Liquidity Costs on Intraday Power Markets: Continuous Trading Versus Auctions

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Abstract

We analyze liquidity costs on continuous and auction-based intraday power markets using a cost-of-round-trip measure that works for both market designs. We use data from the Italian auction-based intraday market and the German continuous market and present descriptive statistics as well as multivariate regression models to analyze determinants of liquidity costs in both markets. To test for differences in liquidity due to market design, we employ a double machine learning technique controlling for several confounding variables. We show that weekly patterns, yearly seasonality, electricity demand, as well as the influence of temperatures significantly affect liquidity costs. Comparing liquidity costs in both market, we find that, overall, liquidity costs are lower on the Italian market. However, Italian costs increase towards later auctions, while the costs on the German continuous intraday market decrease and reach their low close to physical delivery, where costs are lower than on the last Italian market trading the corresponding products.

Keywords: Continuous Market, Auction Market, EPEX SPOT, GME MI, Double Machine Learning

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1. Introduction

In the last two decades electricity markets world-wide have moved from being dominated by highly vertically integrated monopolies to competitive markets populated by many diverse players. To satisfy these companies' requirements, electricity trading takes place in multi-settlement markets that allow trading products with different temporal granularities and with different times to maturity. In particular, the growing share of variable renewable production led to the rising importance of spot markets, making it possible to adapt traded positions until close to delivery as new information arrives.

While in the US the day-ahead market is immediately followed by the real-time balancing market (Ela et al., 2014), European market designs feature a spot market that is split into a day-ahead market and an intraday market where power can be traded until shortly before physical delivery. Currently, there are two prevailing designs of intraday markets in Europe. While most European countries use continuous trading, Italy, Spain, and Portugal mainly use staggered intraday market auctions.

Clearly, the benefits of intraday trading are closely tied to the liquidity of the market, i.e., the ability of firms to trade while experiencing only minimal adverse price effects. Furthermore, liquid markets are less prone to market manipulation and gaming by pivotal players.

However, liquidity in most European intraday markets remains rather low. Weber (2010) finds that markets in Germany and several other European countries are not sufficiently liquid. Garnier and Madlener (2015) conclude that due to this illiquidity, current intraday markets are of limited use in balancing short-term forecast errors in demand and variable renewable production. It is therefore interesting to policy makers and industry professionals alike to identify factors that drive liquidity in the two market designs and understand how the designs themselves influence liquidity.

Consequently, the issue of liquidity in intraday markets has recently attracted some attention in the academic literature. Weber (2010) analyzes the integration of wind energy considering different European market designs and finds that the intraday auctions in Spain are the most attractive in terms of trading volume. Based on transaction data from the German intraday market, Hagemann and Weber (2013) investigate liquidity in intraday power markets using established measures from financial markets. Neuhoff et al. (2016) find that the additional auctions for 15 minutes contracts in the German intraday markets increased liquidity and market depth while reducing price volatility.

Balardy (2018) is one of the first, who uses the German limit order book (LOB) data to analyze liquidity in terms of bid-ask-spreads and market depths. The author finds a positive relation between bid-ask spreads and risk as well as a negative relation between bid-ask spread and adjustment needs, activity, and competition in the market. von Luckner et al. (2017) use the LOB to find an optimal market maker pricing and analyze the market order intensity and the bid-ask spread. Hagemann and Weber (2015) analyze intraday trading volumes on auction-based and continuous intraday markets, and observe higher volumes on the auction-based intraday markets. The authors conclude that this difference is not due to the difference in market design but rather due to idiosyncratic factors affecting the two markets.

The literature on electricity forecasting is in many ways related to our paper. Most models for price forecasts are time-series models using exogenous variables, some of which we also use in our models. For example, as in Narajewski and Ziel (2020) and Uniejewski and Weron (2018), we use time dummies for Saturday, Sunday and Monday, and the day-ahead forecast for load, solar production and wind power as covariates in our regression models. Marcjasz et al. (2020) use dummies for each weekday, forecasts for load, solar production and wind production and its forecast errors, and balancing volumes. Janke and Steinke (2019) use the forecastFs of demand and renewable production, and hourly dummies for each hour.

Despite the importance of the topic, the literature analyzing liquidity costs in intraday power markets remains scarce. To the best of our knowledge, this is the first paper to compare liquidity costs of the two markets in a statistically sound way using the complete order book data of the continuous intraday market and all submitted orders of the intraday auction.

In this paper, we contribute to the discussion by the first analysis of intraday electricity market liquidity that is based on a cost-of-round-trip (CRT) measure which captures all quantitative aspects of liquidity both in auction markets as well as for continuous trading. We provide a univariate analysis of the CRT which is complemented by regression models that explore possible drivers of liquidity costs on the German and Italian market. We find that, depending on the market, liquidity cost are driven by weekly patterns, yearly seasonalities, electricity demand, as well as temperatures.

To directly compare the cost of liquidity and thus measure the impact of market design, we use a state-of-the-art double machine learning method proposed in Chernozhukov et al. (2018) controlling for possible confounding factors identified in the analysis for the CRT for the two markets. Comparing the two markets, by and large the Italian auction-based market exhibits lower CRTs. We observe this result in a univariate analysis and confirm it in a multivariate analysis controlling for the confounding factors identified above. However, this effect gets progressively weaker for larger traded volumes and as trading time approaches physical delivery. In particular, it can be observed that the German continuous intraday market consistently exhibits lower costs for high volumes close to delivery.

Our findings suggest that a combination of several auction-based intraday markets with continuous trading might be able to leverage the benefits of both systems. In particular, auctions can be used to increase liquidity and therefore decrease trading costs by pooling orders for products which are far from delivery. These auctions could be complemented by continuous trading close to delivery, where market participants have the opportunity to trade the forecast errors for demand and variable renewable production at a point in time when accurate forecasts are available (see Ocker and Jaenisch, 2020, for a similar proposal). In fact, Spain already implemented such a hybrid system when it joined the cross-border intraday market project XBID in June 2018. This proposal is close to the literature on optimal implementations of the European target model for a single coupled intraday market as laid out in the European Commission Regulation (EU) 2015/1222. Bellenbaum et al. (2014) discuss different intraday market designs meeting these requirements and come to the conclusion, that a hybrid between continuous trading and auctions potentially combines the advantages of both designs. Similarly, Ehrenmann et al. (2019) propose to add additional auction markets to the existing continuous market, as auction markets are more suitable for small market participants. The authors see a clear advantage of this setting, but the question remains at which time of the day to introduce auction markets and how many. A possible solution that leverages the advantages of both continuous trading and auctions is to have a large number of *frequent* auctions as proposed in Budish et al. (2015) for financial markets and in Deutsche Börse Group (2018) for the intraday power market. Such a design would alleviate some of the problems of continuous trading while still providing market participants with ample opportunities to trade.

The paper is organized as follows. In Section 2, we briefly describe the Italian and German intraday markets. Section 3 describes the market data and our set of explanatory variables. In Section 4, we introduce the cost-of-roundtrip measure and specify the econometric models used to determine the factors driving liquidity costs in both markets as well as the application of double machine learning, which we use to determine the effect of market design on liquidity costs. Section 5 discusses the empirical results. Finally, Section 6 concludes, discusses limitations and policy implications.

