This graph shows that slightly less than 1,000 MWh of virtual supply clears each hour and approximately the same level of virtual demand clears each hour, with roughly half of the virtual supply and virtual demand offers clearing each hour. Because there are over 4,000 nodes in the ISO system and minimum convergence bid offer is 1 MWh, there are many nodes each hour that do not receive node-level convergence bids. Figure 7 shows the average offer and cleared virtual demand and supply virtual bids by hour of the day for October to December of 2012. Particularly, for demand bids, there are significantly higher levels of offered and cleared bids during the peak demand hours of the day, whereas for virtual supply bids the pattern of offers and cleared bids is fairly constant throughout the day.

[Figure 6 about here.]

[Figure 7 about here.]

[Table 5 about here.]

5.3 Results from Test for a Fall in Trading Profits

In this section, we implement the direct tests that $|\mu_{pre}| > |\mu_{post}|$ and $|\mu_{post}| > |\mu_{pre}|$. If we assume that $c^{pre} > c^{post}$ as appears to be the case from the implied trading cost results presented in the previous section, then $|\mu_{pre}| > |\mu_{post}|$ is a test of the null hypothesis that expected trading profits declined as result of the introduction of convergence bidding. The p-values corresponding to these tests for each LAP are presented below in Table 6:

[Table 6 about here.]

We cannot reject the null hypothesis that $|\mu_{pre}| > |\mu_{post}|$ for any of the three LAPs, while we can reject the null hypothesis that $|\mu_{post}| > |\mu_{pre}|$ at the 5% level for two of the three LAPs. If $c^{pre} > c^{post}$, as is implied by the results in Figure3 and Table3, these hypothesis testing results provide evidence in favor of the view that trading profits fell after the introduction of explicit virtual bidding.

5.4 Results from Test for a Fall in Volatility

As outlined in Section 4.6, we expect that the introduction of explicit virtual bidding results in a fall in the volatility in the day-ahead/real-time price difference, as well as in the real-time price. Formally, we compare the covariance matrices associated with the price differences (and real-time price) prior to versus after explicit virtual bidding, testing whether the difference between the covariance matrices is a positive semi-definite matrix. Formally, this is a (24x1) multivariate nonlinear inequality constraints test on the eigenvalues of the difference between the two covariance matrices. These results are documented in Table 7 where we report the probability of obtaining a value from the distribution of the test statistic under the null hypothesis greater than the actual statistic. We reject a size $\alpha = 0.05$ test if this probability is less than 0.05. We fail to reject the null hypothesis if it is greater than 0.05.

[Table 7 about here.]

We fail to reject the null hypothesis that the daily price differences and real time prices prior to explicit convergence bidding are more volatile relative to the differences and real-time prices after explicit convergence bidding. Moreover, we reject the opposite null hypothesis corresponding to volatility before versus after explicit convergence bidding for all cases but the real-time price results for SDG&E. These results are consistent with the claim that explicit convergence bidding resulted in the day-ahead market producing generation and load schedules closer to actual physical conditions in the real-time market, leading to less “residual” deviations between day-ahead schedules and real-time market outcomes. This result is consistent with generation unit owners and load-serving entities taking costly actions to attempt to profit from differences between the day-ahead and real-time prices leading to a more frequent need for the ISO to make significant adjustments to day-ahead generation schedules to meet real-time demand at all locations in the transmission network before the introduction of explicit virtual bidding. Therefore, prior to explicit convergence bidding, large differences between day-ahead and real-time prices reflected both genuine shocks to the electricity production process as well as financially motivated distortions in bid and offer behavior motivated by divergent expectations over day-ahead versus real-time prices. The logic underlying the cause of these variance reduction results is consistent with the market efficiency results presented in the next section.

6 Measuring Market Efficiency Implications of Convergence Bidding

This section describes the data used and analysis performed to assess the market efficiency consequences of the introduction of explicit convergence bidding. The three market outcome measures we compare before versus after the introduction of convergence bidding are: (1) the total millions of British Thermal Units (MMBTUs) of natural gas used each hour to produce the fossil fuel electricity generated during that hour, (2) the total variable cost of

producing the fossil fuel electricity generated during that hour, and (3) the total number of generation units started during that hour. We use a sample period that starts one year before convergence bidding was implemented on February 1, 2011 until one year after it was implemented on January 31, 2012. We nonparametrically control for differences across hours of the day and days of our sample period for differences in the level output of thermal generation units in California, the level of output of intermittent renewable resources (wind and solar resources) and daily wholesale prices of natural gas delivered to both northern and to southern California. To control for the hourly differences in these observable factors as flexibly as possible in computing the difference in the mean values of each performance measure before and after the implementation of convergence bidding, we employ the Robinson (1988) partially linear model to estimate the conditional mean function for each market performance measure.

Constructing the total hourly MMBTUs of energy consumed by all natural gas-fired generation units proceeds as follows. First, the hourly metered output of each natural gas-fired generation unit is obtained from the California ISO's settlement system. This information is combined with the generation unit-level heat rate curve that all natural gas-fired generation unit owners are required to submit as part of the California ISO's local market power mitigation mechanism. This curve is a piecewise linear function that can have ten heat rate level and output quantity pairs up to the full capacity of the generation unit. The vertical axis gives the heat rate denominated in millions of British Thermal Units (MMBTUs) of natural gas burned to produce each additional MWh for the level of output from that generation unit on the horizontal axis. The heat rate value on this piecewise linear curve times the generation unit's metered output for that hour is the first component of the total MMBTUs of energy consumed by that generation unit during the hour.

The total amount of heat necessary to start up any generation units that began operating during that hour is also included in the total amount of MMBTUs consumed in an hour. Natural gas-fired generation unit owners are also required to file information on the total amount of MMBTUs required to start each generation unit with the California ISO as part of its local market power mitigation mechanism. A unit is defined as starting in hour t if its output in hour $t-1$ is zero and its output in hour t is greater than zero. Summing the MMBTUs of energy consumed to produce each unit's metered output in that hour and the MMBTU of energy consumed in that hour to start all units that started during that hour yields, $TOTAL_ENERGY(t)$, the total amount of energy consumed in hour t by the 228 natural gas-fired generation units in the California ISO control area during our sample period.

The total number of generation units started in an hour t , $STARTS(t)$, is the total number of units in hour t that have zero metered output in hour $t-1$ and positive output in hour t . The final market performance measure, $TOTAL_VC(t)$, is the total variable cost of all natural gas-fired generation units in hour t . The marginal cost for each generation unit is computed by multiplying the heat rate associated the unit's metered output for that hour (computed from the piecewise linear heat-rate curve) times the daily price of natural gas for that unit plus the variable operating and maintenance cost that the unit's owner submits to the California ISO for its local market power mitigation mechanism. The total variable cost

for the unit is computed as the product of the marginal cost for the unit times its metered output for the hour. For units that start up in hour t , the total energy to start the unit is converted to a cost by multiplying the MMBTUs of energy consumed to start the unit by the daily price of natural gas. Summing these volume variable costs over all generation units operating in hour t and the start-up costs for all units starting in hour t , yields the value of $TOTAL_VC(t)$.

