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Measuring and Assessing the Evolution of liquidity in Forward Natural Gas Markets: the Case of the UK National Balancing Point

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CEA@Cass Working Paper Series
WP-CEA-08-2017

Measuring and Assessing the Evolution of Liquidity in Forward Natural Gas Markets: the Case of the UK National Balancing Point

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24 July, 2017

Abstract

Following the development of natural gas trading hubs in Europe, forward products have become a response to the higher exposure to price risk faced by energy companies. Yet, a significant share of trade occurs over-the-counter (OTC), where inter-dealer brokers act as intermediaries and deals may be customized. Hence, there are concerns about transparency and market quality, of which liquidity is a main indicator. This study investigates liquidity in the largest one-month-ahead European forward market for natural gas using asynchronous high-frequency data and time-varying measures of spread and price impact that are drawn from the financial market microstructure literature. The usefulness of these measures in the seasonal and evolving National Balancing Point (NBP) is therefore assessed, and different aspects of liquidity and transaction costs are unveiled.

Keywords: Liquidity measures, natural gas markets, OTC trading, time-varying modeling

1 Introduction

Liquidity can be defined as the ability to match buyers and sellers at the lowest transaction costs (O’Hara, 1995). This definition impounds a dynamic feature since, in a liquid market, executing a transaction over a short-time horizon does not entail higher costs than spreading the same transaction over a longer horizon. It also evokes the concept of elasticity, such that small shifts in the

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fundamental values of demand and supply result in negligible price changes when liquidity is high (Hasbrouck, 2007). As a consequence, in a market with many participants, uncompetitive behaviors are prevented and trading activity affects pricing only in a transient and marginal way. Measuring liquidity is thus critical when assessing market quality, since liquidity provides investment signals to market participants and reduces the likelihood of price manipulation. By contrast, illiquidity is a barrier to market entry and a source of competitive disadvantage to smaller players.

In the context of evolving European natural gas markets, how best to measure and assess liquidity has become increasingly relevant, not only to those interested in the cost of hedging and investment decisions, but also to regulators and policy makers, who need to monitor market quality. The liberalization process, by increasing the exposure of market participants to demand-supply imbalances, has fostered the development of forward markets and a move away from the traditional oil-indexed long-term contracts towards hub (spot) pricing. According to International Gas Union (2016), the share of volumes traded indexed to hub prices rather than oil prices has quadrupled in the last ten years. Greater competition and forward trading have also encouraged the participation of financial institutions (investment banks, hedge and pension funds, and trading companies), which have further contributed to the development of hub trading and market liquidity. Yet, the interest of market participants in trading an asset depends upon its value, as well as on the market mechanisms and costs underlying the trading process (Harris, 2003; Hasbrouck, 2007). As natural gas trading garners increased interest in the European markets, liquidity measurement is relevant when price dynamics are considered, and has implications for efficiency, welfare and regulation of the trading mechanisms and market structure.

This paper investigates how to measure and assess liquidity in the OTC forward market at the UK National Balancing Point (NBP, hereafter), which is the main pricing hub for natural gas trading in Europe (Cummins and Murphy, 2015; European Commission, 2015). One-month-ahead forward contracts are used, as these are the busiest contracts and thus the most representative of the European natural gas forward market. Using tick-by-tick indicative quotes, transaction prices and volumes from 2010 to 2014, measures that capture different dimensions of liquidity are estimated.

The study evaluates whether such measures, which have been designed and applied in financial markets, are applicable to the physical natural gas market. A time-varying perspective is adopted, with the intent of exploring changes that might have occurred in market liquidity over the sample period.

The remainder of the paper is organized as follows. In Section 2, the literature on liquidity measurement in energy and financial markets is reviewed. Section 3 focuses on the empirical study, the data and methodology adopted; it also summarizes the market microstructure theory underlying the measures, which are defined and used to assess different dimensions of liquidity. Empirical results are reported in Section 4 and discussed in Section 5. Finally, Section 6 concludes the paper.

2 Measuring Liquidity in Energy and Financial Markets

2.1 Liquidity in Energy Markets

Practitioners in the natural gas and power markets usually refer to the *churn ratio* when measuring liquidity. This measure is the ratio of trading volumes to physical deliveries after the transactions: the higher this ratio, the greater is liquidity. It reveals the vitality of a market and can be seen as equivalent to the turnover ratio, which is used to assess liquidity in stock markets and is computed by dividing the value of the shares traded over a certain period by the average market capitalization. The *churn ratio* is simple to calculate and permits the comparison of liquidity across geographically different markets or hubs, and between commodities (Ofgem, 2009). However, it is a trade-based measure and like other trade-based measures, such as the turnover ratio, the trading frequency, or the trade size, may be a poor measure of liquidity (Aitken and Comerton-Forde, 2003). Notwithstanding the use of trade-based measures is supported by the empirical evidence of a positive correlation between liquidity and trading activity (Fleming, 2003), this correlation may be associated with high volatility, which actually reduces liquidity (Karpoff, 1987). Furthermore, trading activity can be high when a market is in crisis and liquidity is actually low (Roll, 2005).

In natural gas and power markets, trading activity and, in turn, the *churn ratio* are expected to be

weather-dependent. As illustrated in Figure 1, greater *churn ratio* is observed in the summer (July-September), when the traded volumes are lower compared to the winter months. Yet, this ratio is at its lowest in December, and this may be explained by the historically low month-on-month trading volumes observed during this month at European hubs (Platts, 2016).

The *churn ratio* decreases during the summer and may be driven by the annual storage cycle. The first week of April marks the switch from withdrawal (at higher winter prices) to injection (at lower summer prices) (Timera-Energy, 2016), thus the start of the storage-year. During the first week of November, the opposite holds. As inventory level grows in the summer, one might conjecture that physical deliveries reduce relative to the financial trading, thus driving the *churn ratio* up. In addition, shifts in trading activity may occur due to hedging against short-term fluctuations in the summer/winter price spread before the start/end of the storage-year. This spread is a signal for storage-capacity holders and investors in natural gas markets and may have drawn month-on-month increases in the *churn ratio*, as observed in February, and to less extent in March, and in September. Since it is mainly driven by changes in the trading volume relative to the physical deliveries, the *churn ratio* may be a misleading measure of liquidity. In fact, Newbery et al. (2004) highlighted the need to investigate different factors that may impact liquidity in energy markets: volume, price volatility, number of market participants, presence of different prices for the same product, bid-ask spread and transaction costs; because such factors contribute to the optimal market design.

[Insert Figure 1 here]

2.2 Liquidity Measurement in the Literature

Despite the conciseness of the definition of liquidity, a rigorous and empirically relevant measure remains a challenge, especially due to the multiple dimensions that are implicit in its concept. According to Kyle (1985), liquidity encompasses different transactional properties of a market: tightness (the cost of turning around a position over a short period of time), depth (the size of an order flow innovation required to change price by a given amount), and resiliency (the speed at which prices recover from a random, uninformative shock). A tight market results in many participants,

who are unable to assume a dominant position. Depth entails the existence of large incremental volumes that are available for selling (buying) at a price a little above (below) the clearing prices. Finally, the resilience of a market reveals speed and magnitude of the price changes that are associated with the trading activity (Hasbrouck, 2007). Overall, these dimensions highlight dynamic attributes of liquidity and can be interpreted as costs of completing a transaction.

Transactions costs encompass all costs related to the trading process, and include explicit as well as implicit costs (Harris, 2003). Whilst explicit costs refer to order processing costs and are identified in commissions, fees, taxes and other certain costs connected to a trade, implicit costs are more difficult to measure and are associated, for instance, with the impact of trading activity on transaction prices. Traders buy at the ask price and sell at the bid price. The bid-ask spread therefore represents a transaction cost, as impounded in the definition of market tightness. Yet, large-size trades tend to move prices up or down, depending on whether they are a purchase or a sale. This price impact also represents a transaction cost, as implied by the definitions of market depth and resilience. Following the availability of high-frequency intraday data, order-based measures of spread and price impact have been developed to evaluate the implicit costs associated with the trading activity (Hasbrouck, 1991a; Chordia et al., 2000; Goyenko et al., 2009).

2.2.1 Measures of spread

The quoted bid-ask spread and the effective bid-ask spread (Roll, 1984; Stoll, 1989) are financial measures of tightness. Their intuitive meaning is derived from a microstructure model, where customers trade only with the market-maker, who assumes the risk of holding a certain amount of a particular asset, i.e. inventory risk, in order to facilitate the trading process of such an asset. According to this model, in each trade customers incur a transaction cost that is equal to the difference between the actual price and the bid or ask price (Demsetz, 1968). Therefore, the difference between ask and bid prices, which is known as quoted bid-ask spread, represents the transaction cost paid by customers to the market-maker for a round-trip, i.e. a purchase followed by a sale of the same amount, and is the market-maker's compensation for assuming the inventory risk.

Nonetheless, Stoll (1989) observed that even when trades occur between customers and the market-maker, the quoted bid-ask spread can overstate the actual transaction costs, if: a subset of customers is better informed than the market-maker; or, if the market-maker adjusts the bid-ask spread to control the inventory level. Huang and Stoll (1996) therefore proposed to replace the quoted bid-ask spread by the effective bid-ask spread, which is computed as the difference between actual price and the average of the bid and ask quotes, namely the midquote. Accordingly, transaction costs are measured relative to the midquote, which prevails at the time of the trade and is a basis to evaluate whether the buyer is paying a high price and the seller is receiving a low price. As the difference between transaction price and this benchmark would be totally ascribed to trading process, it measures liquidity.