Quantity	**Italy**	**Germany**
Consumption (TWh)	322.2	538.1
PV infeed (TWh)	22.9	41.2
Wind infeed (TWh)	17.3	107.2
Imports (TWh)	47.1	31.5
Exports (TWh)	3.3	82.7
Day-ahead trading volume (TWh)	212.9	234.5
Intraday trading volume (TWh)	25.4	37.8
Volume weighted day-ahead price (€/MWh)	62.22	43.26
Volume weighted intraday price (€/MWh)	61.05	46.6

Table 1: Summary of annual key characteristics of the two markets for 2018. The German day-ahead volume includes Austria and Luxembourg and the trading volume for the German continuous market is restricted to hourly products

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2. Background: Market Designs in Germany and Italy

In this short section, we discuss the relevant facts about the Italian auction-based intraday market and then proceed to discuss the German continuous intraday market. We collect key characteristics of the two markets for the year 2018 from ENTSO-E (2019); GME (2019); Burger (2019) in Table 1, and calculated the Italian weighted prices based on the national price. Note that the traded volumes of the day-ahead market and the intraday market of hourly products of the two markets are comparable. Consumption and production of renewables are higher in Germany, and Italy is a net importer of electricity while Germany generates high volumes for export, since it has significant overcapacities in cheap base-load production. As a result, average spot market prices in Germany are lower than in Italy.

2.1. The Italian IPEX

The Italian spot market offers a platform to trade electricity for delivery in hourly granularity. The day-ahead market in Italy closes at noon on the day before delivery and is followed by seven intraday auction markets, called MI (mercato infragiornaliero). Bid prices are constrained between

€0 and €3000 while bid quantities are restricted to multiples of 1 kWh. For more details see GME (2016).

The Italian power grid consists of the six market zones NORD, CNORD, CSUD, SUD, SICI, and SARD. The MI markets are organized as *uniform price auctions* that aggregate the bids of all zones. The left plot in Figure 1 shows the cleared volume and the clearing price of an exemplary market session. If the resulting national market outcome is physically infeasible due to lack of transmission line capacities between the zones, the result is made feasible by altering the market outcome resulting in different zonal prices for the different Italian market zones. For our analysis, we disregard this complication, by only considering the *national price*, which considers all submitted offers without taking into account the effects of transmission limits between zones.

Table 2 summarizes the characteristics of the Italian intraday market. The lead-time, defined as the time between the last possibility to trade the specific product and its physical delivery, range from 4.25 to 10.5 hours. Since wind power forecasts significantly improve approaching delivery (e.g., Hannele Holttinen, 2013), this relatively long lead-time make it hard to incorporate the last and therefore most precise production forecasts.

2.2. The German EPEX SPOT Market

The German day-ahead market closes at noon of the previous day and is followed by an auction for quarter-hours of the next day at 3 p.m. and a continuous intraday market. For a detailed description we refer to the operational rules in EPEX (2019) and to Table 2 for a summary of trading times.

In contrast to the Italian MI markets, the German intraday market is based on continuous trading with a limit order book (LOB) much like in financial markets. Next to hourly products 1/2-hour and 1/4-hour products are traded. We do not include these products in our analysis, since shorter deliveries serve different purposes than hourly products. In particular, firms use sub-hourly products to model the ramps of their production or consumption, which is possible only to a small extent with hourly products. To be comparable to the Italian market, isolate the effect of market design on liquidity, and avoid diluting our analysis by mixing in different aspects, we therefore only consider hourly products in our analysis. The market for a specific product closes 30 minutes (or 5 minutes within the control area) before delivery, which facilitates trading forecast errors of fluctuating renewable energy sources.

Market	Products	Opening	Closing	Results	Last Update	Lead-Time (h)
			Italian Markets			
MI1	$H1 - H24$	12:55 (d-1)	15:00 (d-1)	15:30 (d-1)	-	-
MI2	$H1 - H24$	12:55 (d-1)	16:30 (d-1)	17:00 (d-1)	$H1 - H4$	$7\frac{1}{2}$ up to $10\frac{1}{2}$
MI3	$H5 - H24$	17:30 (d-1)	23:45 (d-1)	00:15 (d)	$H5 - H8$	$4\frac{1}{4}$ up to $7\frac{1}{4}$
MI4	$H9 - H24$	17:30 (d-1)	3:45 (d)	4:15 (d)	$H9 - H12$	$4\frac{1}{4}$ up to $7\frac{1}{4}$
MI5	$H13 - H24$	17:30 (d-1)	7:45 (d)	8:15 (d)	$H13 - H16$	$4\frac{1}{4}$ up to $7\frac{1}{4}$
MI6	$H17 - H24$	17:30 (d-1)	11:15 (d)	11:45 (d)	$H17 - H20$	$4\frac{3}{4}$ up to $7\frac{3}{4}$
MI7	$H21 - H24$	17:30 (d-1)	15:45 (d)	16:15 (d)	$H21 - H24$	$4\frac{1}{4}$ up to $7\frac{1}{4}$
			German Markets			
Intraday Auction	$QH1 - QH96$	d-45	15:00 (d-1)	15:10 (d-1)	-	-
Continuous H	$H1 - H24$	15:00 (d-1)	D-5'	-	$H1 - H24$	$\frac{5}{60}$
Continuous QH	$QH1 - QH96$	16:00 (d-1)	D-5'	-	$QH1 - QH96$	$\frac{5}{60}$
Continuous HH	$HH1 - HH48$	15:30 (d-1)	D-5'	-	$HH1 - HH48$	$\frac{5}{60}$

Table 2: Operating times of the German and the Italian intraday markets. The table reports the traded products, the opening and closing times of the markets (d-1 indicating a time on the day before delivery), the time when the results are announced, the list of products that are traded the last time on the respective market, as well as the lead time for the products that are traded the last time. H indicates a hourly product, HH stands for half-hour and QH for a quarter-hourly product while D signifies the time of delivery.

Market participants can submit buy and sell offers for prices ranging between −9999.9€/MWh and 9999.9€/MWh, with a minimum bid size of 0.1MWh, and several specified order types (Martin and Otterson, 2018). A submitted bid/offer is cleared immediately if the price is better than the best price of an offer/bid in the LOB. If there is no such matching order, the new order is stored in the LOB and matched with orders arriving at a later point in time. The right plot in Figure 1 shows the best available bid and ask price over time with each tick representing a match between a newly placed order and an order in the order book generating a trade.

3. Data

In Section 3.1, we discuss the market data which we use for the Italian and German intraday market. In Section 3.2, we introduce variables which we use in Section 4 and Section 5 as controls in our comparison of the two market designs.

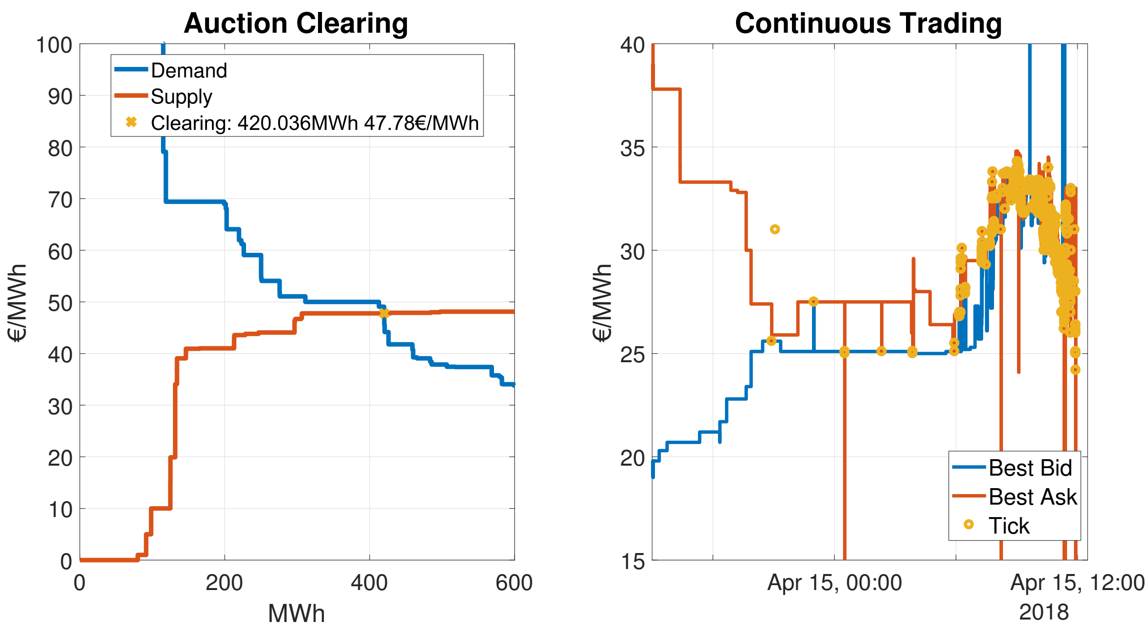

Figure 1: Clearing of the Italian MI3 intraday auction (left) and German continuous trading for the 13th hour on the 15.04.2018. The yellow marker on the left signifies the uniform clearing price of the auction. The markers on the right represent price ticks, i.e., instances when orders were cleared in the German market.