We specify semiparametric functions for each of the three market performance measures in order to estimate the difference in the mean of each of the three hourly market performance measures before versus after the implementation of convergence bidding. All of the hour-of-sample conditional mean functions can be written as $y_t = W_t'\alpha + X_t'\beta + \theta(Z_t) + \epsilon_t$, with $E(\epsilon_t|X_t, W_t, Z_t) = 0$, where y_t is one of our three market performance measures. The function $\theta(Z)$ is an unknown function of the vector Z , W is a (24x1) vector of hour-of-day dummy variables, and α and β are unknown parameter vectors. For all three overall conditional mean functions, X_t is a single dummy variable that takes on the value 1 for all hours after midnight January 31, 2011 and zero otherwise, and Z_t is four dimensional vector composed of the total output in MWhs of all natural gas-fired generation units in California during hour t , the total output in MWhs of all wind and solar generation units in California during hour t , the price of natural gas in northern California (the Pacific Gas and Electric Citygate delivery point) during hour t , and the price of natural gas in Southern California (the Southern California Gas Citygate delivery point) during hour t . For the total starts conditional mean function, y_t equals $STARTS(t)$, for the total energy conditional mean function, y_t equals the natural logarithm of $TOTAL_ENERGY(t)$, and for the total variable cost conditional mean function, y_t equals the natural logarithm of $TOTAL_VC(t)$. We also estimate models that allow separate mean differences in each market performance measure by hour of the day. In this case X_t is a (24x1) vector with k^{th} element X_{tk} , which equals one during hour-of-the-day k for all days from February 1, 2011 until the end of the sample period.

Controlling for both the hourly output of thermal generation units and the hourly output of wind and solar generation unit is necessary because the share of energy produced by renewable resources has grown in significantly over our sample period as a result of California's renewables portfolio standard (RPS), which requires all California load-serving entities to procure 33 percent of their energy from qualified renewable sources by 2020. Figure 8 plots the average hourly output of in-state thermal generation resources and in-state renewable generation resources during the year before virtual bidding and year after virtual bidding. Each point on each curve Figure 8(a) is the average over all days during the year before or year after virtual bidding was implemented of the output of all thermal generation units during that hour of the day. Each point on each curve of Figure 8(b) is computed in the same manner using solar and wind generation units. Figure 8 demonstrates that average hourly output of thermal generation units falls substantially, and much of that fall is taken up by the increase in wind and solar energy produced in California. Figure 9 plots the standard deviations of the hourly output for each hour of the day across days in the sample before and after the implementation of convergence bidding. The standard deviation of both thermal and wind and solar output for all hours of the day are higher after virtual bidding. This is particularly the case for wind and solar output. The intermittency of the these resources

implies that more thermal resources must be held as operating reserves and stand ready to supply additional energy if the wind or solar resources disappear suddenly. Consequently, failing to control for both the hourly output of wind and thermal generation units before versus after the implementation of explicit virtual bidding would not account for the significant increase in average wind and solar energy and increased volatility in thermal output and renewable energy output after the implementation of explicit virtual bidding.

[Figure 8 about here.]

[Figure 9 about here.]

We employ a two-step estimation procedure that recognizes that $\theta(Z_t) = E(y_t - W'_t\alpha + X'_t\beta | Z_t)$ and estimates it using $\hat{\theta}(Z_t, h) = \frac{\sum_{t=1}^T (y_t - W'_t\alpha - X'_t\beta) K((z - Z_t)/h)}{\sum_{t=1}^T K((z - Z_t)/h)}$ to estimate both α and β . The first step finds the values of h , α , and β that minimize $\sum_{j=1}^T [y_j - W'_j\alpha - X'_j\beta - \hat{\theta}_{-j}(Z_j, h)]^2$, where $\hat{\theta}_{-j}(Z_j, h)$ has the same form as $\hat{\theta}(z, h)$ evaluated at $z = Z_j$ except that $\sum_{t=1}^T$ in the numerator and denominator is replaced with $\sum_{t=1, t \neq j}^T$. The second step is a least squares regression of $[y_t - \hat{\theta}(Z_t, h^*)]$ on W_t and X_t , where h^* is the optimized value of h from the first step. Robinson (1988) demonstrates that $\sqrt{T}([\hat{\alpha} \quad \hat{\beta}]' - [\alpha \quad \beta]')$, where $\hat{\alpha}$ and $\hat{\beta}$ are the second-stage estimates of α and β , has an asymptotic normal distribution. Standard error estimates are constructed using the expression for the estimated asymptotic covariance matrix given in Robinson (1988).

6.1 Empirical Results

Table 8 reports the results of estimating the conditional mean function, $y_t = W'_t\alpha + X'_t\beta + \theta(Z_t) + \epsilon_t$, for each measure of market performance for the case that X_t is a single dummy variable that takes on the value 1 for all hours after midnight on January 31, 2011 and zero otherwise. These estimates imply that the conditional mean of total hourly energy (controlling for the total hourly output from all natural gas-fired units, the total hourly output of wind and solar resources, the prices of natural gas in northern and southern California and the hour of the day) is 2.8 percent lower after January 31, 2011. The conditional mean of total hourly starts (controlling for the same variables) is 0.63 starts higher after January 31, 2011. The conditional mean of total variable costs is 2.6 percent lower after January 31, 2011.

[Table 8 about here.]

Figures 10 plots the estimates of hour-of-the-day change in the conditional mean of the three hourly market performance measures after the implementation of convergence bidding along with the pointwise upper and lower 95% confidence intervals for each hour-of-the-day estimate. For the case of total hourly energy, the largest in absolute value reduction occurs in the early morning hours beginning at 12 am and ending at 3 am. The hourly mean reductions are the smallest in absolute value during the hours beginning 5 am and ending at 8 am, with the remaining hours of the day slightly higher in absolute value. For total starts, the largest increase is during the hour starting at 3 pm and ending at 5 pm. Starts

also increase after the implementation of convergence bidding in hours beginning with 4 am and ending at 7 am. For total variable costs, the pattern of the absolute values of the hour-of-the-day reductions is similar to that for total hourly energy. The largest in absolute value reductions occur in morning hours from 12 am to 3 am.

Although the percent hourly total energy and cost reductions are small, on an annual basis the implied cost savings and carbon dioxide emissions reductions can be substantial. The annual total cost of fossil fuel energy is \$2.8 billion the year before convergence bidding and \$2.2 billion the year after convergence bidding. Applying the 2.6 percent reduction to these figures implies an annual cost savings for the variable cost of fossil fuel energy of roughly 70 million dollars per year. Applying the total MMBTU figures, implies that the introduction of convergence bidding reduced the greenhouse gas emissions from fossil fuel generation in California by 2.8 percent. The average heat rate of fossil fuel units in California is approximately 9 MMBTU/MWh and the typical natural gas-fired generation unit produces approximately a half of a ton of carbon dioxide per MWh of energy produced. In the year before explicit virtual bidding, 585 million MMBTUs were consumed to produce electricity and the year after 484 million MMBTUs were consumed. Applying our 2.8 percent reduction figure to these two numbers implies that the introduction of explicit virtual bidding reduced carbon dioxide emissions by between 650,000 and 537,000 tons annually. Both of these results point to sizable economic and environmental benefits from the introduction of explicit virtual bidding in California.

[Figure 10 about here.]