Since their conception, measures of spread have been replicated in different empirical studies of transaction costs in financial markets (e.g. Bessembinder, 1994; Goyenko et al., 2009; Bessembinder and Venkataraman, 2010; Corwin and Schultz, 2012). When considering commodity and energy markets, the effective bid-ask spread appears to have been first used by Locke and Venkatesh (1997) to measure transaction costs in the Chicago Mercantile Exchange (CME) futures market. More recently, Marshall et al. (2012) employed the quoted and effective spreads when investigating transaction costs of commodity futures comprising the S&P Goldman Sachs Commodity Index. In addition, they assessed the effectiveness of low-frequency liquidity proxies when high-frequency data are unavailable, or when liquidity measurement with high-frequency data is computationally intensive and not warranted. Notwithstanding their assessment of transaction costs of commodities, Marshall et al. (2012) focused on the U.S. market. In a subsequent study, Marshall et al. (2013) also adopted measures of spread when examining common and systematic drivers of liquidity in the U.S. commodity markets, and the link between commodity and stock market liquidities. In energy markets, Frestad (2012) used the quoted bid-ask spread to evaluate effectiveness and cost of hedging strategies in the Nordic power market. Overall, the assessment of tightness, as a dimension of liquidity, appears to have been neglected in studies of natural gas markets.

2.2.2 Measures of price impact

In a high-frequency setting, several authors (e.g. Amihud, 2002; Pastor and Stambaugh, 2003; Sadka, 2006; Acharya et al., 2009) have measured price impact to investigate the other two dimensions of liquidity: depth and resiliency. Price impact is defined as the temporary change in transaction prices following a trade, which is captured either by price reversals or by price changes accompanying an order flow.

Price reversals are mainly due to bid-ask bounce effects, i.e. the bounce of the price within a tiny range limited by the bid and ask prices. This bounce is due to impatient buyers and sellers demanding liquidity, or to uninformed traders causing a sudden change in prices (Harris, 2003). Price reversals may have short- or long-term patterns and can be measured by the absolute transaction price change. The basic idea behind this measure follows the definition of bounce and implies that all trades occur at the bid (sale) or ask (purchase) prices. Yet, in practice not all trades take place at the bid/ask prices, this measure can therefore produce biased estimates of the price impact (Harris, 2003). In order to address this bias, different measures based on prices changes have been proposed in financial literature.

Roll (1984) introduced a serial covariance estimator computed from the product of adjacent price changes. Given a price reversal, this estimator tends to be negative following the product of positive and negative price changes. However, if markets were efficient (Fama, 1991), asset prices would fully reflect all the available information and the serial covariance of price changes should be zero, thus implying negligible transaction costs. Hence, a negative serial covariance entails positive transaction costs. However, this measure of liquidity is only unbiased for large sample sizes, or when changes in the bid and ask prices are uncorrelated with the sequence of arrivals of orders (order flow) and inventory costs are zero (Huang and Stoll, 1997).

Estimates of price changes associated with the order flow have been thus proposed in the financial literature and exploit the norm that prices reduce in response to aggressive sales and increase in response to aggressive purchases. Pastor and Stambaugh (2003) measured liquidity based on the temporary price change, in terms of expected return reversal due to order flow, which they defined

as the signed volume in order to discriminate between buyer-initiated and seller-initiated trades. Their measure follows the intuition that low liquidity is accompanied by high volume-related expected return reversal. Hence, impulse response functions can be used to determine the speed of convergence of prices towards their equilibrium after unexpected traded volumes. This is the approach taken by Hasbrouck (1991a) and Dufour and Engle (2000), and more recently by Banti et al. (2012). Hasbrouck (2009) measured price impact as the price-change associated with the signed square-root of the aggregated monetary volume, while Goyenko et al. (2009) measured price impact based on changes in midquote after a signed trade. Finally, order flow, defined as the difference between the number of buyer-initiated and seller-initiated transactions, was found to be related to changes in quotes and prices and has been used as an indirect measure of price impact (e.g. Evans and Lyons, 2002; Payne, 2003; Evans, 2010; Chen et al., 2012).

To date, measures of price impact have been investigated in financial markets, particularly in stock markets. Their application to commodity and energy markets may be challenging due to the difficulty in collecting high-frequency data on order flows and volumes. As a result, how to measure depth and resilience in energy markets is a research question, which to the best of our knowledge remains to be addressed in the context of natural gas markets.

2.2.3 Measuring the relative importance of the different dimensions of liquidity

While acknowledging that liquidity encompasses different dimensions, research in financial markets also focused on measuring the contribution of each dimension to market liquidity by using statistical models to capture information disseminated in transaction prices and signed order flows. Specifically, these models exploit a theoretical expectation of market microstructure, which is that order flow has different impacts on prices, depending upon the prevalence of implicit costs (inventory and adverse selection costs) relative to explicit costs (i.e. order processing costs).

Following the seminal contribution by Roll (1984), who focused on the serial covariance estimator of transaction prices to make inferences on the bid-ask spread, some studies used covariance models to measure the relative weight of order processing costs, inventory costs and adverse selection

costs reflected in the spread (Choi et al., 1988; Stoll, 1989). A different class of models used signed trades to make inferences about the cost components of the spread (Glosten and Harris, 1988; Hasbrouck, 1991a; Madhavan et al., 1997). Nonetheless, Huang and Stoll (1997) highlighted the lack of statistical models of all the three cost components and their relative contribution to transaction costs.

The empirical setting introduced by Huang and Stoll (1997) represents the first "three-way spread decomposition" model, accounting for all components of transaction costs impounded into the bid-ask spread simultaneously, thus allowing for inferences on the different dimensions of liquidity in a unified way. Specifically, the authors proposed a price-impact regression model to measure the three components of transaction costs by exploiting information unveiled in the order flow, which they defined by the trade indicator (+1 for buyer-initiated trade, -1 for seller-initiated trade). This setting moves from the assumption that when adverse selection is assumed, it should be revealed by serial correlation in the trade direction (buy or sell) and buy-sell imbalances. Therefore, changes in prices result from a permanent component, attributable to informed trading, and a transitory component, which is related to inventory control and order processing costs.

A number of empirical studies have employed trade indicators and the proposal by Huang and Stoll (1997) to investigate spread decomposition and the different dimensions of liquidity in financial markets (e.g. Heflin and Shaw, 2000; Sadka, 2006; McGroarty et al., 2007; Chung and Hrazdil, 2010; Osler et al., 2011; Ryu, 2011; Ibikunle et al., 2013; Sankaraguruswamy et al., 2013; Hagströmer et al., 2016). Yet, to best of our knowledge, estimates of spread decompositions appear to have been neglected in studies of natural gas markets.

3 The Study

Given the limitations of the energy economics literature on measuring market liquidity, and the questions posed by the *churn ratio* as a practical measure of liquidity, this study examines the

usefulness of measures of spread and price impact to assess liquidity in natural gas markets. In addition, it investigates the relative importance of the different dimensions of liquidity and how liquidity evolves in the one-month-ahead NBP forward market.

3.1 Data

Records of transactions and quotes for the NBP forward contracts over the period from 7 May, 2010 to 29 December, 2014 are considered. These were made available by Tullett Prebon Information (<http://www.tpinformation.com/indepthdata/commoditiesenergy.aspx>), which is part of the TP ICAP group and an international provider of independent real-time price information from the global OTC financial and commodity markets.

The sample covers about a third of the total OTC market for the NBP in the period. Two data sets are considered, the first includes tick-by-tick indicative quotes and the second includes tick-by-tick transaction prices and volumes. In order to account for the asynchronous nature of the tick-by-tick data, a stepwise cleaning procedure is adopted, which is based on Brownlees and Gallo (2006) and Barndorff-Nielsen et al. (2009). Holidays, weekends, errors and outliers are deleted. For transactions and quotes, the trading window from 7:00 to 17:00 (GMT) on standard working days (Monday-Friday) is considered. Simultaneous records are aggregated in a single record: quotes and transactions are measured by their median; while, volumes and transaction prices are aggregated by using their respective totals.

Following Barndorff-Nielsen et al. (2009), outliers are detected via a non-parametric distance-based approach. Entries for which the bid-ask spread is greater than 10 times the median spread of that day are discarded. Similarly, entries are deleted if the midquote, which as defined above is the average of bid and ask quotes, deviates by more than 10 median absolute deviations from the median midquote on that day. Records are also deleted when the transaction price is negative and when the absolute relative deviation of the transaction price from the prevailing midquote is more than 10 times the median of the absolute relative deviations in the sample. This last rule smooths the trade data using prevailing bid and ask quotes. Similar to Lee and Ready (1991), last quotes are defined

as the quotes occurring at least 5 seconds before the trade.

Month-ahead NBP futures and forward contracts are for delivery in fixed calendar months (e.g. one-month-ahead contracts on March 15, 2014 are for delivery in April 2014). These contracts cease trading two business days prior to the first calendar day of the delivery month (Intercontinental Exchange (ICE), 2017). Therefore, entries corresponding to transactions recorded during the roll-over period, i.e. after the end of the trading period and before delivery, have been discarded. Overall, the data cleaning results in discarding less than 13% observations.