3.1. Market Data

All offers submitted to the Italian intraday market are available on the website of the Italian Power Exchange (IPEX). The offers contain information about the side (sell or buy), product/hour, intraday market (MI1-MI7), zone, price and volume and can be used to calculate the *national price*.

The LOB of the German continuous intraday market can be purchased from EPEX SPOT SE. The data-set includes information about the side (sell or buy), product/hour, validity period, control area, as well as the price and volume of every submitted bid/offer. We note that the EPEX allows for the submission of so called iceberg orders, for which the bid quantity is only gradually revealed as parts of the order get executed. We only consider those parts of iceberg orders that were actually executed in our analysis. For more information about the LOB-data we refer to Martin and Otterson (2018).

The German intraday trading system was subject to frequent changes in the recent years with effects on market liquidity, especially shortly before delivery. In order to have a dataset with consistent market rules, we restrict our analysis of both markets to the time from 20.11.2017, a few

	Variable	Frequency	Unit	Source
$R_t^{S,I}$	Italian solar production	hourly	MWh	https://transparency.entsoe.eu
$F_t^{S,I}$	Italian solar forecast	hourly	MWh	https://transparency.entsoe.eu
$R_t^{W,I}$	Italian wind production	hourly	MWh	https://transparency.entsoe.eu
$F_t^{W,I}$	Italian wind forecast	hourly	MWh	https://transparency.entsoe.eu
$R_t^{D,I}$	Italian demand	hourly	MWh	https://transparency.entsoe.eu
$F_t^{D,I}$	Italian demand forecast	hourly	MWh	https://transparency.entsoe.eu
$R_t^{S,G}$	German solar production	$\frac{1}{4}$-hourly	MWh	https://transparency.entsoe.eu
$F_t^{S,G}$	German solar forecast	$\frac{1}{4}$-hourly	MWh	https://transparency.entsoe.eu
$R_t^{W,G}$	German wind production	$\frac{1}{4}$-hourly	MWh	https://transparency.entsoe.eu
$F_t^{W,G}$	German wind forecast	$\frac{1}{4}$-hourly	MWh	https://transparency.entsoe.eu
$R_t^{D,G}$	German demand	$\frac{1}{4}$-hourly	MWh	https://transparency.entsoe.eu
$F_t^{D,G}$	German demand forecast	$\frac{1}{4}$-hourly	MWh	https://transparency.entsoe.eu
D_t	Daylight of Munich	daily	days	https://galupki.de
T_t^I	Temperature of Milan	hourly	°C	www.arpalombardia.it
T_t^G	Temperature of Berlin	hourly	°C	www.dwd.de
W_t	Weekends	daily	Boolean	-

Table 3: Overview of data used in the analysis.

days after the trading system M7 (version 6.0) was launched to the 15.06.2018, when the XBID project was introduced.

3.2. Explanatory Variables

Table 3 provides an overview of the variables which potentially have an impact on the CRT and which we control in our comparison of the two market designs in Section 5.

Motivated by Goodarzi et al. (2019); Kulakov and Ziel (2020) who show that forecast errors in renewable production influence intrady prices and by Balardy (2018) who observes an impact of renewable energy sources on bid-ask spreads, we include data on forecasts and actual production of variable renewables in both countries. Since we exclusively analyse hourly products, we consider the average over the four quarter-hourly quantities to obtain hourly values. We use the day-ahead forecasts for renewable production as published by ENTSO-E. While the forecasts used by individual market participants for trading might be different, we think that the chosen forecast captures the overall sentiment of the market well.

Temperature influences power markets, because power is used for temperature regulation of buildings. Hence, we introduce a heating- and a cooling-function as described in Fan and Hyndman (2012) for Italy and Germany. The cooling function of Italy C_t^I and Germany C_t^G are defined as $\max(T_t - 19.5°\mathrm{C}, 0)$, where T_t is the hourly temperature at time t in Italy (Milan) or Germany (Berlin). Analogously, we introduce the heating function for Italy H_t^I and Germany H_t^G as $\min(T_t - 17.5°\mathrm{C}, 0)$. The choice of the two cities as temperature proxies is motivated by the fact that Milan is the leading industrial city in Italy and Berlin is the largest German city. A more detailed modeling of the influence of temperatures could be based on weighted temperatures from several areas in Germany and Italy as was for example done in Graf and Wozabal (2013); Kovacevic and Wozabal (2014); Pape et al. (2016). However, for the purpose of this paper we stick to the abovementioned simple approach.

Prices on power markets follow a seasonal and weekly pattern. Hence, as in Kovacevic and Wozabal (2014) and Graf and Wozabal (2013), we use a variable containing the length of daylight D_t in units of days to capture annual seasonality of the observations. As these quantities are similar for both countries, we use the day-length of Munich located in the south of Germany for both markets. Moreover, as in Narajewski and Ziel (2020) and Uniejewski and Weron (2018) we introduce dummy variables $W_t = (W_t^{Mon}, W_t^{Sat}, W_t^{Sun})$ for Monday, Saturday, and Sunday for weekends W_t to model weekly price patterns.

To capture the overall market size and therefore the scarcity of supply in a given period t, we use the forecast as well as the actual demand for Italy and Germany. An alternative way to capture the scarcity in an electricity system would be the so called *load-supply-ratio* (LSR) as defined by Pape et al. (2016). The LSR takes into account detailed modeling of supply and demand and is a more accurate measure of scarcity than mere electricity demand. However, the demand is easier to include in our analysis, since it requires much less detailed data.

4. Methodology

In this section, we first detail how we measure liquidity costs in the two markets by a cost-of-round-trip measure in Section 4.1. In Section 4.2, we introduce a multivariate regression model to analyse the impact of possible confounding factors in the comparison of the two market designs.

Finally, in Section 4.3, we discuss a double machine learning method in order to measure whether the continuous markets in Germany or the auction markets in Italy lead to higher CRTs.

4.1. Liquidity Measures

Market liquidity describes the possibility to quickly buy or sell an asset without affecting the market price. This rather vague definition of liquidity does not lend itself to a quantitative analysis of the phenomenon. In fact, there is no single established quantitative measure of liquidity in the literature that captures all aspects of market liquidity.

Hagemann and Weber (2013) introduced six dimensions of liquidity for continuous energy markets using established measures from the literature on financial markets. The first dimension is *tightness* and is measured using bid-ask spreads defined as the difference between the best bid and best ask price. The second dimension is *resiliency* describing the market's ability to bounce back to an equilibrium price after a temporary distortion. The third dimension is *price impact* or *market depth* and describes the impact of large orders which might require several offers beyond the best price to be cleared. The fourth dimension is known as *short-run price volatility*. The fifth dimension captures delay and search costs describing the propensity of traders to delay trades to obtain better prices. The sixth dimension describes trading activity in the form of traded volume, number of trades, and number of active traders.