7 Implications of Results for Design of Electricity Markets

The results in the previous sections provide evidence that the introduction of explicit virtual bidding significantly reduced the transactions costs associated with attempting to profit from differences between the day-ahead and real-time market prices at the same location in the transmission network. In addition, these results demonstrate economically significant economic and global environmental benefits associated with the introduction of convergence bidding. Although it was possible to implicit virtual bid before the introduction of explicit virtual bidding, the evidence from our analysis is that the introduction of this product significantly improved the degree of price convergence between the day-ahead and real-time markets and reduced the cost of serving load in the California ISO control area.

These results emphasize an important role for forward financial markets in improving the performance of short-term commodity markets. The financial commitments that producers and consumers make in forward markets can provide important information and feedback to market participants that improves the subsequent performance of short-term physical markets. Although convergence bids are purely financial transactions, they reduce the incentive of both generation unit owners and load-serving entities to take forward market positions designed to raise prices in the short-term market. These results argue in favor of recognizing

the fundamentally financial nature of day-ahead wholesale electricity markets. If explicitly financial products are not available, markets participants will still attempt to engage in profitable financial transactions, even though these transactions may require costly deviations from what the generation unit owner would do if explicit virtual bidding was possible. This appears to be the case before virtual bidding was implemented in the California market. Therefore, rather than resisting the desire of many market participants to allow purely financial transactions, these actions should be allowed and encouraged through explicit virtual bidding as a way to improve the performance of the wholesale electricity market.

References

- Berger, Roger L, and Jason C Hsu.** 1996. “Bioequivalence trials, intersection-union tests and equivalence confidence sets.” *Statistical Science*, 11(4): 283–319.
- Bohn, Roger E, Michael C Caramanis, and Fred C Schweppe.** 1984. “Optimal pricing in electrical networks over space and time.” *The Rand Journal of Economics*, 360–376.
- Fang, Zheng, and Andres Santos.** 2014. “Inference on directionally differentiable functions.” *arXiv preprint arXiv:1404.3763*.
- Hong, Han, and Jessie Li.** 2015. “The Numerical Delta Method and Bootstrap.”
- Munk, Axel, and Rafael Pflüger.** 1999. “ 1α Equivariant Confidence Rules for Convex Alternatives are $\alpha/2$ -Level TestsWith Applications to the Multivariate Assessment of Bioequivalence.” *Journal of the American Statistical Association*, 94(448): 1311–1319.
- Newey, Whitney K, and Kenneth D West.** 1987. “A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix.” *Econometrica: Journal of the Econometric Society*, 703–708.
- Perlman, Michael D, and Lang Wu.** 1999. “The emperors new tests.” *Statistical Science*, 14(4): 355–369.
- Robinson, Peter M.** 1988. “Root-N-consistent semiparametric regression.” *Econometrica: Journal of the Econometric Society*, 931–954.
- Romano, Joseph P.** 2005. “Optimal testing of equivalence hypotheses.” *Annals of statistics*, 1036–1047.
- Wolak, Frank A.** 1989. “Local and Global Testing of Linear and Nonlinear Inequality Constraints in Nonlinear Econometric Models.” *Econometric Theory*, 51(1): 1–35.
- Wolak, Frank A.** 2003. “Diagnosing the California electricity crisis.” *The Electricity Journal*, 16(7): 11–37.

List of Figures

1	Hourly Graphs of Day-Ahead/Real-Time Price Differences: Before and After EVB	29
2	Hourly Graphs of Price Differences with 95% C.I: Before and After EVB	30
3	Bootstrap Distribution of $\phi(\bar{X})$ with 95% C.I: Before and After EVB	31
4	Nodal-Level Distribution of Confidence Intervals: Before and After EVB	32
5	Bootstrap Distribution of the Difference in Trading Costs	33
6	Average Hourly MW Virtual Supply and Demand Offered and Cleared: Monthly	34
7	Average Hourly MW Virtual Supply and Demand Offered and Cleared: Hourly	35
8	Average Total Output By Type of Resource: By Hour of Day	36
9	Standard Deviation of Total Output By Type of Resource: By Hour of Day	37
10	Hour-of-the-Day Percent Change Estimates from Semi-Parametric Regressions	38

Figure 1: Hourly Graphs of Day-Ahead/Real-Time Price Differences: Before and After EVB