The data are then sampled at regularly spaced time-intervals. According to Foucault et al. (2013), regular time intervals are required to ensure that prices have adjusted to the information content of the cumulative transactions over time. Similar to Zhang et al. (2005) and Boffelli and Urga (2015), the trading window is split into fixed-time intervals. For each time interval, the following information is extracted: the end-of-interval price, the end-of-interval quotes, the end-of-interval trading volume, the total trading volume over the interval, the total trade size over the interval, and the total number of transactions over the interval. When a time interval does not contain observations, the most recent recorded observation is used. Finally, in the spirit of Boffelli and Urga (2015), the first record of each day is excluded from the sample, because it could reflect the adjustment to the overnight information and thus exhibit excessive variability, when compared to the other observations in the same day. This resampling procedure is performed at different frequencies: 5, 15, 30, and 60 minutes. The aim is to identify the best behaved sample to be analyzed, which minimizes volatility clustering, kurtosis and autocorrelation in the midquote and transaction price return series.

3.2 Measuring Liquidity

3.2.1 Measures of spread

One of the simplest and most intuitive liquidity measures is the quoted bid-ask spread, which is the difference between the best quoted ask price and the best quoted bid price (Amihud and Mendelson, 1986). However, this measure does not capture transactions executed at prices within the bid

and ask quotes (Stoll, 1989; Bessembinder, 2003). Moreover, in the OTC natural gas markets, active market-makers, who post firm bid and ask quotes, are absent. Quotes are therefore indicative and tradable at mid-market prices, as provided by the broker based on actual trading orders and expressions of interest. In this context, a more reliable measure of transaction costs, which reflects negotiated transactions either inside or outside the indicative quotes, is the effective half-spread. The effective half-spread measures transaction costs as the difference between actual transaction prices and midquotes from the most recent bid and ask quotes, which are viewed as a proxy for the underlying value of the asset (Bessembinder, 2003; Foucault et al., 2013). It can be measured either in absolute basis points, or as a percentage of the midquote (Bessembinder, 1994; Goyenko et al., 2009; Bessembinder and Venkataraman, 2010; Corwin and Schultz, 2012). In this study, the percentage effective half-spread (EHS) is adopted, because percentage measures are most extensively used in literature and permit comparison between assets (e.g. Chordia et al., 2001; Corwin and Schultz, 2012). The percentage effective half-spread is defined as follows:

$$EHS_\tau = D_\tau \left(\frac{P_\tau - M_\tau}{M_\tau} \right), \quad (1)$$

where P_τ is the price of the τ^{th} transaction, evaluated at the trading time, M_τ is the midquote at the same time. D_τ is the trade indicator taking values 1 for buyer-initiated transactions, and -1 for seller-initiated transactions. In the financial literature, this indicator is usually set according to the algorithm by Lee and Ready (1991), as described by several authors (e.g. Goyenko et al., 2009; Foucault et al., 2013). A transaction is therefore classified as buyer-initiated if its transaction price is closer to the prevailing ask quote than bid quote, and as seller-initiated otherwise. If a transaction is priced exactly at the midquote, it is buyer-initiated when its price is higher than the price of the previous transaction ("uptick"); conversely, it is classified as seller-initiated ("downtick").

Since the effective half-spread recognizes that transactions can occur at prices other than the midquote, it estimates the transaction cost actually paid by a liquidity demander (i.e. the buying dealer), as well as the gross revenue earned by the liquidity supplier (i.e. the selling dealer). According to market microstructure theory, bid-ask spreads must cover three costs that are incurred

by providers of liquidity: order-processing costs, inventory costs and asymmetric-information costs. As explained by Stoll (1978), the intuition behind inventory costs, which represent the non-informational component of the effective spread, is that transaction costs should lead to a temporary deviation of the price from the underlying asset value. This temporary component is highlighted by a price reversal after the transaction (Bessembinder and Venkataraman, 2010) and can be captured by the percentage realized half-spread (RHS), which is defined as:

$$RHS_{\tau} = D_{\tau} \left(\frac{P_{\tau} - M_{\tau+1}}{M_{\tau}} \right). \quad (2)$$

where $M_{\tau+1}$ represents the midquote after the transaction, used as a proxy for the post-transaction value of the asset, and reflects the liquidity supplier compensation. According to Amihud and Mendelson (1980), the realized half-spread represents the compensation of the risk adverse liquidity supplier for bearing the price risk of an order imbalance. It can also be interpreted as the transaction costs net of the adverse selection component. Given private information about the asset value, the price reversal may be partial rather than full, prices should then adjust by increasing after a buyer-initiated transaction, or by falling after a seller-initiated transaction.

3.2.2 Measures of price impact

Movements in the effective half-spread also reflect adverse selection costs due to asymmetric information (Glosten and Milgrom, 1985). This informational and permanent component is measured by the price impact of a transaction that, according to Goyenko et al. (2009) and focusing on the changes in the asset value (i.e. midquote) after a transaction, is defined as follows:

$$PI_{\tau} = D_{\tau} \left(\frac{M_{\tau+1} - M_{\tau}}{M_{\tau}} \right) = EHS_{\tau} - RHS_{\tau}. \quad (3)$$

The three measures described above explain the components of costs in a single small transaction. However, liquidity adjusts to the pressure exerted by larger transactions, which are often executed in multiple transactions (Hasbrouck, 2009; Hendershott and Menkveld, 2014). Hence, in order

to investigate this aspect of liquidity, a second measure of price impact is adopted. It is a slight modification of the one proposed by Hasbrouck (2009) and is drawn from the classical work of Kyle (1985). In contrast to previous literature, this measure will be allowed to be time-varying thus enabling the identification of changes in the link between trading activity and price returns. Furthermore, in estimating this measure the physical volume, rather than its monetary value, is used. This second measure of price impact relies on the theoretical framework by Campbell et al. (1993) and Llorente et al. (2002), who analysed the dynamic relationships between stock returns and traded volumes as well as the role of order flow in future price movements. Since trading volume allows for the identification of the periods in which either inventory imbalances or informational shocks occur (Llorente et al., 2002), it can provide valuable information about price movements to participants and monitors in the market. This measure is in the spirit of Kyle (1985), where liquidity is defined as the response of prices to order flow, and Brennan and Subrahmanyam (1996), who measured liquidity through the magnitude of price changes due to signed order flow. In particular, prices increase in buyer-initiated transactions and decrease in seller-initiated transactions. The impact is increasing with the size of order flow, which is defined as the difference between buyer-initiated and seller-initiated transactions. Since prices adjust to the information impounded in the order flow gradually, they may not be immediately revised to reflect public information (Hasbrouck, 1991b). To overcome the issue of price adjustment to information over time, the cumulative signed volume over fixed time intervals is considered to assess order flow as a predictor of price changes. Following Glosten and Harris (1988) and Hasbrouck (1991b), and to account for dynamics in the different dimensions of liquidity, in this study the price impact is measured by the time-varying coefficient λ_n that relates transaction price returns to the order flow in the following linear regression model:

$$r_{n,t} = \lambda_n S_{n,t} + u_{n,t}, \quad (4)$$

where $r_{n,t}$ is the return over a fixed time interval t , $t = 1, \dots, T$, in the rolling window n and $S_{n,t} = \sum_{\tau} sign(v_{n,t,\tau}) \sqrt{v_{n,t,\tau}}$ is the signed square-root of the order flow in the same interval and rolling window. This measure reflects the buying pressure and is computed as the aggregated

signed physical volumes $v_{n,t,\tau}$, where τ indexes the transactions in the fixed time interval t and rolling window n ; $u_{n,t}$ is the white noise error term, such that $E(u_{n,t}) = 0, \forall t; E(u_{n,t}u_{n,s}) = 0, \forall t \neq s; \text{Var}(u_{n,t}) = \sigma^2 < \infty$. The time-varying coefficient λ_n is estimated by assuming rolling windows of size m over the full sample of size T . Increments between successive rolling windows of one unit of time are assumed, thus leading to $N = T - m + 1$ estimates of the coefficient λ_n over the full sample. The reciprocal of λ_n can be interpreted as a measure of market depth: the lower the value of λ_n , the less sensitive are prices to buying pressure, thus to order flow.

3.2.3 Estimating the contribution of the different dimensions of liquidity

Price impact regression analysis is used in order to estimate the contribution of the different costs of providing liquidity, thus allowing inference on the relative importance of each dimension of liquidity. Specifically, a regression of changes in transaction prices on contemporaneous and lagged measures of order flow is estimated, which accounts for the information impounded in the order arrivals. Following Huang and Stoll (1997), a "three-way decomposition" of the price impacts is adopted, and permits the identification of the transaction cost components of the bid-ask spread, namely order processing cost, inventory cost and adverse selection cost. Order flow d_t is defined by the trade indicator taking values $+1$ for buyer-initiated trade and -1 for seller-initiated trade. Its direction is inferred through Lee and Ready (1991) algorithm and is assumed to be generated by a first-order autocorrelated process:

$$d_t = \varphi d_{t-1} + \eta_t, \quad (5)$$

where η_t is the white noise error term (*i.e.* $E(\eta_t) = 0, \forall t; E(\eta_t\eta_s) = 0, \forall t \neq s; \text{Var}(\eta_t) = \sigma^2 < \infty$). Autocorrelation reflects the expectation that investors react similarly to informative events, thus creating a flow of orders on the same direction. It also satisfies the assumption that investors prefer to reduce the price impact of large-size transactions by executing them through a series of smaller orders. Therefore, a positive autocorrelation should be observed in the order flow. Yet, when inventory risk is considered, a negative autocorrelation is induced in the order flow, led by inventory rebalancing, which drives price reversals (Stoll, 1978; Foucault et al., 2013; Hendershott

and Menkveld, 2014).