Irvine et al. (2000) introduced a CRT-measure as the *per dollar cost of roundtrip trade of D dollars*. In particular, the number of shares that corresponds to the dollar amount D are calculated based on the best-bid and best-ask, and afterwards the LOB is used to calculate the resulting cost of buying and selling the determined number of shares. Since the interpretation in terms of quantities is more natural in power markets, we modify this definition by proposing a CRT measure which depends on volume V instead of the amount of money and captures all aforementioned cost related dimensions of liquidity. Moreover, we modify the measure to be applicable to both continuous trading as well as auction markets.

Conceptually, the CRT is the per unit cost incurred by buying a certain quantity V of power and then immediately selling it again. Note that in a liquid market CRT is close to zero. Choosing a small V yields measurements close to the bid-ask spread while larger volumes increasingly measure the depth of the order book plus all additional costs.

More formally, we define a volume oriented measure by sorting the buy- and sell side of the

LOB at each point in time t by price to obtain $\cdots < P^t_{-2} < P^t_{-1} < P^t_{-0} < P^t_0 < P^t_1 < P^t_2 < \cdots$, where P^t_{-0} is the highest bid-price and P^t_0 is the lowest ask-price. We denote the corresponding bid quantities by Q^t_i. For a given quantity V in MWh, we define how much of an order i would be cleared when placing a market order of size V by

$$\bar{Q}^t_i(V) = \min\left(\max\left(V - \sum_{k=0}^{i-1} Q^t_k, 0\right), Q^t_i\right),\ \bar{Q}^t_{-i}(V) = \min\left(\max\left(V - \sum_{k=-i+1}^{-0} Q^t_k, 0\right), Q^t_{-i}\right).$$

We then define the cost-of-round-trip measure for a fixed value V as

$$CRT_t(V) = \underbrace{\frac{1}{V}\sum_k P^t_k \bar{Q}^t_k(V)}_{\text{average cost}} - \underbrace{\frac{1}{V}\sum_k P^t_{-k}\bar{Q}^t_{-k}(V)}_{\text{average revenue}}. \tag{1}$$

In a continuous market it is possible to execute the buy and sell decisions that are used to define the CRT, making equation (1) directly applicable. However, we note that, in principle, a trader in a continuous market has the option to *spread* her trades over a longer period of time, waiting for more orders on the other side of the market to arrive. In this way, some of the liquidity costs measured by the CRT can be avoided at the cost of the risk of adversely changing prices during the extended time of bidding. The CRT on the continuous intraday market can therefore be seen as an overestimation that accurately reflects liquidity costs only for an *impatient trader* placing market orders.

To use the CRT in an auction market, we add a market order for buying V units to the existing orders and record the marginal price instead of per unit cost when clearing the auction modified in this way. We then subtract the hypothetical sell price of V units which we calculate adding a market order of size V on the sell side instead and divide the result by V.

The resulting CRT-measure of the auction market consists of one value for each market and volume. In contrast, the CRT-measure of a certain product in a continuous market is a function of time and potentially changes with each modification of the LOB. As is illustrated in the right panel of Figure 1 large market orders might lead to temporary extreme values of the CRT-measure distorting our measurement. We therefore use the mean over 15 minutes instead of $CRT_t(V)$ at any fixed time t. To this end, we consider a discrete form of the continuous time varying CRT-measure by considering averages over 15 minute intervals before time τ

$$CRT_\tau(V) = \frac{1}{15}\int_{\tau-15}^{\tau} CRT_t(V)\,dt = \frac{1}{15}\sum_{k=2}^{N} \frac{CRT_{t_k}(V) + CRT_{t_{k-1}}(V)}{2}(t_k - t_{k-1}),$$

where $t_1, \ldots, t_N$ are the N points in time where the LOB changes in the 15-minute time interval $[\tau - 15, \tau]$. In the following, we use the index τ in CRT_τ to refer to a 15-minute average and CRT_t to refer to an instantaneous CRT at time t. The computed average thus reflects the *expected CRT* a trader would have to pay, if she picks a random trading time in the given time interval.

The Italian intraday market has seven fixed times when the market is cleared. We use clearing times of MI2 to MI7 to analyze the two markets, i.e., measure the CRT for the German markets at the times when the Italian markets are cleared. The reason for the exclusion of MI1 is that the German intraday auction closes nearly at the same time as MI1, which results in less liquidity on the continuous market at this point in time and thus a distortion. We compare the CRT of the remaining Italian intraday auctions with the mean German CRT over the 15 minutes before the closing of the Italian intraday auction. To this end, we define $\mathcal{D}_h^I$ as the closing times of the Italian intraday markets, where the hourly product h is traded. For example, $\mathcal{D}_1^I = \{16\colon 30\}$ while $\mathcal{D}_{24}^I = \{16\colon 30, 23\colon 45, 3\colon 45, 7\colon 45, 11\colon 15, 15\colon 45\}$, where the first two time stamps are from the day before delivery.

The German continuous intraday market allows participants to trade until 30 minutes before physical delivery on a national market. Hence, we will also compare the first two 15-minute CRT-means within the last hour of the German continuous intraday market with the CRT-measure of the last available market of the Italian intraday auction for the corresponding product. Correspondingly, the points in time which we consider for the German market are $\mathcal{D}_h^G = \mathcal{D}_h^I \cup \{h - 60, h - 45\}$.

We generate observations corresponding to $V = 0.1$MWh, which is the smallest value that can be traded on the German intraday markets as well as for $V = 5$MWh, 10MWh, 15MWh and 50MWh. On some days the order book does not contain orders of combined size V on either the bid or the ask side at a time $t_i \in [\tau - 15, \tau]$. For our analysis, we calculate over 313 million clearings for the German market. In 0.0466% of these cases at least one side of the limit order book is empty and we exclude these timestamps in our calculation of the 15-minute intervals. In further 0.0804% of the cases not the whole quantity V is available on at least one side of the market. To define CRT for these cases, we use the last available price to clear the remaining quantity in order to calculate a CRT.

4.2. Analysis of the CRT

In this section, we analyze the impact of the variables described in Section 3.2 on the CRTs of the two markets. To this end, we define an index $\mathcal{J} = (V, h, \tau)$ for every volume V, product $h = 1, \ldots, 24$, and time to delivery $\tau \in \mathcal{D}_h^G$ or $\tau \in \mathcal{D}_h^I$ and construct the following linear regression models for Italy and Germany

$$CRT_{\mathcal{J}}^G = X_{\mathcal{J}}^G \beta_{\mathcal{J}}^G + \epsilon_{\mathcal{J}}^G \quad \text{and} \quad CRT_{\mathcal{J}}^I = X_{\mathcal{J}}^I \beta_{\mathcal{J}}^I + \epsilon_{\mathcal{J}}^I, \tag{2}$$

where

$$\begin{aligned} X_{\mathcal{J}}^G &= (X_{\mathcal{J}}, C_{\mathcal{J}}^G, H_{\mathcal{J}}^G, R_{\mathcal{J}}^{W,G}, F_{\mathcal{J}}^{W,G}, R_{\mathcal{J}}^{S,G}, F_{\mathcal{J}}^{S,G}, R_{\mathcal{J}}^{D,G}, F_{\mathcal{J}}^{D,G}) \\ X_{\mathcal{J}}^I &= (X_{\mathcal{J}}, C_{\mathcal{J}}^I, H_{\mathcal{J}}^I, R_{\mathcal{J}}^{W,I}, F_{\mathcal{J}}^{W,I}, R_{\mathcal{J}}^{S,I}, F_{\mathcal{J}}^{S,I}, R_{\mathcal{J}}^{D,I}, F_{\mathcal{J}}^{D,I}), \end{aligned}$$

$X_{\mathcal{J}} = (1, W_{\mathcal{J}}, D_{\mathcal{J}})$ are the regressors that are market independent, and $CRT_{\mathcal{J}}^G$ and $CRT_{\mathcal{J}}^I$ are the CRTs of the German and Italian market, respectively. All regressors are standardized by subtracting the mean and dividing by the standard deviation. The standardization helps to simplify the interpretation of the effects of covariates with different scales.