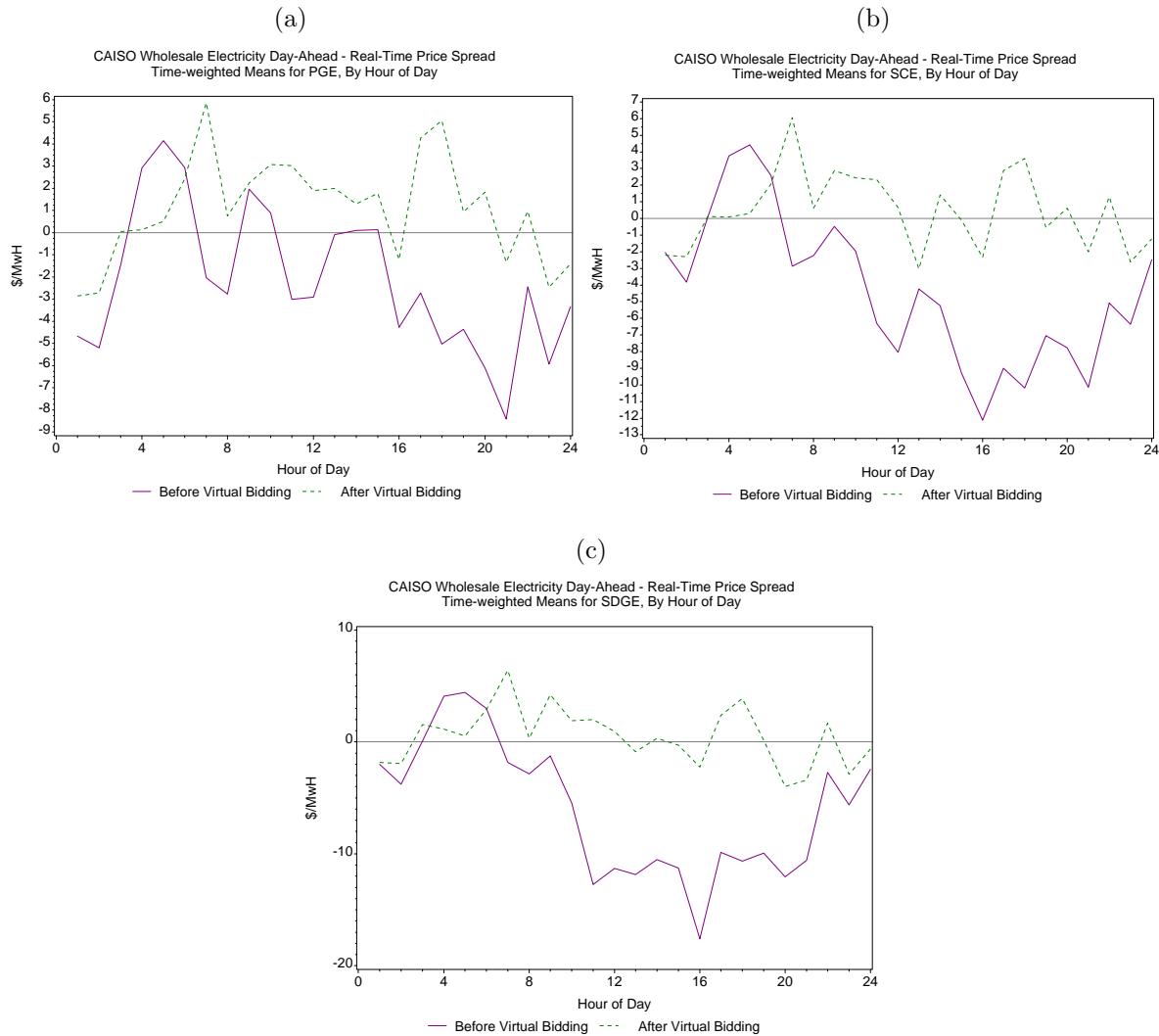


Figure 2: Hourly Graphs of Price Differences with 95% C.I.: Before and After EVB

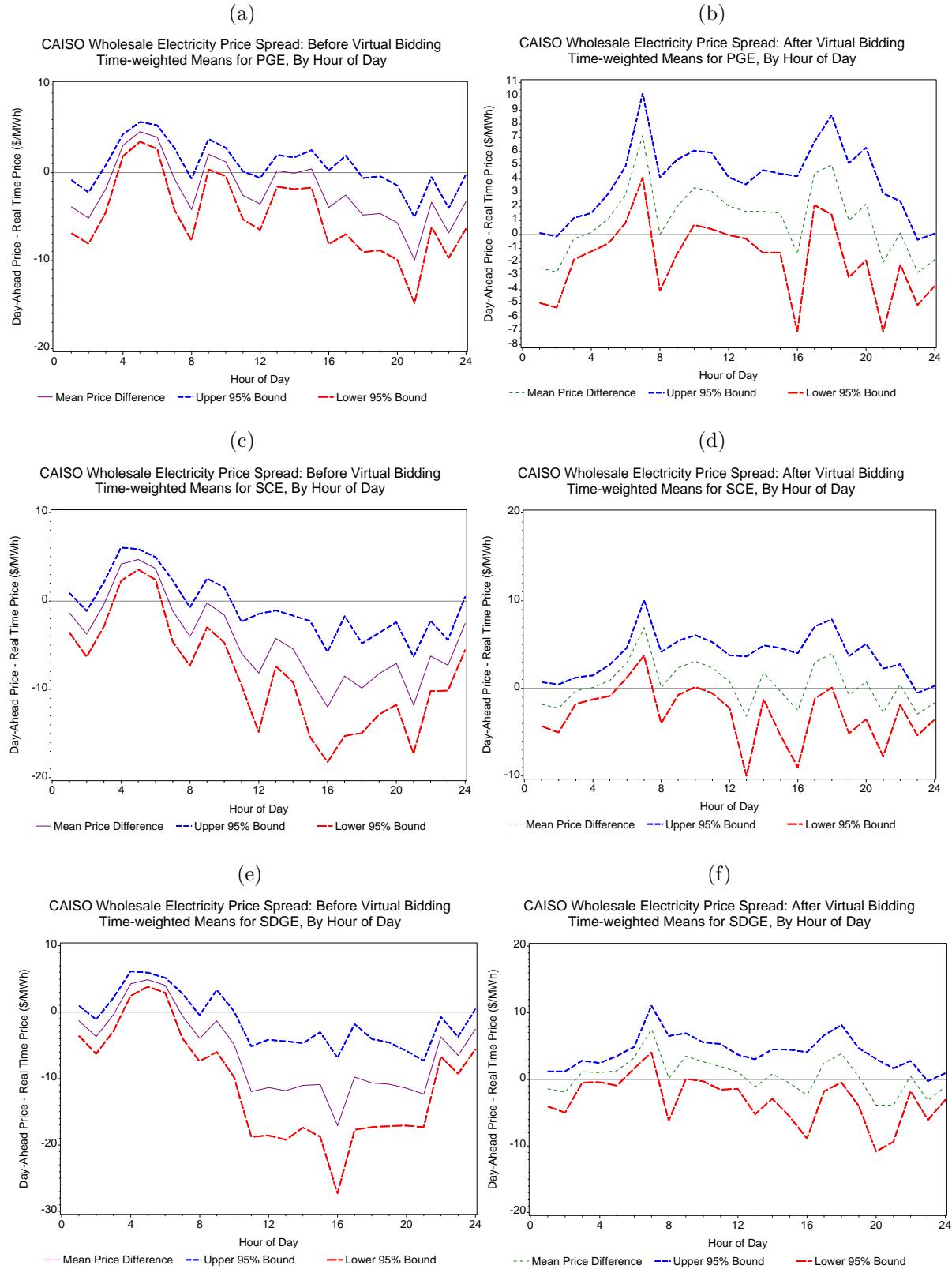


Figure 3: Bootstrap Distribution of $\phi(\bar{X})$ with 95% C.I.: Before and After EVB