Based on Huang and Stoll (1997), order flow is assumed to affect price changes r_t according to the following specification:

$$r_t = \gamma \Delta d_t + (\alpha + \beta) \gamma d_t - \alpha \gamma \varphi d_{t-1} + \varepsilon_t, \quad (6)$$

where $\Delta d_t = d_t - d_{t-1}$; γ represents the order-processing cost component and captures the bid-ask bounce effect, thus providing a measure of market tightness; α unveils the informativeness of order flow, i.e. the adverse selection component, thus allowing measurement of the long-term impact of order flow on prices and inference on market depth; β reflects inventory costs thus permitting to distinguish them from adverse selection costs, since in the short-term these two cost components have the same effect on prices (Foucault et al., 2013). Finally, the error term captures the effects of public information other than trades (e.g. macro-economic factors, business cycles). Hence, by jointly estimating (5) and (6), the identification of the three components of transaction costs is allowed, thus providing a way to measure their relative contribution to liquidity. Estimation is carried out using the generalized method of moments (GMM) and the Newey and West (1987) estimator to accommodate serial correlation and heteroscedasticity of unknown form in the error term.

3.3 Deseasonalizing and Detrending Liquidity Measures

Given the seasonality and trend that can be observed in the time series, it is important to ensure that predictable market activity variation affecting the variables in a similar way are removed. In other words, the focus of the analysis should be on the irregular component (the residual series). Following, Chordia et al. (2005), the raw time series y is regressed on a set of adjustment variables, X , which in this study are: 11 month-of-the-year dummies (February - December); 4 day-of-the-week dummies (Tuesday-Friday); a time-trend. In order to standardize the estimated residuals, the

following regression is computed:

$$\log(\hat{u}^2) = X\gamma + v, \quad (7)$$

and the adjusted time series to be analyzed is:

$$\tilde{y} = a + b \left(\frac{\hat{u}}{\exp(X\hat{\gamma}/2)} \right), \quad (8)$$

where a and b are set so that raw and adjusted sample means and variances are the same, and thus the units of measurement of the original and adjusted time series are the same.

3.4 Preliminary Data Analysis

Descriptive statistics of the series resampled at different frequencies (5, 15, 30 and 60 minutes) are reported in Table 1. Number of observations (column two) and observations per day (column three) are in the top of Panel (a), along with the average ask and bid indicative quotes (in pence/therm), and the corresponding midquotes (columns four, five and six). Standard errors are in brackets. The first (M_{25}) and third (M_{75}) interquartile of the midquotes are in column seven and eight, respectively. The distribution of the midquote returns, after being multiplied by 10^2 , is summarized in the bottom of Panel (a). The first four moments are in columns two to five (Mean, Std.Dev., Skewness and Kurtosis). The first lag of the autocorrelation function ρ_1 is in column six. Columns seven and eight show, respectively, the Ljung-Box statistics for the null hypothesis of serial independence and the ARCH test for the null hypothesis of homoscedasticity at the 50th order of lags. This order accounts for a time window spanning from 4 hours (data resampled at 5-minute frequency) to one week (Monday-Friday, at 60-minute frequency). In Panel (b) of Table 1, the descriptive statistics of the trading variables (top) and the distribution of transaction price returns (bottom) are shown. Number of observations and observations per day are in columns two and three, respectively. The average volume (1,000 therm/day), trading size (million £) and transaction price (pence/therm) observed in each interval are shown in columns three to five along with their standard errors (in brackets). The first (P_{25}) and third (P_{75}) interquartile of the price series are in columns seven and

eight. The first four moments of the price returns pre-multiplied by 10^2 are in columns two to five. The first-order autocorrelation function, the Ljung-Box statistics and the ARCH tests are in columns six to eight.

Resampled midquote and price return series show high skewness and kurtosis, which however reduce with the resampling frequency. That is, higher skewness and kurtosis are observed in the data resampled at 5-minute frequency (21.14 and 2,176 of midquote returns, respectively; 18.85 and 1,873 of price returns), when 121 observations per day are recorded, compared to the data resampled at 60-minute frequency and 11 daily observations (5.851 and 174.7 of midquote returns; 5.412 and 160.2 of price returns). ARCH effects are rejected at 1% significance level, while serial-correlations appears to be significant mainly at lower frequencies (30 and 60 minutes). Therefore, the focus of subsequent analysis is on 60-minute resampling, because this frequency minimizes leptokurtosis and asymmetric effects and leads to a sample of size $T=11,638$ observations, or 1,058 trading days and 11 observations per day.

[Insert Table 1 here]

NBP transaction prices and midquotes at 60-minute frequency are in Figure 2. A doubling of prices and midquotes (Figure 2, (a)-(b)) is observed between May 2010 and December 2013, and a significant drop since January 2014. The increase is more pronounced in the period from the second-half of 2012 to the first-quarter of 2013, and may be linked to natural gas demand-supply imbalances in the UK and Continental Europe, a Norwegian supply disruption, low storage level, and sustained cold weather in the UK, mainly evident in March 2013 (European Commission, 2013; Timera-Energy, 2013). Subsequently, the increasing availability of liquified natural gas (LNG) from the international markets and the slump in international coal prices are likely to have contributed to reductions in natural gas demand since the second-half of 2013, thus leading to declining one-month-ahead NBP forward prices.

Returns based on the transaction prices and midquotes (Figure 2, (c)-(d)) show volatility clustering, excess kurtosis and heteroscedasticity, which are typically observed in financial time series and justify our adoption of measures from the financial literature. An increase in the volatility of the

return series can be also observed during 2014.

[Insert Figure 2 here]

Trading activity in the one-month-ahead NBP forward market is summarized in Figure 3. The number of transactions in the 60-minute intervals and by day of the week (Monday-Friday) is depicted in chart (a). There is higher concentration of trading as the market opens (8:00-10:00) and preceding the day's closure (15:00-16:00). Hence, trading frequency is investigated. Specifically, the number of times where no transactions are recorded in the 60-minute intervals was considered, by day of the week, and its frequency (in percentage) was computed (chart (b)). On average, this frequency is 49% between 16:00 and 17:00, i.e. at the end of the business day. Its value increases to 54% on Fridays. This observation is in line with financial markets, where lower trading activity is observed lunchtime and before trading closure (e.g. Covrig and Melvin, 2002). Consequently, the subsequent analysis is constrained to the trading window 8:00-16:00, which results in $T=10,580$ observations.

The number of transactions per day, over the full sample (chart (c)), indicates decreasing trading activity since May 2013. A seasonal pattern is also observed: transactions per day are greater from September to November and during the winter (January to March), and are likely to reflect weather-dependencies in the natural gas demand. Finally, chart (d) shows the daily trading volume (in therm/day) and its variance, which increase, most noticeably from May 2013 onwards. Together, charts (c) and (d) indicate increasing physical trade size, which is likely to be driven by changes in trading behavior and market composition. As predicted by market microstructure theory, both trading activity and return volatility contribute to liquidity. Given the trends and seasonalities observed above, the time-varying behavior of liquidity in the period is analyzed in the next section.

[Insert Figure 3 here]

4 Results

4.1 On the Distribution of Liquidity Measures in the One-month-ahead NBP Forward Market

Descriptive statistics of the daily average percentage effective half-spread in (1) and its two components, the daily average percentage realized half-spread in (2) and price impact in (3), are presented in Table 2. Daily averages were computed as time-weighted average of the intraday measures, through multiplying each intraday measure by the relative time it was observed during the day. For each measure, mean, standard deviation (Std. Dev.), lower quartile (Q_{25}), median and upper quartile (Q_{75}) from the empirical distributions are shown in columns two to six. The first-order autocorrelation coefficient is in column seven. The distributions are asymmetric and positively autocorrelated. On average, daily transaction costs in the one-month-ahead NBP forward market are 0.311% and split between a transitory and non-informational component of 0.171%, given by the percentage realized half-spread, and a permanent and informational component of 0.140%, given by the price impact measure. That is, on average, inventory costs represent 55% of the transaction costs, the remaining 45% is due to asymmetric information. The t-test for comparing the realized half-spread and price impact means is significant at 5% significance level. Similarly, non-parametric sign tests for the equality between the respective medians and interquartiles are significant at 5% level. Consequently, there are differences between the distributions of the realized half-spread and price impact measures, thus implying distinct behaviors of the different dimensions of liquidity in the one-month-ahead NBP forward market.

4.1.1 On the evolution of liquidity measures in the one-month-ahead NBP forward market

The time-weighted daily average liquidity measures are depicted in chart (a) of Figure 4. Sudden one-day changes are observed, which mainly occur during the contract roll-over, between the last trading day of one month, when the contract expires, and the first trading day of the following month, when the new contract begins to be traded (e.g. 28/07-02/08/2010). Therefore, intra-month

effects are noticeable as the contract approaches delivery. Nonetheless, the focus of this study is on long-term dynamics.

Lower transaction costs are observed from October to March, thus suggesting greater liquidity in the winter. Monthly medians of the liquidity measures, by year, are depicted in charts (b)-(d). They seem to tally with the previous observation on monthly behavior in Figure 3, thus further highlighting the weather-dependent seasonal component of liquidity in the one-month-ahead NBP forward market that resembles the observed pattern of trading activity.

The deseasonalization described in Section 3.3 is summarized in Table 3. It can be observed that the liquidity measures tend to be higher from April to October and lower from November to March, thus implying greater transaction costs and lower liquidity in the summer than in the winter, in accordance with Figure 4. Furthermore, the liquidity measures are higher on Mondays relative to other trading days. Finally, a significant negative trend is found in the time series, thus implying continuous improvement in market liquidity throughout the period.