We estimate the models in equation (2) separately, for every index $\mathcal{J}$. This yields 420 models for the Italian intraday auction market, and 660 models for the German continuous intraday market, because we additionally analyze the two 15-minutes intervals shortly before physical delivery for the German market. For example, for $h = 1$, we compare the liquidity cost on the two 15-minute intervals that start 60 minutes and 45 minutes before physical delivery on the German market with the latest available intraday market in $\mathcal{D}_1^I$, i.e., MI2.

4.3. Double/Debiased Machine Learning

In this section, we describe how we compare the impact of the two market designs on the CRT while controlling for the impact of confounding variables. In particular, we directly compare the CRT in the two markets while controlling for linear and non-linear effects of the regressors introduced in Section 3.2. For this purpose, for every volume V, product h, and every trading time $\tau \in \mathcal{D}_h^G$, we combine the data on $CRT_{\mathcal{J}}^G$ and $CRT_{\mathcal{J}}^I$ into a combined $CRT_{\mathcal{J}}^C$ by stacking the two vectors on top of each other. For $\tau \in \mathcal{D}_h^G \setminus \mathcal{D}_h^I$, we use the CRTs of the corresponding last market where the hour was traded on an Italian intraday market.

We then define a sparse matrix

$$X_{\mathcal{J}}^{C} = \begin{pmatrix} X_{\mathcal{J}} & X_{\mathcal{J}}^{G} & 0 \\ X_{\mathcal{J}} & 0 & X_{\mathcal{J}}^{I} \end{pmatrix}$$

by padding market specific observations with zeros. We compute all quadratic interactions to capture non-linear effects obtaining

$$\begin{pmatrix} \multirow{2}{*}{$Y_{\mathcal{J}}^{F}$} & Y_{\mathcal{J}}^{G} & 0 \\ & 0 & Y_{\mathcal{J}}^{I} \end{pmatrix},$$

where $Y_{\mathcal{J}}^{G}$ and $Y_{\mathcal{J}}^{I}$ consist of interactions that contain a market specific variable for Germany and Italy, respectively, while $Y_{\mathcal{J}}^{F}$ contains interactions of variables in $X_{\mathcal{J}}$. Next, we delete all columns with fewer than 10 observations different from zero.

We then replace the zeros of the sparse submatrices with the corresponding mean to obtain

$$\begin{pmatrix} \multirow{2}{*}{$Y_{\mathcal{J}}^{F}$} & Y_{\mathcal{J}}^{G} & \bar{Y}_{\mathcal{J}}^{I} \\ & \bar{Y}_{\mathcal{J}}^{G} & Y_{\mathcal{J}}^{I} \end{pmatrix}. \tag{3}$$

We standardize (3) by subtracting the mean and dividing by the standard deviation and denote the resulting matrix by $Y_{\mathcal{J}}^{C}$.

Note that replacing the zeros by the respective means in (3) ensures that there is no variable in $Y_{\mathcal{J}}^{C}$, which has a different mean for the subset for Italian and German observations. We introduce a dummy variable G that takes the value 1 for CRT values from the German market and 0 for data from the Italian market. Using these regressors, we specify a combined linear model

$$CRT_{\mathcal{J}}^{C} = \alpha_{\mathcal{J}} G_{\mathcal{J}} + Y_{\mathcal{J}}^{C} \beta_{\mathcal{J}}^{C} + \epsilon_{\mathcal{J}}, \tag{4}$$

which is able to control for interactions between the variables and non-linear effects. Moreover, all regressors have mean zero and the introduced dummy variable $G_{\mathcal{J}}$ is the only available variable to describe the systematic differences in CRTs between the two countries.

Our aim is to obtain consistent estimates of the effect of the market design $\alpha_{\mathcal{J}}$ as well as confidence intervals. Equation (4) has many regressors and we are no longer able to apply OLS due to overfitting. Hence, we would have to select a subset of regressors using a model selection mechanism and then estimate the coefficient α from the reduced model. However, as pointed out by Leeb and Pötscher (2005), model selection distorts inference and especially small parameters cannot be estimated consistently. Additionally, the same data set would be used twice: the first time for model selection and the second time to estimate $\alpha_{\mathcal{J}}$ and its p-value in the resulting regression. Another naive method would be to estimate the model (4) using a LASSO regression and directly analyze $\alpha_{\mathcal{J}}$. However, the resulting estimates are biased due to the L1-regularization term introduced in LASSO.

In order to avoid biased estimates for $\alpha_{\mathcal{J}}$, we use a double machine learning procedure by Chernozhukov et al. (2018) as implemented in STATA. The method uses Neyman-orthogonal moments/scores to eliminate the regularization bias and cross-fitting to eliminate the bias resulting from over-fitting of nuisance functions. In particular, we use LASSO regression for model selection in (4) where the penalty parameter is chosen using 10-fold cross validation. We resample 10 times for the calculation of an unbiased estimate $\tilde{\alpha}_{\mathcal{J}}$ for the parameter $\alpha_{\mathcal{J}}$ in the selected models. We refer to StataCorpLLC (2019) for a detailed exposition of the method.

5. Results and Discussion

In this section, we first consider a descriptive analysis of CRT in Section 5.1. In Section 5.2, we construct two linear regression models to analyze the impact of confounding variables on the liquidity costs of the two markets. Finally, we analyze the difference of the two market designs using double-machine learning in Section 5.3.

5.1. Univariate and Bivariate Analysis of CRT

The descriptive statistics of the CRT-measures are summarized in Table 4. The first panel reports the average CRTs as measured at the points in time $\mathcal{D}_h^I$ and $\mathcal{D}_h^G$ which we use in our comparisons between the markets. However, since trading in the German continuous intraday market occurs mostly within the last three hours before delivery, we also define a *trading volume weighted CRT*, which allows us to compare CRTs of a specific product over longer periods of time as

$$CRT_{V,h} = \sum_{\tau} \frac{CRT_{V,h,\tau} Q_{h,\tau}}{\sum_\tau Q_{h,\tau}},$$

where $Q_{h,\tau}$ is the traded volume for product h and time to delivery τ. The above sum is over all quarter hours τ where a specific product h is traded. Similarly, when computing $CRT_{V,h}$ for the Italian markets, the cleared volumes for each auction market and the corresponding calculated CRTs are used. The results of these computations are reported in the lower panel of Table 4.

Subset	N	mean	std	min	25%	50%	75%	max
Average CRTs at $\mathcal{D}_h^I$ and $\mathcal{D}_h^G$								
GER, 0.1MWh	27453	5.85	6.27	0.10	2.40	4.50	7.50	137.70
GER, 5MWh	27453	6.25	6.67	0.10	2.81	4.90	7.95	147.50
GER, 10MWh	27453	6.69	7.00	0.10	3.00	5.02	8.33	162.75
GER, 15MWh	27453	7.18	7.34	0.10	3.40	5.62	8.93	168.50
GER, 50MWh	27453	10.66	10.24	0.10	5.65	8.51	12.85	198.55
ITA, 0.1MWh	17471	1.26	1.72	0.01	0.25	0.72	1.59	27.63
ITA, 5MWh	17471	2.13	2.68	0.01	0.50	1.22	2.82	38.08
ITA, 10MWh	17471	2.74	3.29	0.01	0.67	1.72	3.60	46.79
ITA, 15MWh	17471	3.33	3.88	0.01	0.92	2.11	4.34	50.45
ITA, 50MWh	17471	6.45	6.65	0.01	2.18	4.50	8.26	63.47
Trading Volume Weighted CRTs								
GER, 0.1MWh	4991	1.99	1.23	0.55	1.24	1.64	2.34	14.32
GER, 5MWh	4991	2.20	1.33	0.62	1.40	1.83	2.60	24.31
GER, 10MWh	4991	2.38	1.42	0.72	1.54	1.99	2.79	35.52
GER, 15MWh	4991	2.56	1.49	0.81	1.69	2.17	3.00	39.55
GER, 50MWh	4991	3.90	2.09	1.32	2.67	3.37	4.52	58.61
ITA, 0.1MWh	4991	0.84	0.62	0.01	0.43	0.70	1.07	5.98
ITA, 5MWh	4991	1.36	0.93	0.01	0.73	1.15	1.75	8.29
ITA, 10MWh	4991	1.71	1.13	0.01	0.95	1.46	2.18	9.49
ITA, 15MWh	4991	2.05	1.32	0.01	1.15	1.73	2.63	12.10
ITA, 50MWh	4991	3.84	2.35	0.01	2.21	3.32	4.84	21.25

Table 4: Descriptive statistics of CRT-measures and traded-volumes CRT-measures from 17.11.2017 to 15.06.2018.