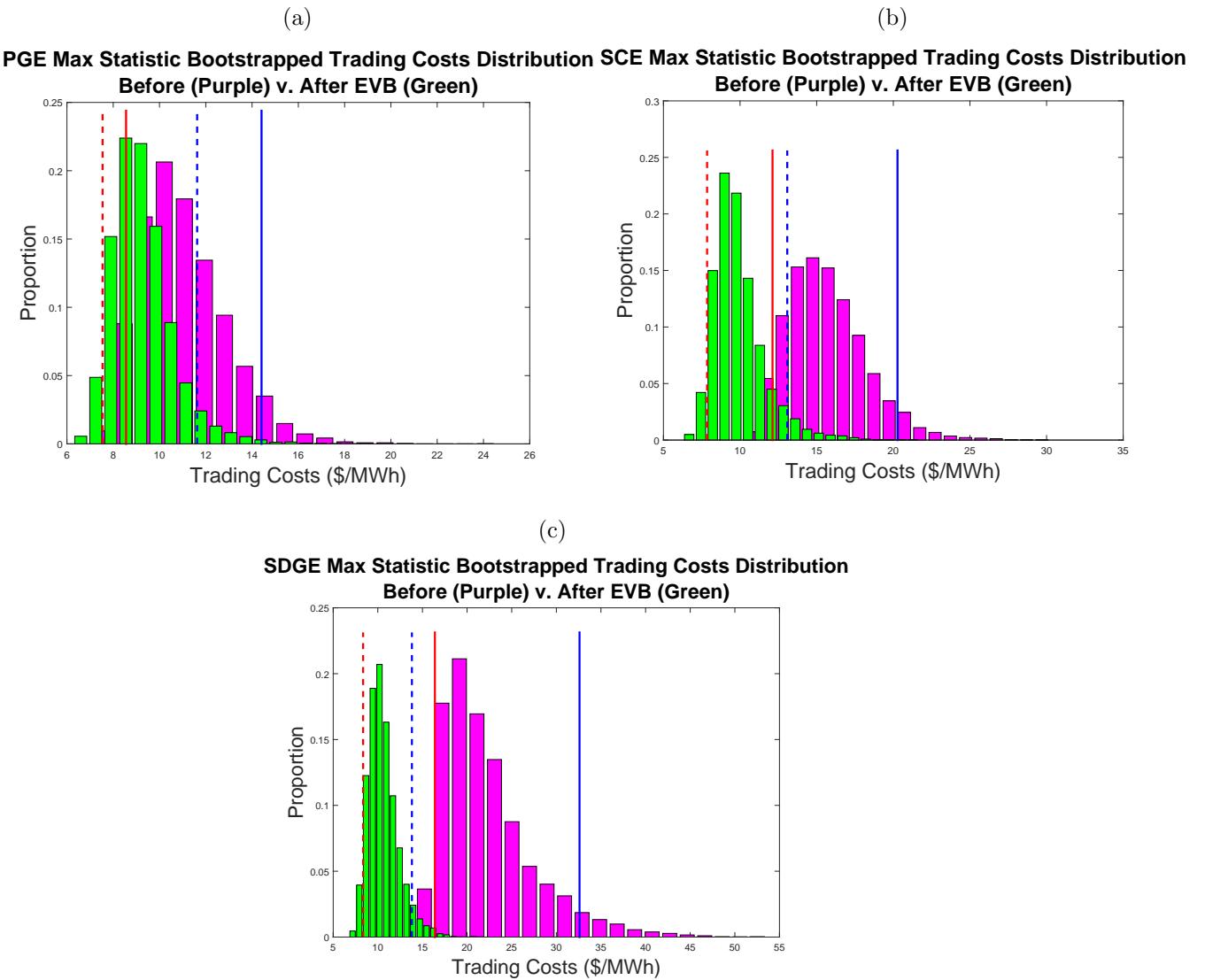


Figure 4: Nodal-Level Distribution of Confidence Intervals: Before and After EVB

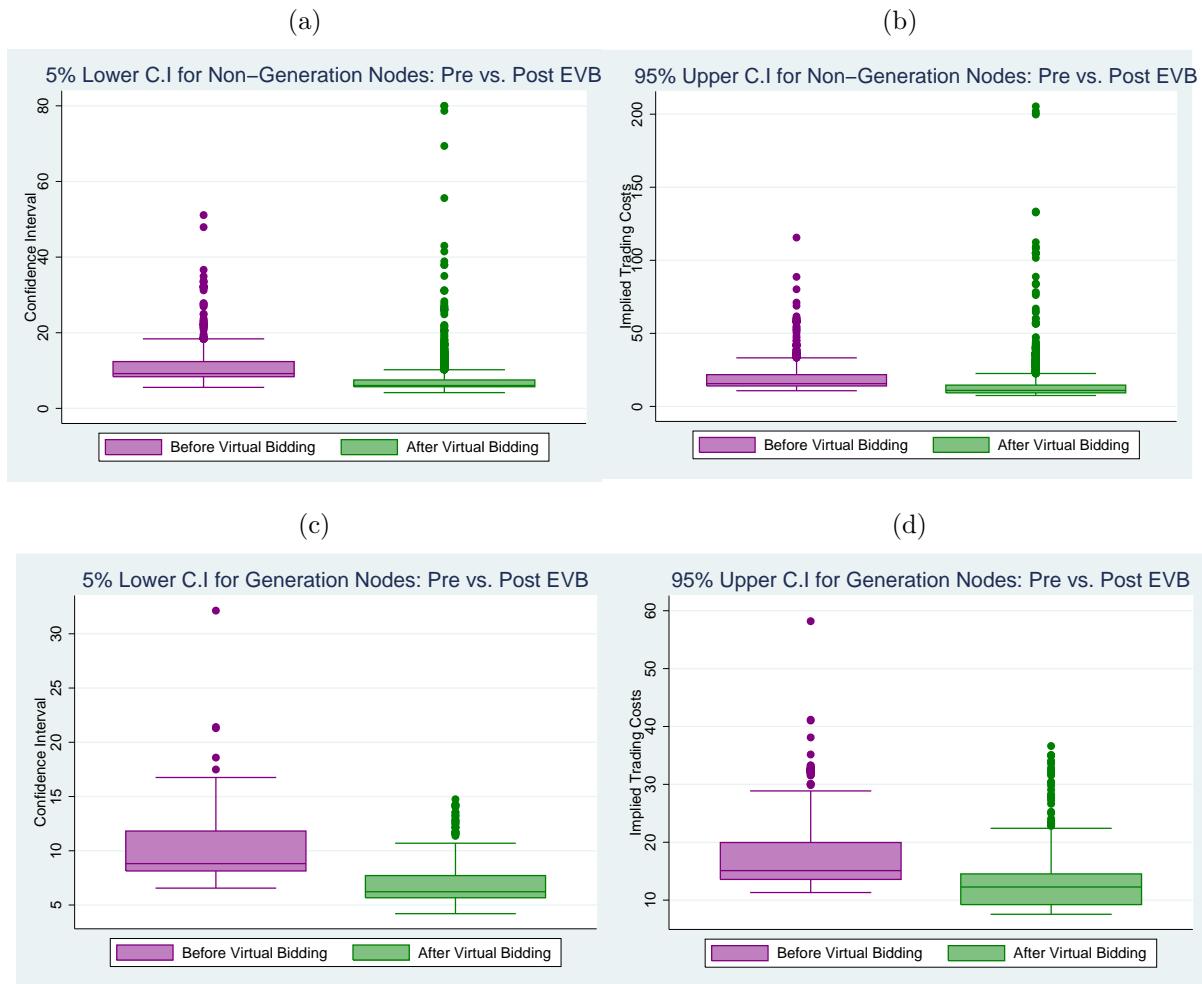


Figure 5: Bootstrap Distribution of the Difference in Trading Costs

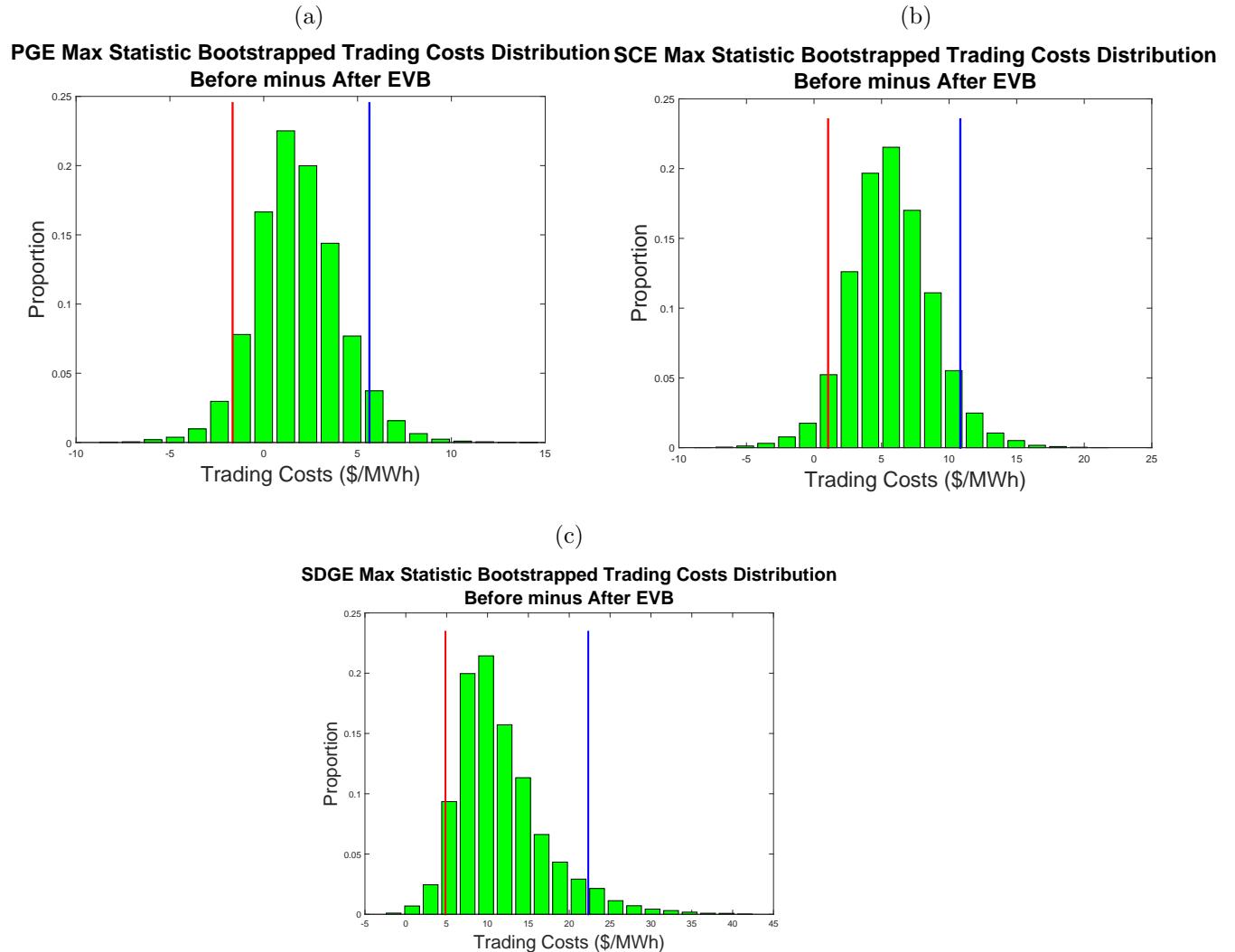