[Insert Tables 2 and 3 here]

The seasonal adjusted daily liquidity measures are reported in Figure 5, and show an increase in the transaction costs during 2014. Furthermore, liquidity in one-month-ahead NBP forward market is more volatile in 2014, when compared to the previous period. Considering the time series (Figure 4), the deseasonalized measures are higher during the winter, as indicated by their medians (charts (b)-(d)). This pattern is clearer in 2013 and 2014, particularly when the effective and realized half-spread measures are considered.

[Insert Figures 4 and 5 here]

4.1.2 On the distribution of seasonally adjusted measures of liquidity

Descriptive statistics of the seasonally adjusted daily measures are presented in Table 4. Lower asymmetry in the distributions of the effective and realized half-spread measures relative to the non-adjusted series can be observed, as shown by the mean and median values (columns two and

five). Conversely, higher asymmetry of distribution is noticeable in the adjusted price impact, when compared with its non-adjusted measure.

Parameter estimates of the adjustment regressions of the daily trading volume and number of transactions are presented in Table 5. Monthly effects are significant and imply lower and more volatile trading activity in the summer. Trading appears to be lower on Mondays relative to rest of the week. Finally, a significant and negative trend is found in the daily volume and number of transactions.

[Insert Tables 4 and 5 here]

4.1.3 On the evolution of seasonally adjusted measures of liquidity

The adjusted series of the daily trading volume and number of transactions are shown in Figure 6. Data are displayed by year and by month. Especially in 2014, the series highlight a reduction in trading activity, which may be associated with an increase in the transaction costs and consequent decrease in liquidity, as described above.

[Insert Figure 6 here]

Table 6 presents the Spearman's rank correlation coefficients between changes in the seasonal adjusted daily liquidity measures and trading variables. The non-parametric Spearman's rank coefficient has been used since it allows for possible non-linear dependencies between variables, while minimizing the effect of extreme values (Gibbons and Chakraborti, 2003). Correlation is high and positive between changes in the effective and realized half-spreads (0.533), and between changes in the effective half-spread and price impact (0.421); correlation is negative between changes in the realized half-spread and price impact (-0.394). Furthermore, correlation is positive between changes in realized half-spread and daily transactions and trading volumes (0.107 and 0.135), and negative between changes in price impact and daily transactions and trading volumes (-0.113 and -0.114). Overall, the distributions of the individual measures and their evolution imply seasonality and increasing liquidity in the period analyzed. The bivariate correlations confirm the existence of distinct dimensions of liquidity.

4.2 The Association between Transaction Price Returns and Order Flow

The second measure of price impact λ_n in (4), linking transaction price returns to order flow over 60-minute intervals, assesses the pressure exerted by trading activity on the one-month-ahead NBP forward market liquidity. A rolling window size $m=5,000$ is considered over the sample size $T=10,580$, leading to $N=5,581$ estimates of the measure. Parameter estimates of the adjustment regressions accounting for seasonalities and trends in the returns and order flow series are presented in Table 7 and show the intraday patterns. Price returns and order flow tend to be higher in the morning and lunchtime, suggesting a positive association between intraday price returns and order flow. Furthermore, both series are stationary.

[Insert Tables 6 and 7 here]

Adjusted price returns and order flow are used to estimate the time-varying price impact measure λ_n . Confidence intervals, based on Newey-West autocorrelation and heteroscedasticity robust standard errors are depicted in Figure 7- chart (a). A gradual decrease in the measure over the period up to March 2014, and an increase in its level and variance in the subsequent period are observed. When compared with the total order flow over the rolling windows in Figure 7- chart(b), λ_n indicates a positive association between price returns and order flow, which however reduces with increasing order flow. High association between returns and order flow is observed in 2014, which corresponds to a drop in the order and implies lower liquidity, as previously observed in Figure 5.

[Insert Figure 7 here]

4.3 Interpreting the Different Dimensions of Liquidity

Parameter estimates of three way-decomposition of the price impact in (5)-(6) are reported in Table 8. The estimated order-processing costs represent 23.7% of the transaction costs (coefficient γ). Adverse selection (α) and inventory (β) account, respectively, for 14.7% and 50.5% of the transaction costs. Coefficients are significantly different from zero and suggest that inventory costs represent the largest component of transaction costs. A Wald (1943) test for the null hypothesis

of β greater than α is not rejected at 10% level of significance thus supporting this suggestion and findings in Table 6.

Results in Table 8 also highlight positive autocorrelation in the order flow ($\varphi=0.269$). Notwithstanding inventory effects should lead to negatively autocorrelated orders, a positive finding is consistent with the assumption that investors tend to split large-size orders, which would require correspondingly large inventory, by executing them at a single price against different orders to reduce price impact. Results do not change when considering clusters of trades at the same price and unchanged quotes as single orders. The estimated coefficient φ can be regarded as an upper bound on the autocorrelation in order flow Huang and Stoll (1997).

[Insert Table 8 here]

5 Findings and Implications

The measures of spread and price impact from the financial literature, which were adopted in this study, were designed to capture different dimensions of liquidity in financial markets. As a whole, they were found to be applicable to natural gas markets and show an improvement in liquidity of the one-month-ahead NBP forward market from May 2010 to December 2014, which is in line with assessments by the UK independent regulator Ofgem (Ofgem, 2016). Estimated transaction costs were on average 0.31%, according to the mean of the daily percentage effective half-spread, and are in line with estimates by Marshall et al. (2012) concerning the U.S. natural gas futures market. These are estimates of long-term trends in the one-month-ahead NBP forward market, since the analysis has accounted for the predictable variations in the time series. Indeed, the importance of deseasonalizing and detrending the time series can be inferred when the seasonally adjusted measures in Figure 5 are compared with the *churn ratio* in Figure 1 and the unadjusted measures in Figure 4. Low *churn ratio* implies low liquidity, as observed during the winter season. This pattern is unclear when observing the unadjusted measures, but becomes noticeable in the adjusted measures. That is, liquidity in the one-month-ahead NBP forward market is seasonal and is likely to be

driven by trading activity: the lower the trading activity, the lower is the liquidity. This can also be inferred from the traded volumes in Figure 1 and the seasonally adjusted trading activity in Figure 6.

There is support for market microstructure theory (Glosten and Milgrom, 1985; Kyle, 1985; Easley and O’Hara, 1987) and, more broadly, for the view that trading activity affects liquidity, thus extending its implications to physical energy markets. Overall, energy prices have been found to be stationary and mean-reverting (de Jong and Huisman, 2002; Escribano et al., 2011; Lucia and Schwartz, 2002; Huisman and Mahieu, 2003; Lee et al., 2006; Elder and Serletis, 2008; Lee and Lee, 2009) but also non-stationary and persistent (Koopman et al., 2007; Maslyuk and Smyth, 2008; Bosco et al., 2010; Ghoshray and Johnson, 2010; Ozdemir et al., 2013; Barros et al., 2014; Presno et al., 2014). Nonetheless, it is noteworthy that a significant share of this research focused on the period 1990s-early 2000s, which was characterised by low price volatility in energy markets and more stable and stationary price time series. As highlighted by Geman (2007), the properties of the natural gas price series may have changed from mean-reverting to random walk since 2000-2001, which are further supported by the studies of Nick (2016) and Asche et al. (2017). Yet, in contrast to financial markets, natural gas markets are characterized by seasonalities, which affect trading activity and liquidity.

Although some inferences can be made based on the *churn ratio*, it does not allow for the identification of the different dimensions of liquidity, or to measure their relative contribution. The liquidity measures drawn from financial literature and used in this study indicate that over 50% of transaction costs in the period are explained by the inventory component, based on the percentage realized half-spread and the three-way decomposition of transaction costs. Therefore, liquidity dynamics in the one-month-ahead NBP forward market have a stronger association with inventory costs than with asymmetric information. As described in the seminal work of Stoll (1978), greater trading activity may induce inventory imbalances in the market, leading to changes in the bid-ask spreads, and consequently higher transaction costs and lower liquidity. An alternative interpretation of these findings is that trading activity reduces dealers’ inventory positions, and thus increases the

cost of immediacy. This view is supported by the estimates of price impact, λ_n , which underscores a positive correlation between the one-month-ahead NBP forward price returns and the order flow, as has been observed in the context of financial markets (Payne, 2003). In addition, the gradual decrease in this association during the period 2010-13 implies lower immediacy costs, greater depth and resilience of the market, which might reflect the observed lower demand for natural gas, high inventory, and reduced trading activity in that period. The correlation between price returns and order flow increases in 2014, thus implying greater inventory imbalances and low liquidity. Overall, these dynamics support the microstructure theory and the likelihood that trading activity in the one-month-ahead NBP forward market, when driven by increasing oversupply and portfolio rebalancing arguments, might have led to higher correlation of order flow and volatility with liquidity in 2014. This reasoning is supported by Figure 3, which depicts an increasing daily trading volume, lower NBP prices and higher price volatility in 2014, and Figure 5, which amounts to decreasing liquidity in the period.

As a result of the US shale gas revolution, high volumes of coal and LNG came to Europe during 2012-13, when reduced gas and electricity demand due to the economic crisis and low carbon prices in the EU Emissions Trading System were also observed. Together these factors led to a sustained gas to coal switch in the UK power sector (Ofgem, 2015), which may explain the reduced price volatility and the improving liquidity in the period, in line with observations by Hartley (2015). During 2013-14, NBP saw a drop in physical deliveries, in favor of the TTF hub (European Commission, 2015), and a progressive shift of trades from the OTC to exchanges. In 2014, the premium of oil-linked contracts over hub prices in Continental Europe was a strong incentive to buy from hubs, in anticipation of the higher volumes to be taken at lower oil-indexed prices that followed the drop in oil prices from July 2014. This likely behavior of market participants together with a gradual exit of investors from the commodities markets, which had been observed since 2013, might have increased price pressure, and in turn contributed to reduce liquidity and foster price volatility during the second half of 2014. This scenario is consistent with the observed increase in the price impact measure λ_n during 2014, as well as the greater variability of the other liquidity measures in

the same period.