The analysis reveals that the CRT for all volumes is higher for the German market on average for both ways of measurement. Comparing the maxima of the distributions, we observe that the corresponding CRTs for the German market far exceed the maximal CRTs observed in the Italian markets. However, the results for the averages are not entirely driven by the right tail of the distribution as the analysis of the other quantiles reveals. Another interesting observation is that while the CRT for the Italian market increases sharply with V, this effect is much less pronounced on the German market, where costs are high even for small volumes due to the bid-ask spread on the German market.

The univariate analysis along the dimension volume does not capture changes with the time to

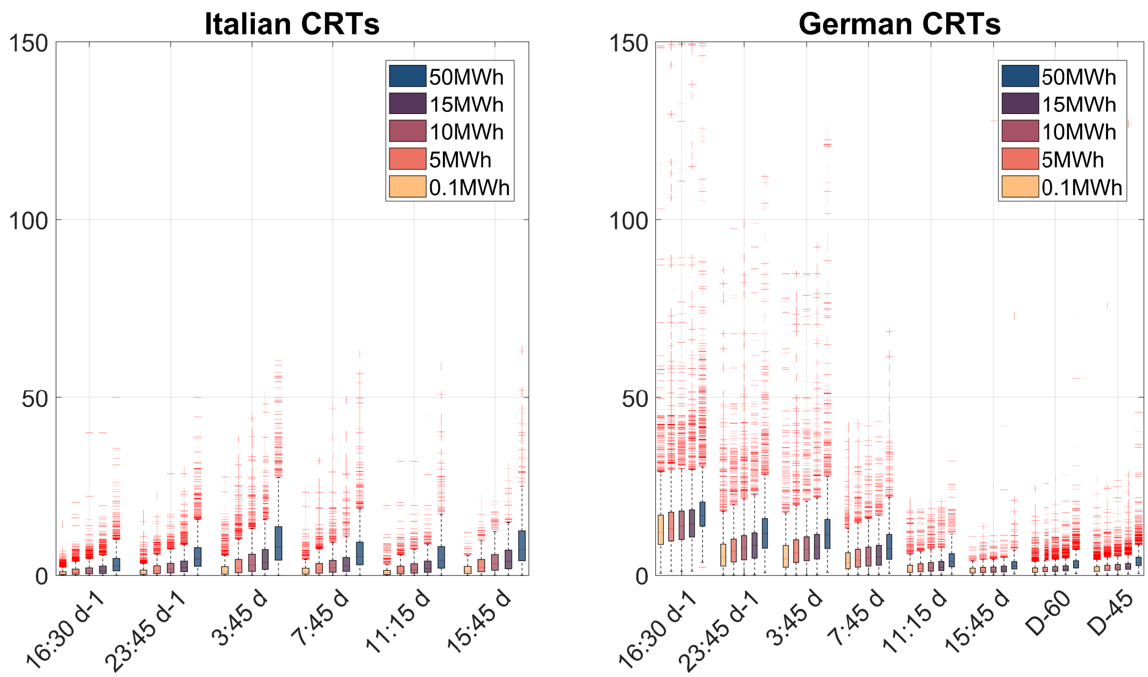

Figure 2: Boxplots of CRTs grouped by trading time and volume.

delivery. Hence, we show the dependence of the results on the time to delivery in the boxplots in Figure 2 for the CRTs calculated at $\mathcal{D}_h^I$ and $\mathcal{D}_h^G$. We note that liquidity costs on the Italian market are low during the first two auction markets, and are relatively high for the MI4 and MI7. The German CRTs decrease towards one hour before physical delivery and increase afterwards – this *L-shape* was also observed in Balardy (2018).

5.2. Effects in the Individual Markets

In this section, we analyze the effect of the explanatory variables X^I and X^G as introduced in Section 4.2 on the CRT in the respective markets. In order to do so, we fit the linear regression models (2) using the *fitlm* function as implemented in *MATLAB R2017a*. We consider the same data-set as used in the previous section grouped by volume, product, and time to delivery.

We consider a regressor to be significant in a regression, if its p-value is smaller than 0.05 and order the regressors according to the number of models that they are significant in. The upper row of plots in Figure 3 shows the distribution of coefficients of the four regressors which are most often significant in the estimated models for the Italian market. The lower four plots repeat this analysis

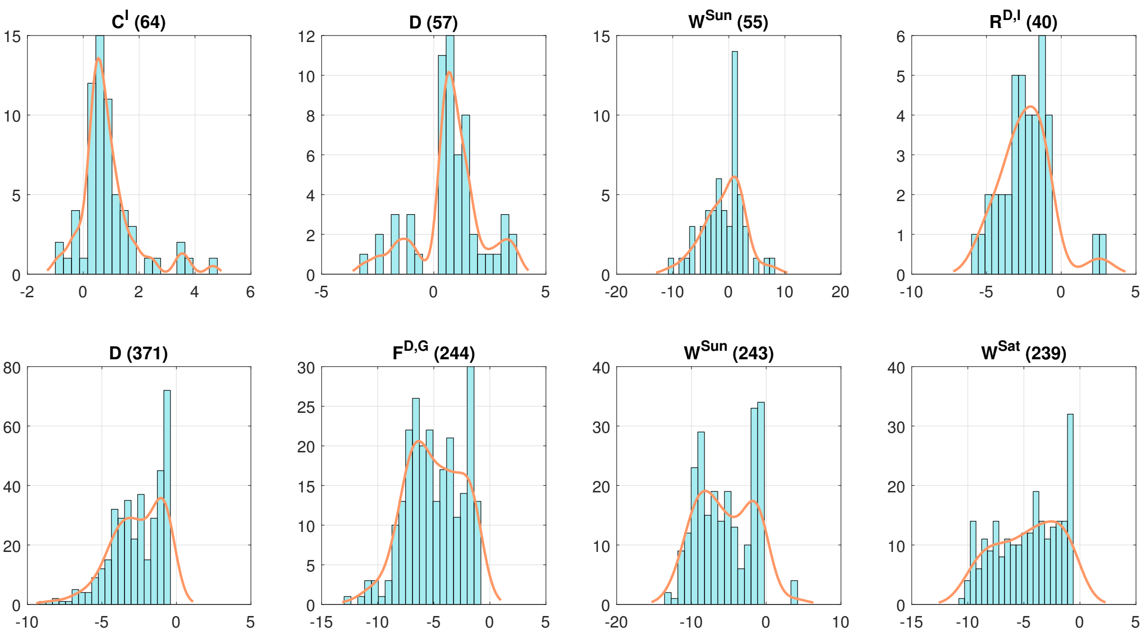

Figure 3: Distribution of the top 4 significant estimates of the selected controls of Italy (above) and Germany (below). The x-axis of the plots represents the values of the estimated coefficients.

for the German market.