Figure 6: Average Hourly MW Virtual Supply and Demand Offered and Cleared: Monthly

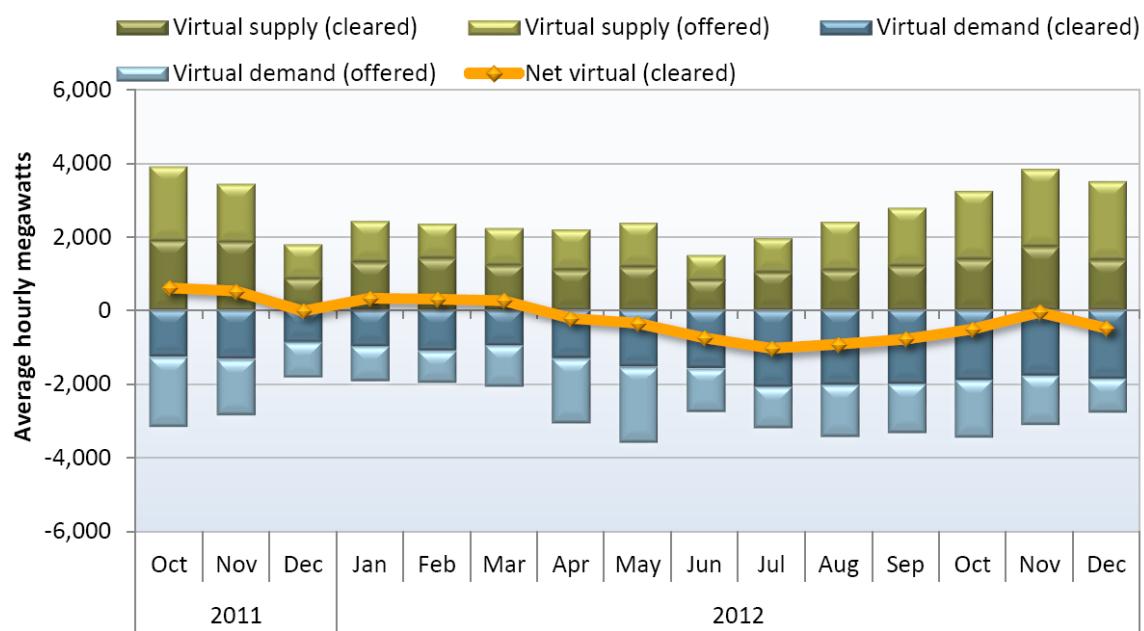


Figure 7: Average Hourly MW Virtual Supply and Demand Offered and Cleared: Hourly

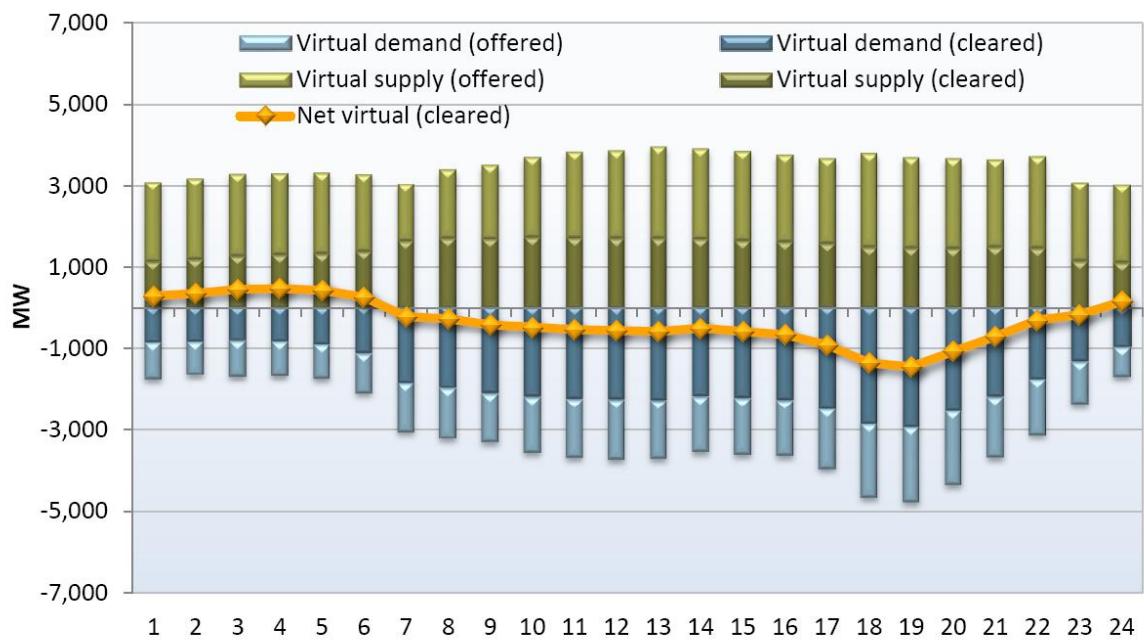
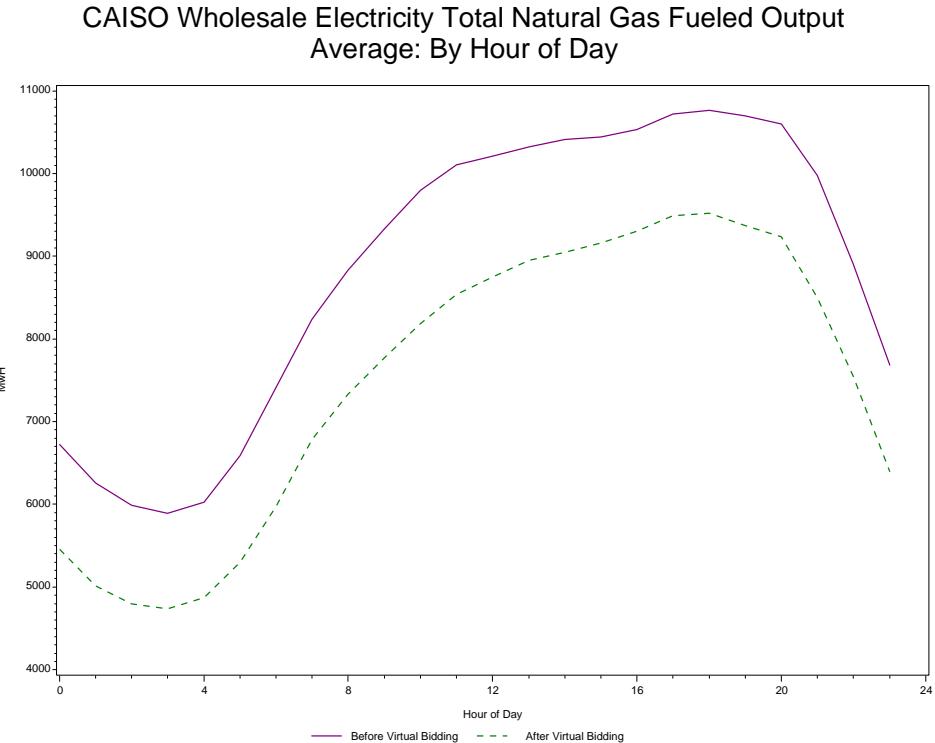