Yet, the competitiveness of coal prices has been partially offset by the introduction of the carbon price floor in the UK since 2013, which reached £18/tonne in April 2015, and by the reduced share of oil-indexed gas prices in Europe. One may expect increasing natural gas demand in the medium term in the UK, particularly after the UK Government cancelled its £1 billion investment in carbon capture and storage technology and restricted coal-fired power plants by 2023, ahead of a full switch off by 2025 (Government of the United Kingdom, 2015). This expectation concerning the demand, coupled with low levels of investment in new flexible gas capacity (i.e. storage capacity, Ofgem (2015)), question the sustainability of the observed trends in liquidity and price volatility in the UK natural gas market. As argued by Felix et al. (2013), storage operators anticipate market liquidity and take this expectation into account in their operating decisions: the lower is liquidity, the higher is the market price, and the lower is the storage value. Storage also represents a real option, because it offers the immediate possibilities to trade natural gas or to wait for changing markets conditions, as prescribed by the theory of storage (Fama and French, 1987, 1988). Thus, low liquidity is a constraint for forward trading when storage value and operation are accounted for. Given the observed positive association between liquidity and price volatility, there are implications for hedging and inventory management, likewise for energy policy decisions, and further research should focus on this association.

In all, this analysis highlights how seasonality is critical in energy markets. Liquidity in the one-month-ahead NBP forward market reflects the weather-dependency in the demand for natural gas. Yet, the present findings demonstrate the importance of trading activity and fundamental values of demand, supply and inventory, as well as the behavior of market participants, in explaining movements in liquidity of natural gas markets. Factors influencing inventory risk and order imbalances can play an important role in explaining the NBP forward market liquidity. Although the reported findings are limited to the share of the market that was analyzed, they support expectations based on previous studies of different markets and reports on the behavior of market players in the UK natural gas market (e.g. Ofgem, 2015).

6 Conclusions

This article illustrates similarities between the natural gas and financial markets, and the usefulness of liquidity measures from financial markets to assess transaction costs and, more generally, the evolution of different dimensions of liquidity in natural gas markets. The three-way decomposition of transaction costs and the price impact measure λ_n have helped to link trading activity to price returns. In particular, the measure λ_n , which differently from previous literature has been estimated in a time-varying fashion, has enabled the assessment of the depth and resilience of the one-month-ahead NBP forward market in the period studied. Such aspects of liquidity cannot be captured by the *churn ratio*, which is traditionally used for monitoring liquidity in energy markets. Consequently, the modified measure of price impact λ_n that was adopted in this study can be valuable to regulators and market analysts when monitoring market quality.

Higher transactions costs imply lower asset prices and higher rate of returns, which are then required to compensate investors for bearing the liquidity cost. They also have consequences for the ability of a market to offer sufficient opportunities for trading, such that individual trades can only have a limited impact on prices. A low liquidity may impede trading, thereby making it easier for a single player to assume a dominant position, with added implications for price fluctuations and volatility. In this respect, the observed decrease in the number of transactions per day, coupled with higher variability in their average volumes, may signal increasing market concentration in the one-month-ahead NBP forward market. If this were the case, the participation of the smaller energy companies in the NBP could be threatened, with strong consequences for competitiveness, investment decisions and overall market efficiency. Yet, the dataset used in this study does not discriminate across market participants, thus limiting the evaluation of trading behaviors. In addition, the assessment of liquidity dimensions and dynamics was restricted to the share of market here examined. With greater availability of data following the implementation of EU directives on market transparency, additional indicators of market quality can be examined and compared. This is an avenue for future research, which may provide further insights on the European energy market quality.

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Table 1: Descriptive statistics of the resampled quotes and transactions at different frequencies

Panel (a): Quotes							
Sample	Obs.	Obs. p.d.	Ask	Bid	Miquote	M_{25}	M_{75}
5 mins	128,018	121	57.05 (8.96)	56.95 (8.97)	57.00 (8.97)	52.50	64.90
15 mins	43,378	41	57.05 (8.96)	56.95 (8.97)	57.00 (8.97)	52.50	64.90
30 mins	22,218	21	57.05 (8.96)	56.95 (8.97)	57.00 (8.97)	52.50	64.90
60 mins	11,638	11	57.05 (8.96)	56.95 (8.97)	57.00 (8.97)	52.52	64.90
Midquote returns							
Sample	Mean	Std. Dev.	Skewness	Kurtosis	ρ_1	Ljung-Box(50)	ARCH(50)
5 mins	0.0002	0.180	21.14	2,176	0.005	59.01	0.480
15 mins	0.0007	0.313	11.83	696.8	-0.002	79.40*	1.803
30 mins	0.0013	0.442	8.384	349.7	0.004	68.78*	4.251
60 mins	0.0026	0.626	5.851	174.7	0.019	84.61**	7.736
Panel (b): Transactions							
Sample	Obs.	Obs. p.d.	Volume	Size	Price	P_{25}	P_{75}
5 mins	128,018	121	21.62 (87.24)	0.01 (0.05)	57.00 (8.97)	52.55	64.90
15 mins	43,378	41	63.79 (159.9)	0.04 (0.10)	57.00 (8.97)	52.55	64.90
30 mins	22,218	21	125.5 (237.7)	0.07 (0.14)	57.00 (8.97)	52.55	64.90
60 mins	11,638	11	237.8 (351.4)	0.14 (0.21)	57.00 (8.97)	52.55	64.90
Price Returns							
Sample	Mean	Std. Dev.	Skewness	Kurtosis	ρ_1	Ljung-Box(50)	ARCH(50)
5 mins	0.0002	0.183	18.85	1,872	0.006	49.89	0.677
15 mins	0.0005	0.318	10.96	627.9	0.006	74.26*	2.427
30 mins	0.0011	0.451	7.668	313.2	-0.004	82.42**	4.799
60 mins	0.0022	0.631	5.412	160.2	0.002	83.93**	7.502

Note: The table reports the descriptive statistics of the time series resampled at different frequencies (5, 15, 30 and 60 minutes). The number of observations (column two) and observations per day (column three) are in the top of Panel (a), along with the average ask and bid indicative quotes (pence/therm), and the corresponding midquotes (columns four, five and six). Standard errors are in brackets. The first (M_{25}) and third (M_{75}) interquartile of the midquotes are in column seven and eight, respectively. Descriptive statistics of the transaction series are shown in the top of Panel (b). Number of observations and observations per day are in columns two and three. The average volume (1,000 therm/day), size (million £) and transaction price (pence/therm) observed in each interval are shown in columns three to five along with their standard errors (in brackets). Columns seven and eight show the first (P_{25}) and third (P_{75}) interquartile of the price series. The distributions of the midquote and transaction price return series, pre-multiplied by 10^2 , are summarized in the bottom of Panels (a) and (b). The first four moments are in columns two to five (Mean, Std.Dev., Skewness and Kurtosis). The first-order autocorrelation function, ρ_1 , is in column six. Columns seven and eight report, respectively, the Ljung-Box statistics for the null hypothesis of serial independence and the ARCH test for the null hypothesis of homoscedasticity. These tests were computed at the 50th order of lags, which accounts for a time window spanning one day (series resampled at 5-minute frequency) to one week (Monday-Friday, data resampled at 60-minute frequency). ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table 2: Descriptive statistics of the daily average percentage liquidity measures

	Mean	Std. Dev.	Q^{25}	Median	Q^{75}	ρ_1
Effective half-spread	0.311	0.222	0.164	0.243	0.388	0.589***
Realized half-spread	0.171	0.185	0.064	0.129	0.241	0.378**
Price Impact	0.140	0.146	0.062	0.113	0.184	0.258**

Note: The table reports descriptive statistics of the daily average liquidity measures over a sample size $T=1,058$ daily observations. These measures were computed as time-weighted average of the observed intraday measures, through multiplying each intraday measure by the relative time it was observed during the day. For each measure, mean, standard deviation (Std. Dev.), lower quartile (Q_{25}), median and upper quartile (Q_{75}) from the empirical distributions are shown, likewise the estimated first-order autocorrelation. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table 3: Parameter estimates of the adjustment regressions of the daily liquidity measures

		Effective half-spread			Realised half-spread			Price impact		
		Coeff.	Std.Err.	t-Stat	Coeff.	Std.Err.	t-Stat	Coeff.	Std.Err.	t-Stat
Intercept		0.450***	0.040	11.19	0.257***	0.031	8.270	0.193***	0.018	10.91
Month	February	0.038	0.042	0.925	0.034	0.030	1.112	0.005	0.020	0.231
	March	0.021	0.037	0.568	0.003	0.029	0.105	0.018	0.014	1.243
	April	0.139***	0.039	3.552	0.079**	0.031	2.531	0.059**	0.023	2.562
	May	0.194***	0.058	3.325	0.115***	0.033	3.471	0.080**	0.030	2.647
	June	0.175**	0.059	2.971	0.108**	0.036	2.972	0.067**	0.023	2.953
	July	0.156**	0.058	2.680	0.106**	0.037	2.890	0.050**	0.024	2.068
	August	0.177***	0.043	4.118	0.083**	0.030	2.767	0.094***	0.023	4.033
	September	0.137***	0.044	3.147	0.098***	0.029	3.401	0.039**	0.017	2.290
	October	0.115**	0.040	2.870	0.094***	0.030	3.130	0.022*	0.013	1.609
	November	0.027	0.046	0.573	0.011	0.035	0.307	0.016	0.016	0.998
	December	0.031	0.045	0.692	-0.021	0.033	-0.645	0.053*	0.027	1.927
Day of the week										
	Tuesday	-0.079***	0.016	-5.032	-0.033*	0.017	-1.877	-0.047***	0.014	-3.435
	Wednesday	-0.089***	0.016	-5.492	-0.041**	0.017	-2.326	-0.049***	0.015	-3.334
	Thursday	-0.092***	0.016	-5.739	-0.040**	0.016	-2.503	-0.051***	0.014	-3.717
	Friday	-0.068***	0.016	-4.169	-0.018	0.018	-1.037	-0.049***	0.014	-3.407
Trend		-0.0003***	0.00004	-7.561	-0.0002***	0.00003	-9.00	-0.0001***	0.00002	-4.987

Note: The table reports the parameter estimates of the adjustment regressions of the daily liquidity measures on 11 month-of-the-year dummies (February - December); 4 day-of-the-week dummies (Tuesday-Friday); a time-trend, over a sample size $T=1,058$ observations. Robust standard errors are based on Newey-West estimator. ***, **, * denote 1%, 5% and 10% significance level, respectively.