For Germany, the most important regressor is the seasonality D_t modeled as the length of daylight, which has a significant positive impact in 371 out of 660 models. As the estimated coefficients are unambiguously negative, this implies lower liquidity costs in summers.

The next most significant regressor is the forecast demand $F^{D,G}$, which is significant in 244 models and has also a clearly negative coefficient implying that higher (forecast) demands lead to more trading, which in turn decreases liquidity costs.

The last two depicted regressors are the dummies for Sundays and Saturdays which are significant in 243 and 239 models, respectively. On a first glance, the negative signs of the estimated regressors might seem surprising, since there is less trading on the weekend lowering liquidity costs. However, this effect is already captured by the regressor $F^{D,G}$ so that the weekend dummies only measure the weekly patterns which do not directly depend on demand. The dummies for Saturday and Sunday, thus allow for a more moderate increase in liquidity costs on these days as would be modeled by the effect of lower demand alone.

By and large the German market shows clear effects and the corresponding regressors are significant in many of the considered models, which underlines the importance of considering these variables as controls when we measure the effect of market design on liquidity costs in Section 4.3.

The situation for the Italian models is not nearly as clear cut. Generally speaking, the proposed regressors are significant much less often and the signs are more ambiguous making easy explanations of the results harder. This is in line with Hagemann and Weber (2015), who find that the trading volume on the Italian auction market cannot be explained very well by fundamental variables.

The most important regressor for the Italian market is cooling C^I which significantly affects liquidity in 64 out of 420 models for the Italian market with a mostly positive sign implying that the increased demand by air-conditioning, which is widely used in Italy, leads to a positive impact on liquidity cost on hot days.

The length of daylight D^I, which is significant in 57 models is the second most important regressor in Italy. As the figure shows, the estimated coefficients are mostly positive indicating a positive impact of the length of daylight on the CRT. This implies a seasonal effect with higher liquidity cost in summers. This is in contrast to the German situation, where the effect on the seasonal variable is reversed.

The Sunday dummy is significant in 55 models. The sign of the regressor is rather ambiguous and hard to interpret, since, similar to the German market, there is an interaction with the realized demand, which is also contained among the top 4 regressors.

Lastly, the realized demand $R_t^{D,I}$ affects the CRT on the Italian market significantly in 40 models, where it mostly has a negative effect on the CRT.

5.3. Comparison of Market Designs

Our aim in this section is to analyze the difference of the CRTs of the two markets controlling the effect of confounding variables. For that purpose, we use the function *xporegress* of STATA StataCorpLLC (2019) to estimate the models presented in Section 4.3.

The output of our analysis is an estimate, a valid confidence interval, and the corresponding p-value for the parameter α in model (4). Table 5 summarizes the results in form of a heatmap showing estimates and p-values. The columns indicate different hourly products, while the rows indicate time to delivery. To distinguish between the different quantities V, we divide the table into five panels.

We compare CRTs for products with the same time to delivery, and the CRTs for the two 15 minutes intervals on the German continuous intraday market before delivery of a specific product with the last auction market in Italy where the corresponding product is traded. Cells marked grey indicate products that can not be compared, since they are no longer traded on the Italian market. A cell is colored red if the estimate for $\alpha_{\mathcal{J}}$ in the corresponding model is positive, i.e., the CRT in the Italian market is lower than in the German market. Analogously, cells are colored blue if $\alpha_{\mathcal{J}}$ is negative. The intensity of the color reflects the magnitude of the p-value with more intense coloring for lower p-values, i.e., more significant results as indicated in the color map in the last row of the table.

As expected from the univariate results in Section 5.1, the majority of cells are red indicating higher cost of liquidity on the German market. Comparing the overall results of the five different panels, this effect weakens for higher volumes V, indicating that the German market is relatively less affected by large volume bids as can also be seen in Figure 2.

Observing the first rows of the five panels, it becomes clear that there is a strong influence of the time to delivery on the estimated parameter $\alpha_{\mathcal{J}}$. In particular, the Italian market has clearly lower liquidity cost at the time of clearing of the first two Italian intraday markets for all volumes V. However, looking at single columns corresponding to products $h = 1, \ldots, 24$, this effect weakens as trading times move closer to delivery. These results are consistent with the analysis in Figure 2 and the fact that traded volumes tend to decrease for later Italian auction markets, while the German market is most active close to delivery.

The last two rows of every panel compare the first two 15-minutes intervals in the last hours before delivery in the German market with the last Italian auction market where the respective hour can be traded. In these 15-minute intervals the German market reaches its highest liquidity and exhibits significantly lower liquidity cost as the Italian markets, except for small volumes.

In summary, the German market gets relatively more liquid towards physical delivery, with higher liquidity in the German market close to delivery and for larger volumes V. This is also supported by looking at single rows where we mostly observe increasing estimates for $\alpha_{\mathcal{J}}$ with increasing products $h = 1, \ldots, 24$.

Looking at the first non-gray blocks in every row corresponding to MI3-MI7, i.e., the hours that can be traded the last time on an Italian market, we observe that liquidity cost on the Italian market is higher than on the German market. These markets are the last possibility to trade