Figure 8: Average Total Output By Type of Resource: By Hour of Day

(a)



(b)

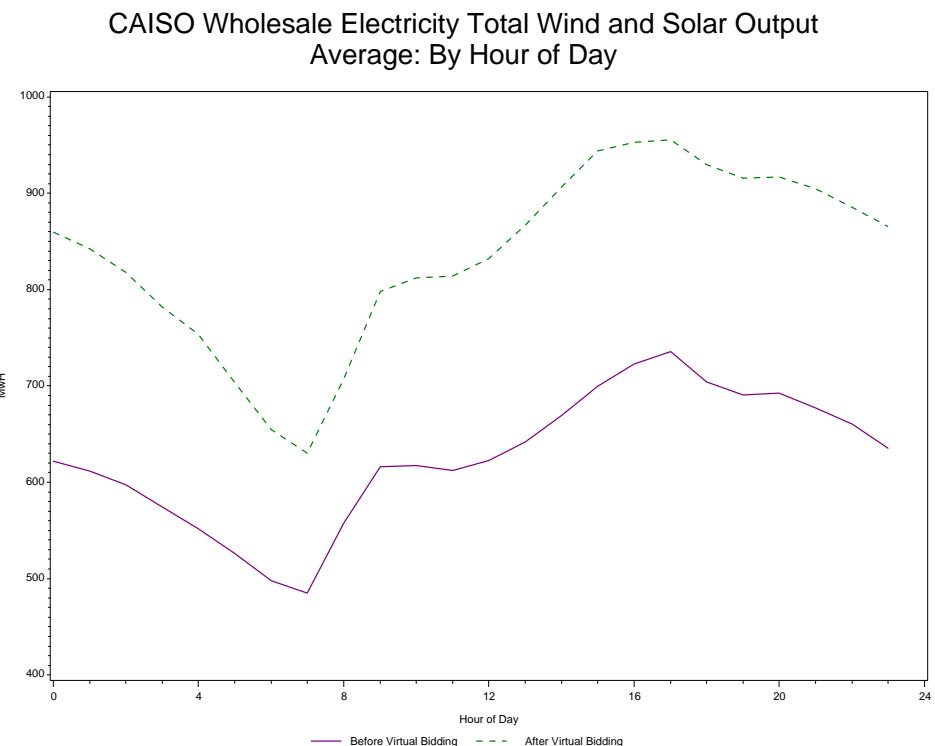


Figure 9: Standard Deviation of Total Output By Type of Resource: By Hour of Day

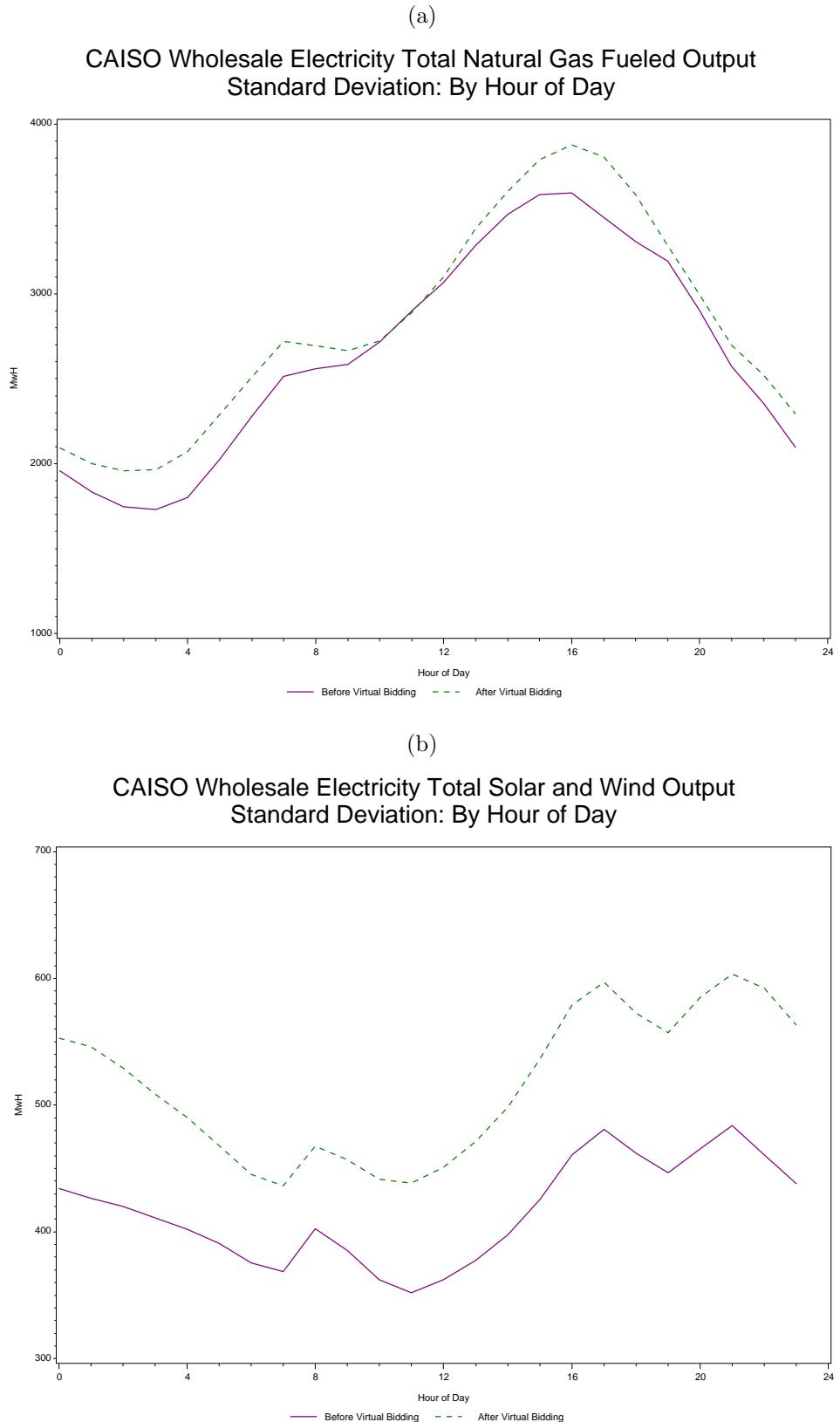
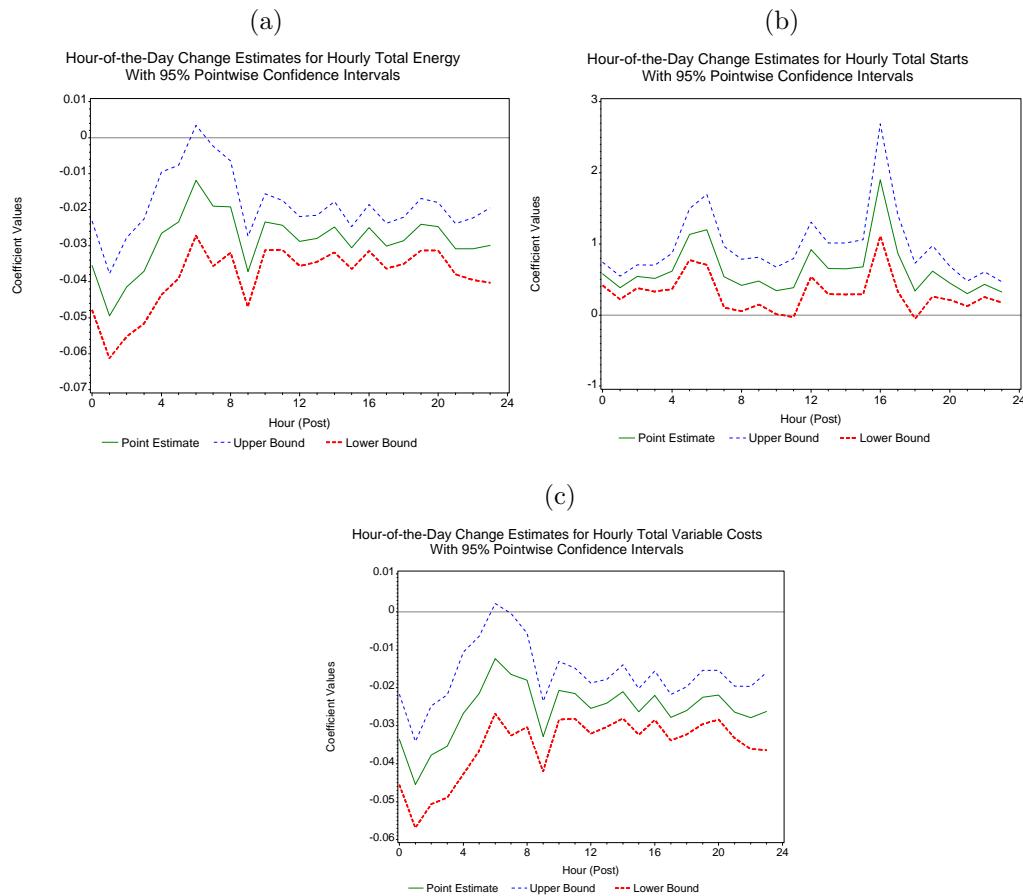


Figure 10: Hour-of-the-Day Percent Change Estimates from Semi-Parametric Regressions



List of Tables

1	Test Statistics for Joint Test of Zero Mean Price Differences	40
2	Test Statistics for Autocorrelation ($1 < L \leq 10$) in Daily Price Differences	41
3	LAP level Implied Trading Costs— c_{lower} and c_{upper}	42
4	Proportion of Nodes that Reject the Two Null Hypotheses	43
5	Regression Results Associated with Implied Trading Costs— c_{lower} and c_{upper}	44
6	P-values associated with the Absolute Difference Tests	45
7	P-values associated with Volatility Tests	46
8	Semiparametric Coefficient Results	47

Table 1: Test Statistics for Joint Test of Zero Mean Price Differences

	Before EVB	After EVB
PG&E	141.738	88.158
SCE	140.140	105.127
SDG&E	157.742	86.084

Table 2: Test Statistics for Autocorrelation ($1 < L \leq 10$) in Daily Price Differences

	Before EVB	After EVB
PG&E	2862.2	2767.0
SCE	2789.2	2842.6
SDG&E	3082.1	2700.7

Table 3: LAP level Implied Trading Costs— c_{lower} and c_{upper}

		Before EVB	After EVB