Table 4: Descriptive statistics of the seasonally adjusted daily liquidity measures

	Mean	St. Dev.	Q^{25}	Median	Q^{75}	ρ_1
Effective half-spread	0.311	0.222	0.173	0.262	0.393	0.397***
Realized half-spread	0.171	0.185	0.078	0.145	0.237	0.156***
Price impact	0.140	0.146	0.059	0.112	0.196	0.189***

Note: The table reports descriptive statistics of the seasonally adjusted liquidity measures over a sample size $T=1,058$ observations. For each measure, mean, standard deviation (St. Dev.), lower quartile (Q_{25}), median and upper quartile (Q_{75}) from the empirical distributions are shown, likewise the estimated auto-correlations at lag one. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table 5: Parameter estimates of the adjustment regressions of the daily trading variables

		Trading volume			Number of transactions		
		Coeff.	Std.Err.	t-Stat	Coeff.	Std.Err.	t-Stat
Intercept		8.031***	0.800	10.039	4.648***	0.660	7.042
Month	February	0.065	0.090	0.726	0.122*	0.067	1.809
	March	-0.147	0.094	-1.564	-0.161***	0.084	-1.912
	April	-0.283***	0.088	-3.211	-0.231***	0.065	-3.545
	May	-0.399***	0.103	-3.888	-0.380***	0.072	-5.314
	June	-0.530***	0.101	-5.236	-0.577***	0.084	-6.907
	July	-0.593***	0.095	-6.231	-0.570***	0.076	-7.516
	August	-0.469***	0.097	-4.821	-0.543***	0.079	-6.915
	September	-0.324***	0.095	-3.420	-0.375***	0.077	-4.861
	October	-0.175*	0.092	-1.890	-0.235***	0.069	-3.396
	November	-0.079	0.092	-0.866	-0.168**	0.077	-2.171
	December	-0.726***	0.114	-6.367	-0.847***	0.102	-8.340
Day of the week							
	Tuesday	0.265***	0.044	6.014	0.169***	0.035	4.806
	Wednesday	0.195***	0.048	4.073	0.100**	0.045	2.229
	Thursday	0.207***	0.048	4.307	0.119**	0.040	2.941
Trend	Friday	0.089*	0.050	1.792	0.027	0.039	0.699
		-0.0003***	0.00006	-4.490	-0.0006***	0.00006	-10.785

Note: The table reports the parameter estimates of the adjustment regressions of the daily trading volume and number of transactions on 11 month-of-the-year dummies (February - December); 4 day-of-the-week dummies (Tuesday-Friday); a time-trend, over a sample size $T=1,058$ observations. Robust standard errors are based on Newey-West estimator. ***, **, * denote 1%, 5% and 10% significance level, respectively.

Table 6: Association between changes in liquidity and trading activity: Spearman's rank correlation coefficients

	Effective half-spread	Realized half-spread	Price Impact	Number of transactions
Realized half-spread	0.533***			
Price Impact	0.421***	-0.394***		
Number of transactions	-0.003	0.107***	-0.113***	
Trading Volume	0.031	0.135***	-0.114***	0.729***

Note: The table gives the Spearman's correlation coefficients between the daily liquidity measures and trading variables. ***, ** and * denote significance at 1%, 5% and 10%, respectively, under the null hypothesis of no correlation.

Table 7: Parameter estimates of the adjustment regressions of the price returns and order flow resampled at 60-minute intervals

		Price returns			Order flow		
		Coeff.	Std.Er.	t-Stat	Coeff.	Std.Er.	t-Stat
Intercept		-0.005	0.027	-0.204	-0.106	2.570	-0.041
Month	February	0.005	0.027	0.186	2.508	3.017	0.831
	March	0.030	0.027	1.125	2.200	2.618	0.840
	April	-0.042	0.030	-1.372	-6.212**	3.001	-2.070
	May	-0.019	0.026	-0.731	-2.260	2.774	-0.815
	June	0.022	0.026	0.837	-2.279	2.672	-0.853
	July	0.006	0.026	0.211	-1.118	2.516	-0.444
	August	0.020	0.025	0.791	-0.823	2.736	-0.301
	September	0.056	0.036	1.561	-0.464	2.798	-0.166
	October	0.050*	0.029	1.753	-1.346	2.626	-0.513
	November	0.030	0.023	1.297	0.446	2.533	0.176
	December	0.001	0.025	0.026	-2.854	2.267	-1.259
Day of the week							
	Tuesday	-0.041*	0.022	-1.848	-0.330	1.498	-0.220
	Wednesday	-0.016	0.022	-0.740	1.350	1.512	0.893
	Thursday	-0.024	0.021	-1.137	-0.273	1.458	-0.187
	Friday	0.010	0.022	0.451	1.994	1.488	1.377
Hour of the day							
	8.00	-0.043	0.033	-1.306	5.999***	2.2.047	2.931
	9.00	0.071**	0.028	2.519	4.127**	1.830	2.255
	10.00	0.053**	0.027	1.955	5.133***	1.574	3.260
	11.00	0.024	0.016	1.470	2.047	1.450	1.412
	12.00	0.020	0.017	1.201	2.050	1.335	1.536
	13.00	0.026*	0.015	1.732	3.152**	1.330	2.370
	14.00	0.022	0.016	1.352	1.567	1.518	1.033
	15.00	0.010	0.021	0.462	-0.134	1.625	-0.083
Trend		-0.002	0.002	-0.891	-0.030	0.158	-0.188

Note: The table reports the parameter estimates of the adjustment regressions of the price returns and order flow on 11 month-of-the-year dummies (February - December); 4 day-of-the-week dummies (Tuesday-Friday); 8 hour-of-the-day dummies (8:00-15:00); a time-trend, over a sample size $T=10,580$ observations resampled at 60-minute frequency. Time-trend coefficients and standard errors have been pre-multiplied by 10^3 . Robust standard errors are based on Newey-West estimator. ***, **, * denote 1%, 5% and 10% significance level, respectively.

Table 8: Parameter estimates of three way-decomposition of the transaction costs

	Coeff.	Std.Err.	t-Stat
γ	0.237***	0.007	34.06
α	0.147*	0.086	1.703
β	0.505***	0.087	5.820
φ	0.269***	0.037	7.248
<i>Adjusted R</i> ²	0.132		

Note: The table reports the parameter estimates of three way-decomposition of the price impact using GMM over a sample size $T=10,580$ observations. γ is the estimated order-processing component; α is the estimated adverse selection component; β is the estimated inventory cost component; φ is the estimated first-order autocorrelation of the order flow process. Constant terms are suppressed in the table. Robust standard errors are based on Newey-West estimator. ***, **, * denote 1%, 5% and 10% significance level, respectively.

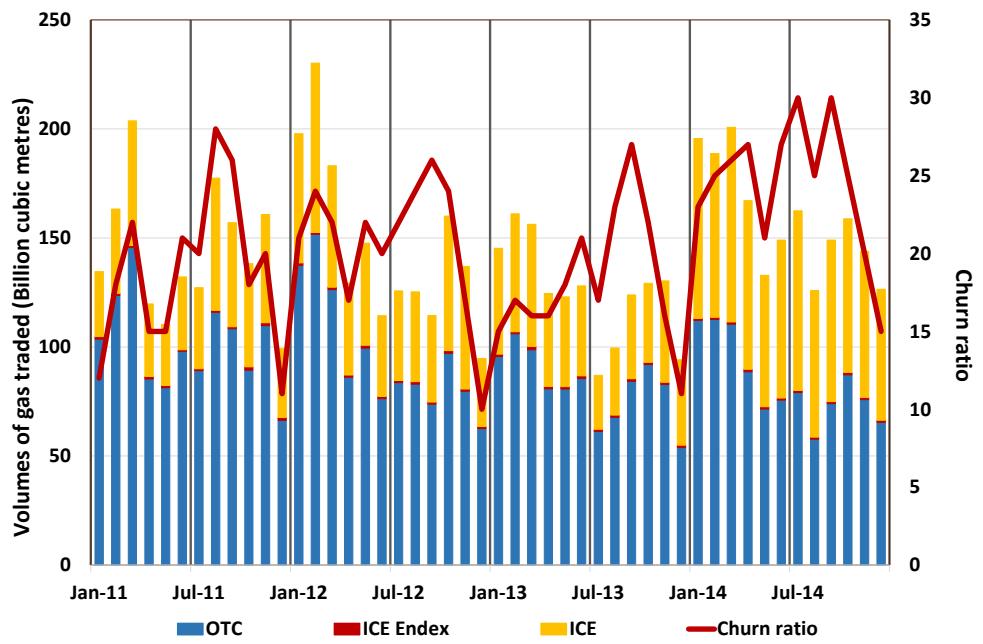


Figure 1: Monthly NBP traded volume and churn ratio (Source data: Ofgem-Data portal)