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
V=0.1MWh																								
16:30 d-1	10.49	10.85	10.83	11.01	11.76	11.85	12.07	11.96	12.13	13.32	13.39	13.38	13.85	14.09	13.94	14.37	14.28	14.44	14.35	14.49	14.59	14.65	14.48	14.56
23:45 d-1					0.47	1.27	2.23	3.25	4.09	4.72	5.62	6.31	6.88	7.50	6.89	7.40	7.31	7.04	6.63	7.39	7.40	7.63	7.05	7.69
3:45 d									-0.90	0.22	1.69	2.37	5.27	5.77	4.94	5.59	5.44	6.02	5.28	6.45	6.40	6.26	6.04	6.75
7:45 d													0.17	0.46	1.17	1.78	3.51	4.53	3.50	4.02	4.94	5.77	5.23	5.54
11:15 d																	-0.01	0.42	0.46	0.86	1.38	1.91	2.23	2.43
15:45 d																					-0.86	-0.31	-0.01	0.44
D-60	0.69	0.80	0.49	0.78	0.56	0.74	0.61	0.89	-1.46	-1.80	-1.60	-1.52	-0.41	-0.50	-0.57	-0.25	0.18	0.42	0.38	0.39	-0.37	0.07	0.17	0.67
D-45	0.91	1.00	0.85	0.97	0.90	0.91	1.00	1.04	-1.36	-1.57	-1.28	-1.22	-0.09	-0.24	-0.18	0.02	0.54	0.71	0.85	0.77	0.07	0.46	0.80	0.99
V=5MWh																								
16:30 d-1	10.58	11.31	11.24	11.54	12.40	12.60	12.68	12.35	12.62	13.92	13.84	14.16	14.78	14.89	14.80	14.98	14.76	14.91	15.00	14.97	14.94	15.43	15.23	15.57
23:45 d-1					-0.58	0.28	1.63	2.39	3.72	4.69	6.29	7.20	7.83	8.39	7.84	8.15	7.97	8.10	7.94	8.15	8.44	8.45	8.33	9.01
3:45 d									-3.70	-2.09	-0.39	1.14	5.41	6.26	5.64	6.07	6.02	6.42	5.88	6.67	7.30	6.76	7.09	7.83
7:45 d													-0.94	-0.52	0.20	0.92	3.32	4.62	3.58	3.73	4.94	5.86	5.82	6.17
11:15 d																	-0.78	-0.23	-0.25	0.27	0.92	1.85	2.00	2.41
15:45 d																					-2.82	-1.43	-1.01	-0.62
D-60	0.16	0.46	0.09	0.35	-0.42	-0.19	-0.11	-0.22	-4.21	-4.23	-4.10	-3.48	-1.49	-1.51	-1.63	-1.26	-0.59	-0.19	-0.31	-0.29	-2.22	-0.98	-0.71	-0.33
D-45	0.76	0.81	0.59	0.71	0.08	0.16	0.53	0.03	-4.01	-3.88	-3.65	-3.08	-1.05	-1.16	-1.14	-0.89	-0.09	0.24	0.25	0.21	-1.62	-0.41	0.14	0.21
V=10MWh																								
16:30 d-1	10.71	11.41	11.35	11.52	12.68	12.88	12.94	12.65	12.89	14.09	14.09	14.66	15.24	15.29	15.26	15.35	15.05	15.27	15.40	15.08	15.05	15.81	15.54	16.00
23:45 d-1					-1.17	-0.13	1.17	2.02	3.42	4.79	6.36	7.46	8.20	8.94	8.23	8.66	8.49	8.81	8.53	8.76	8.89	9.04	9.10	9.64
3:45 d									-5.39	-3.25	-1.38	0.62	5.26	6.43	5.70	6.17	6.25	6.39	5.91	6.90	7.04	7.04	7.46	8.27
7:45 d													-1.46	-1.15	-0.28	0.33	3.06	4.69	3.59	3.33	4.85	5.81	6.04	6.53
11:15 d																	-1.12	-0.75	-0.77	-0.15	0.68	1.55	1.99	2.45
15:45 d																					-4.23	-2.25	-1.64	-0.75
D-60	-0.07	0.21	-0.18	-0.01	-1.04	-0.65	-0.65	-0.73	-5.91	-5.52	-5.41	-4.43	-2.04	-2.17	-2.20	-2.04	-0.94	-0.71	-0.88	-0.82	-3.60	-1.77	-1.43	-1.02
D-45	0.75	0.58	0.36	0.36	-0.50	-0.27	0.05	-0.48	-5.69	-5.13	-4.90	-3.98	-1.55	-1.80	-1.67	-1.62	-0.41	-0.24	-0.28	-0.29	-2.96	-1.03	-0.51	-0.40
V=15MWh																								
16:30 d-1	10.80	11.68	11.56	11.68	12.90	12.98	13.10	12.82	13.12	14.37	14.47	14.99	15.69	15.72	15.60	15.68	15.41	15.52	15.66	15.04	15.30	16.18	15.98	16.41
23:45 d-1					-1.80	-0.52	0.80	1.49	2.89	4.61	6.33	7.65	8.49	9.38	8.55	9.20	8.77	9.04	8.81	8.97	9.16	9.44	9.58	10.10
3:45 d									-7.12	-4.95	-2.36	-0.23	5.03	6.39	5.43	5.88	6.39	6.60	5.98	6.79	6.61	6.68	7.58	8.44
7:45 d													-1.80	-1.46	-0.73	-0.21	2.82	4.51	3.54	3.03	4.68	5.53	6.16	6.85
11:15 d																	-1.43	-1.20	-1.27	-0.58	0.26	1.37	2.01	2.57
15:45 d																					-5.66	-2.93	-2.17	-0.72
D-60	-0.29	0.11	-0.29	-0.29	-1.67	-1.07	-1.10	-1.32	-7.67	-7.36	-6.60	-5.61	-2.39	-2.52	-2.72	-2.74	-1.31	-1.17	-1.42	-1.28	-5.09	-2.38	-1.97	-1.43
D-45	0.62	0.50	0.29	0.08	-1.10	-0.68	-0.38	-1.07	-7.45	-6.92	-6.05	-5.11	-1.87	-2.12	-2.15	-2.30	-0.74	-0.67	-0.76	-0.70	-4.39	-1.71	-1.03	-0.78
V=50MWh																								
16:30 d-1	12.62	13.54	13.64	13.09	15.04	14.95	15.21	14.73	14.20	15.86	16.76	17.47	18.02	18.19	17.85	17.71	17.54	17.53	17.26	16.37	16.88	18.29	18.36	19.06
23:45 d-1					-4.14	-2.48	-0.35	-0.72	1.67	3.88	6.90	8.68	10.60	11.71	10.58	11.17	11.08	10.58	10.20	9.86	9.72	11.21	12.09	12.89
3:45 d									-13.59	-10.58	-6.47	-2.86	4.52	6.98	5.65	6.24	6.88	6.62	5.72	5.43	4.97	6.92	9.21	10.39
7:45 d													-3.48	-3.15	-2.95	-2.06	1.98	3.64	2.65	1.71	2.60	5.38	7.29	8.70
11:15 d																	-3.54	-3.01	-3.29	-3.39	-2.01	0.69	2.37	3.52
15:45 d																					-10.28	-6.90	-4.38	-0.78
D-60	-0.49	-0.09	-0.72	-0.84	-3.87	-3.08	-2.46	-4.01	-14.33	-14.14	-12.49	-10.63	-4.22	-4.62	-5.35	-5.37	-3.50	-3.11	-3.69	-4.24	-10.53	-6.12	-4.10	-2.23
D-45	0.91	0.51	0.22	-0.46	-3.08	-2.43	-1.47	-3.72	-14.27	-13.38	-11.64	-9.81	-3.49	-3.98	-4.51	-4.77	-2.67	-2.36	-2.68	-3.28	-9.48	-4.97	-2.74	-0.93

Legend

NaN	5e-07	1e-06	5e-06	1e-05	5e-05	1e-04	5e-04	1e-03	5e-03	1e-02	5e-02	1e-01	5e-02	1e-02	5e-03	1e-03	5e-04	1e-04	5e-05	1e-05	5e-06	1e-06	5e-07

Table 5: Results in €/MWh using all possible combinations until quadratic terms with standardized regressors and re-sampling (10).

forecast updates of renewable energy sources in the corresponding hours and trading volumes are correspondingly relatively high. Apparently, the high CRTs are thus a consequence of tight market situations caused by either large demands or large free production capacities flooding the market for low prices.

6. Conclusions and Policy Implications

This article explores liquidity costs of the German continuous intraday market and the Italian auction-based intraday market. For that purpose, we introduce a cost-of-round-trip measure to analyze liquidity costs. Grouping the data of each market by volume and trading time, we compare cost of liquidity in the two markets using descriptive statistics. Secondly, we analyze the impact of several explanatory variables on the two markets separately. Thirdly, we compare the two market designs by controlling the impact of the confounding variables.

We find that liquidity costs are generally lower in the Italian auction market, whereby the difference tends to decrease with the traded quantity of power and as trading gets closer to physical delivery. The latter finding is consistent with the *L-shape* of the German bid-ask spread observed by Balardy (2018).

Our results show that the cost of liquidity in both countries is influenced by weekly and yearly seasonalities, temperatures via cooling demand, and the overall demand for electricity.

Our study has some limitations. Firstly, the German market provides the possibility to place iceberg orders, i.e., orders where the full volume is not visible but gets revealed gradually as parts of the order are cleared. The existence of a significant amount of these *invisible* orders might lead us to underestimate the liquidity and correspondingly overestimate the CRT on the German market. Secondly, the CRT on the Italian intraday auction markets might be higher due to zonal prices in Italy in auctions where there is congestion of transmission lines between market zones.

Our analysis suggests that a hybrid system might leverage the advantages of both market designs and decrease liquidity costs on intraday markets (Bellenbaum et al., 2014; Ehrenmann et al., 2019; Ocker and Jaenisch, 2020). In particular, auction markets for hours far from delivery might help to increase liquidity by pooling orders, while continuous intraday markets starting close to delivery would be an optimal tool to integrate forecast errors for the output from variable renewables shortly before physical delivery. A similar design was recently introduced for the Spanish intraday market and it is planned for the Italian market as well. Alternatively, one could use a system of *frequent* *batch auctions* as proposed in Budish et al. (2015); Deutsche Börse Group (2018) to combine the advantages of continuous trading and auctions.

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