Lower 5% C.I	PG&E	8.591	7.531
	SCE	12.112	7.845
	SDG&E	16.453	8.393
Upper 95% C.I	PG&E	14.385	11.684
	SCE	20.185	13.209
	SDG&E	32.391	13.825

Table 4: Proportion of Nodes that Reject the Two Null Hypotheses

	Total	1(Gen Node)	1(Non-Gen Node)
1(5% Lower Bound; 0)	0.707	0.659	0.711
1(95% Upper Bound; 0)	0.042	0.076	0.039
Number of Observations	4316	355	3961

Table 5: Regression Results Associated with Implied Trading Costs– c_{lower} and c_{upper}

VARIABLES	(1)	(2)
	5% Lower Bound	95% Lower Bound
1(Post EVB)*1(Gen Node)	0.532 (0.174)	1.421 (0.431)
1(Post EVB)	-3.527 (0.0752)	-5.404 (0.193)
1(Gen Node)	-0.654 (0.119)	-1.765 (0.250)
Constant	10.72 (0.0538)	19.16 (0.118)
Observations	9,791	9,791
R-squared	0.202	0.080

Robust standard errors in parentheses

Table 6: P-values associated with the Absolute Difference Tests

	$ \mu_{pre} > \mu_{post} $	$ \mu_{post} > \mu_{pre} $
PG&E	0.705	0.144
SCE	0.908	0.006
SDG&E	0.687	0.040

Table 7: P-values associated with Volatility Tests

	LAP	Price Difference	Real-Time Price
Pre - Post	PGE	0.284	0.516
	SCE	0.509	0.697
	SDGE	0.476	0.647
Post - Pre	PGE	0.001	0.016
	SCE	0.001	0.034
	SDGE	0.028	0.165

Table 8: Semiparametric Coefficient Results

Dependent variable	$\ln(TOTAL_ENERGY(t))$	$STARTS(t)$	$\ln(TOTAL_VC(t))$
β	-0.0284	0.6328	-0.0257
Standard error	0.0015	0.0496	0.0015