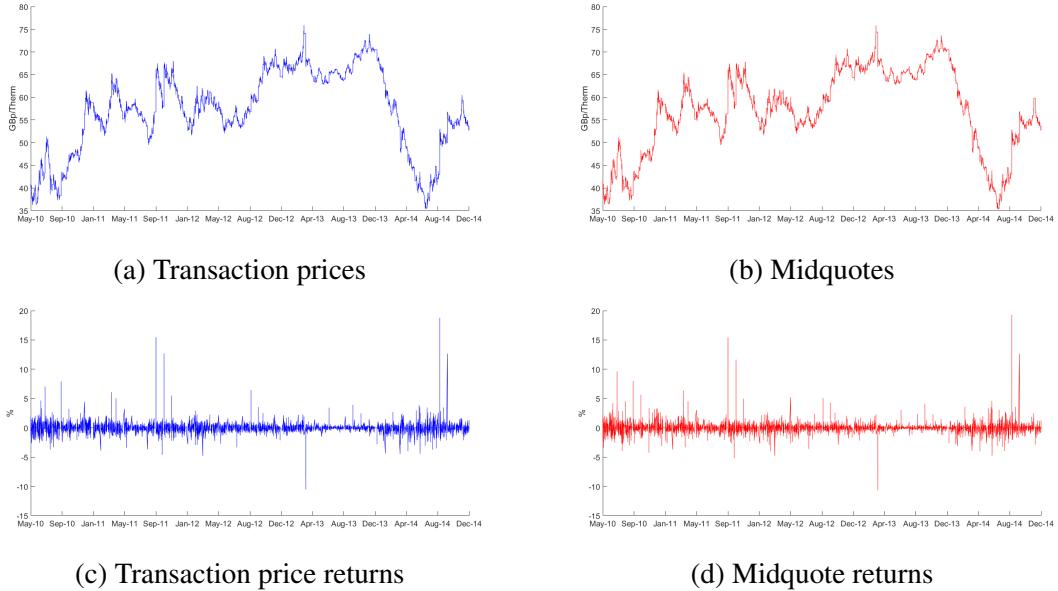


Figure 2: NBP transaction price and midquote series at 60-minute frequency

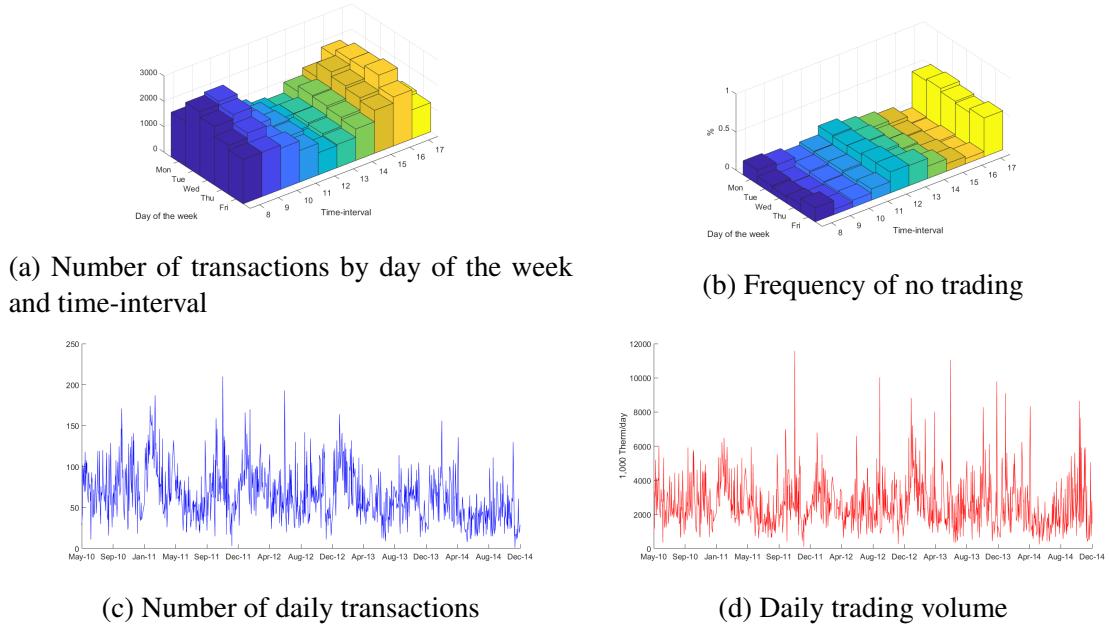
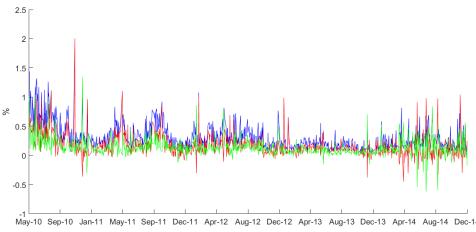
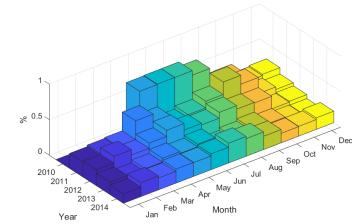


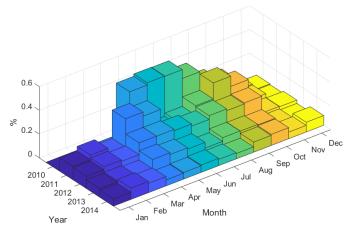
Figure 3: Number of transactions and no trading frequency



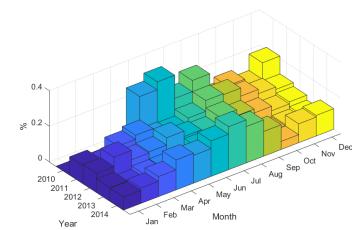
(a) Daily time-weighted averages: Effective half-spread (blue line); Realized half-spread (red); Price impact (green)



(b) Effective half-spread medians

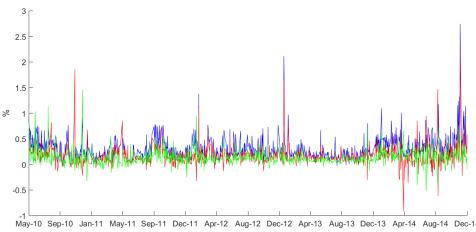


(c) Realized half-spread medians

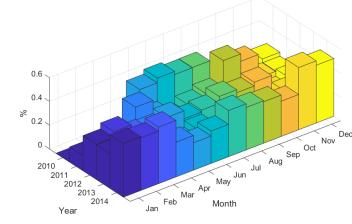


(d) Price impact medians

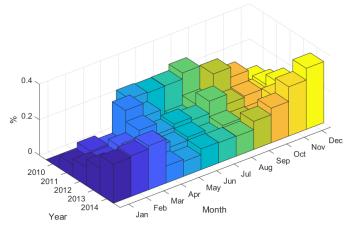
Figure 4: Liquidity measures in the one-month-ahead NBP forward market



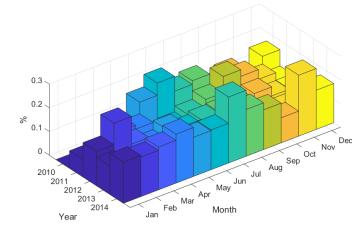
(a) Daily time-weighted averages: Effective half-spread (blue line); Realized half-spread (red); Price impact (green)



(b) Effective half-spread medians

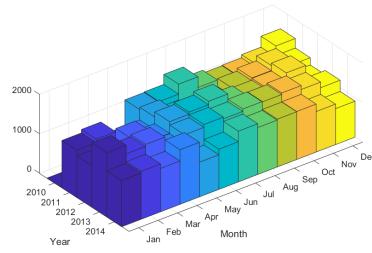


(c) Realized half-spread medians

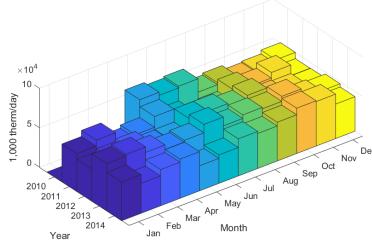


(d) Price impact medians

Figure 5: Seasonally adjusted liquidity measures

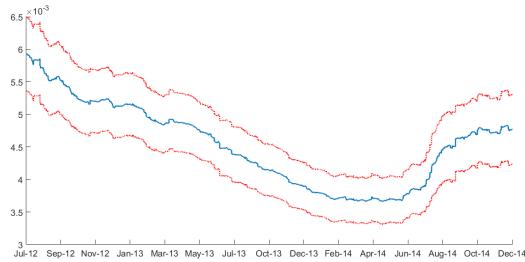


(a) Number of transactions



(b) Trading volume

Figure 6: Seasonally adjusted daily trading variables



(a) λ (blue line) \pm 2 std. err. (red)



(b) Order flow

Figure 7: Time-varying price impact measure λ and order flow over the rolling windows